SEMI-AUTOMATIC CATHETER MODEL GENERATION USING BIPLANE X-RAY IMAGES

Sebastian Kaeppler\textsuperscript{1*} Wen Wu\textsuperscript{2} Terrence Chen\textsuperscript{2} Martin Koch\textsuperscript{1} 
Atilla P. Kiraly\textsuperscript{2} Norbert Strobel\textsuperscript{3} Joachim Hornegger\textsuperscript{1}

\textsuperscript{1} Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany
\textsuperscript{2} Siemens Corporation, Corporate Technology, Princeton, NJ, USA
\textsuperscript{3} Siemens AG, Healthcare Sector, Forchheim, Germany

ABSTRACT
Recently, techniques for the automatic detection or tracking of surgical instruments in X-ray guided computer-assisted interventions have emerged. The purposes of these methods are to facilitate either inter-modality registration, motion compensation, enhanced visualization or automatic landmark generation in augmented-reality applications. Most techniques incorporate a model of the device as prior information to evaluate results obtained from a low-level detector. In this paper, we present novel approaches which are able to generate both 2-D and 3-D models of circular and linear catheters from biplane X-ray images with only minimal user input. We apply these methods in the context of Electrophysiology to generate models of ablation and mapping catheters. An evaluation on clinical datasets yielded promising results.

Index Terms— X-ray, Biplane, Ablation, Mapping, Catheter, Model, Semi-automatic, Reconstruction, Detection, Electrophysiology

1. INTRODUCTION
C-arm fluoroscopy is the standard imaging modality for cardiac catheterization procedures. In addition to the standard fluoroscopic images, pre- and intra-procedurally acquired volumetric images can be rendered on top of the 2-D images to improve navigation. During the last few years, automatic device detection and tracking methods for X-ray images have been proposed. These methods enable a variety of further applications and improvements, such as motion compensation [1, 2], intra-modality registration [3], enhanced visualization or automated landmark generation. Almost all methods are based on a common principle - low-level detection results are evaluated in the context of a model, representing the shape of the device that is to be detected. While the model can be fixed in the detection algorithm for some devices, the variety or adjustability of others requires a manual delineation of the device by the user to initialize the detection algorithm. However, increased user interaction might reduce the clinical acceptance of such methods. In order to overcome this disadvantage, we propose two novel semi-automatic algorithms for 2-D catheter detection and 3-D shape model generation using a biplane X-ray image pair. The first algorithm is capable of detecting and reconstructing flexible linear catheters, for example diagnostic or ablation catheters. The second algorithm is for circular catheters, such as the mapping or the pigtail catheter. The method for linear catheters requires only one click on the catheter body in one imaging plane. The method for circular catheters requires one click on the catheter top in each plane. Both methods are capable of generating 2-D and 3-D catheter models. Additionally, the position of electrodes on the catheter can be detected and reconstructed. The resulting 3-D models may not only be used to initialize detection algorithms, but also for 3-D visualization of the catheter. While our algorithms are designed for biplane images, they can easily be adapted to generate 2-D models from monoplane images. Compared to previous work on catheter detection and reconstruction [4, 5, 6], our methods favor speed and robustness on challenging images over generality by including more prior knowledge of the catheter that is to be detected.

2. METHODS
We demonstrate the effectiveness of our algorithms by applying them to two catheter types commonly used in Electrophysiology (EP) procedures: ablation and circular mapping catheters. Note that our algorithms may easily be adjusted to other types of catheters by a change of parameters.

2.1. Linear Ablation Catheter
Ablation catheters are linear catheters with a diameter of about 2.4 mm. The distal part of the catheter consists of a tip, and depending on type and manufacturer, two or three additional electrodes. This part is of interest for detection and visualization. We separate the catheter model generation process into four stages: Joint 2-D body detection, 2-D body refinement, 3-D model reconstruction and 3-D electrode detection. Initially, the user has to select a point on the catheter body in one of the image planes. A quadratic region of inter-
est (ROI) with a side length of 5 cm is centered around the click in the image plane (Fig. 1(a)). In the other image plane, the ROI is determined by the epipolar lines of top and bottom of the ROI that was determined in the first plane. In both planes, the ROI is further restricted by obtaining the positions of the shutter blades. As described in [2], we employ two probabilistic boosting tree classifiers with Haar-like features on the ROI. One is trained to detect the tip of the catheter, the other to detect electrodes. For catheters with only two additional electrodes, we treat the end of the tip as an electrode. Local maxima of the detection maps are found using non maximum suppression. We refer to these 2-D points as tip and electrode candidates and denote them as $t_A$ and $e_A$ for plane A, and $t_B$ and $e_B$ for plane B, respectively. For the tip, we keep two candidates with the highest probability in each plane, for the electrodes we keep six. Using these candidates, we perform a joint coarse detection of the catheter body in both planes by evaluating a set of hypotheses. Each hypothesis $H$ is determined by selecting a tip and an electrode candidate in each plane $(t_A^H, t_B^H, e_A^H, e_B^H)$. Hypotheses and detection candidates in one plane are depicted in Fig. 1(b). We exhaustively evaluate all 144 resulting hypotheses by a scoring function. The score $S(H)$ for hypothesis $H$ consists of a 3-D tip probability $T(H)$ and two 2-D body scores $B_A(H), B_B(H)$ and is computed as

$$S(H) = T(H) \cdot (B_A(H) + B_B(H)).$$  (1)

The tip probability $T(H)$ is modeled by multiplying the 2-D detection probabilities of the tip candidates with each other and the probability of their correspondence

$$T(H) = p(t_A^H) \cdot p(t_B^H) \cdot p_{cor}(t_A^H, t_B^H).$$  (2)

The correspondence probability $p_{cor}(t_A^H, t_B^H)$ measures the likelihood of the correspondence of the two 2-D points based on the symmetric epipolar distance.

The body scores for each plane are computed by fitting a 2-D line, where the start point is the tip candidate, the direction is the vector from the tip candidate to the electrode candidate, and the length is a device- and geometry-dependent value. All tip and electrode candidates as well as the point supplied by the user contribute to the score of the body based on their detection probability and their orthogonal distance to this line. Candidates in one plane whose epipolar lines do not intersect with the hypothesis’ line in the other plane do not contribute to the score.

After the scoring process, only the hypothesis with the highest score is kept. In each plane, a rectangle is positioned around the previously determined line and all electrode and tip candidates which are not within the rectangle are removed. The next step in the body detection process is the 2-D model refinement. A 2-D second degree polynomial curve is fitted to the detection candidates in each plane (Fig. 1(c)). The catheter tip is used as starting point, and the fitting is performed using weighted ridge regression, with the weights corresponding to the detection probabilities of the electrode candidates. Regularization is applied to the curve’s curvature to yield a more robust fit.

The third step is 3-D body reconstruction. One of the polynomial curves is densely sampled. For each sample point, its epipolar line in the other image is computed and intersected with the other 2-D curve. Since we intersect a line with a 2-D second degree polynomial curve, we may get two solutions. The intersection point corresponding to the previously determined line model is selected. For each pair of corresponding points, a 3-D point is triangulated. The set of 3-D points represents the catheter body in 3-D. The reconstruction process is stopped after a 3-D model with a predetermined and catheter specific length (in this case, 17 mm) has been reconstructed.

To detect the 3-D positions of the catheter electrodes, each 3-D point is assigned a score which is the sum of the probabilities of its corresponding 2-D points. In this context, we use the maximum of the tip and electrode classifier probabilities as probability in 2-D. Afterwards the 3-D model is split up into segments with a length of 0.5 mm, starting after the tip. For each segment, the 3-D point with the highest score is determined and stored as a 3-D electrode candidate. Different hypotheses for catheter electrode configurations are generated by selecting all combinations of three 3-D electrode candidates which satisfy physical constraints (minimum and maximum electrode distance, minimum catheter length). Each hypothesis is evaluated by another scoring function, which multiplies the scores of the three 3-D electrode candidates. Electrode candidates corresponding to a local maximum of the probability along the 3-D model boost the hypothesis.
score by factor two. The three 3-D electrode candidates of
the hypothesis with the highest score are chosen as catheter
electrodes. If necessary, the 3-D tip and electrode points can
be forward projected to obtain 2-D electrode locations. The
final result of our detection algorithm is shown in Fig. 1(d).

2.2. Circular Mapping Catheter

The mapping catheter consists of a circular tip that is posi-
tioned at the ostia of the Pulmonary Veins to measure elec-
trical signals. Typical mapping catheters have ten to twenty
electrodes. Our semi-automatic detection of its tip is based
on a fast shape candidate generation-and-testing approach.
Promising candidates are stored and optimized before a final
hypothesis selection stage. The detection and reconstruction
process is started with the user marking the top of the circu-
lar tip in both planes (Fig. 2(a)). Using these corresponding
points, a 3-D point is triangulated. A rectangular ROI is posi-
tioned at the top of the catheter.

As before, a probabilistic boosting tree with Haar-like fea-
tures is applied to detect electrode candidates \( e_A, e_B \) in 2-D.
The fifteen candidates with the strongest response are stored.
Similar to the approach presented in [1], we also perform
vesselness filtering of the image, followed by thresholding,
skeletonization and distance map computation. However, we
refine the vesselness map after thresholding by removing all
filter responses which are not connected to an electrode can-
didate (Fig. 2(b)).

Since the catheter tip is circular, we chose to represent it as
a circle in 3-D, which can be parameterized with six para-
eters: 3-D center, radius and direction. Using the constraint
that the 3-D point supplied by the user is the top of the circle,
the center may be computed analytically for a given radius
and direction. We uniformly sample radii and directions on a
half sphere (due to the symmetricity of a circle) and use them
calculate the center of a 3-D circle hypothesis. In total we gen-
erate about 11000 hypotheses with ten different radii, ranging
from 6.0 to 15.0 mm. Thus, we sample about 1100 directions
per radius. Each hypothesis \( H \) is assigned a probability \( p(H) \),
which is computed as:

\[
p(H) = p_A(H) \cdot p_B(H) \cdot p_{\text{prior}}(H) \cdot p_{\text{const}}(H).
\]  

(3)

The prior term \( p_{\text{prior}}(H) \) models prior knowledge about the
radius of the catheter. Since the mapping catheter is posi-
tioned at the ostia of a pulmonary vein, we model it as a
mixtures of gaussians, with parameters taken from medical
literature [7]. The soft constraint term, \( p_{\text{const}}(H) \), prevents
solutions which are too far away from the points marked by
the user. At this stage, this particular term has no effect since
all hypotheses were created using the user supplied points as
constraint.

The data terms \( p_A(H) \) and \( p_B(H) \) measure the fit of the
hypothesis to the image in plane A and B, respectively. We
model each of these data probabilities by averaging two
probabilistic sub-measurements. The first one measures how
many of the detected electrode candidates are accounted for
by the hypotheses. We reduce the detection probability of
each electrode candidate based on its distance to the forward
projected 3-D circle. The sum of all distance-adjusted proba-
bilities is divided by the sum of the original probabilities and
multiplied by a constant, yielding the first measurement. The
second measurement of the fit of the circle hypothesis uses
the distance map. We uniformly sample points on the 3-D
circle and forward project them. The distance map is sampled
on these points. Due to foreshortening, too many samples
may fall on top and bottom of the resulting ellipse in 2-D.
We employ a weighting scheme to counter this effect and
compute a weighted average of the distance to the detected
catheter body. The resulting value is mapped into a value
range of [0..1].

All hypotheses with a probability below a predetermined
threshold are discarded. We chose the value for the thresh-
solding such that typically 100 to 200 hypotheses remain.
The parameters of the remaining hypotheses (one example
is shown in Fig. 2(c)) are optimized by applying a limited
number of iterations of the well known Broyden-Fletcher-
Goldfarb-Shanno (BFGS) method to minimize the function

\[
p'(H) = -[p'_A(H) \cdot p'_B(H) \cdot p_{\text{prior}}(H) \cdot p_{\text{const}}(H)].
\]  

(4)

This function is a variant of Eq. (3). The soft constraint
term is more relaxed and the data terms only consider the
distance map. Omission of the electrode information leads to
a smoother objective function which is less susceptible to get
stuck in a local minimum. Essentially, this step may be con-
sidered as 2-D/3-D registration comparable to the approach
presented in [1]. Afterwards, all hypotheses which have been
optimized are evaluated a second time using Eq. (3). This
step is justified, since Eq. (3) captures more information,
while Eq. (4) is more suitable for parameter optimization.

The hypothesis with the highest probability is selected as
3-D catheter model. 2-D models may easily be obtained by
forward projecting the 3-D model, as depicted in Fig. 2(d).
To obtain electrode positions in 2-D, the electrode candidate
probabilities are first adjusted based on their distance to the
2-D model. The candidates with the highest probability are
selected. 3-D coordinates of electrodes can be obtained by
back projecting the 2-D electrode candidates onto the catheter
model in 3-D.

3. EXPERIMENTAL RESULTS

3.1. Evaluation workflow

In our evaluation of the linear ablation catheter reconstruc-
tion, the second electrode of the catheter in plane A was
marked and the reconstruction was started automatically
hereafter. Since we had no ground truth 3-D model of the
catheter available, we forward projected the detected tip
and electrodes into both 2-D images. We measured the dis-
tance between the detected and manually annotated tip and
Fig. 2. Mapping catheter detection steps: (a) biplane input images, (b) preprocessing results, (c) intermediate shape candidate, (d) final result. The user clicks are depicted in red, the electrode candidates in blue.

3.2. Evaluation results

For our evaluation, we used 46 biplane images to evaluate the ablation catheter reconstruction. For the mapping catheter reconstruction, we used 37 image pairs. The images were acquired in two clinics during live interventions. Applying the criterion described above resulted in a successful initialization rate of 91 % (42/46) for the ablation and 92 % (34/37) for the mapping catheter. On our test system (Intel Core i7-2720QM, 8GB RAM), the maximum runtime was 702 ms for the mapping, and 436 ms for the ablation catheter detection.

4. CONCLUSION

In this paper, we proposed two semi-automatic methods to detect and reconstruct linear and circular catheters in both 2-D and 3-D using a biplane X-ray image pair. An evaluation of both techniques using clinical data demonstrated their performance and robustness. Compared to previous work, the proposed methods incorporate more knowledge about the catheters that are to be detected. We believe that this information is necessary to achieve acceptable performance in challenging scenarios.

Our method to reconstruct linear catheters could easily be turned into a fully automatic catheter detection by removing the restriction to a region of interest and the user initialization term in the body selection. Initial results in this direction are promising. Additionally, both algorithms may easily be adapted to 2-D operation on single plane images by simply removing the data terms considering the second plane. We are also currently investigating how additional seed points can be integrated into the framework to correct failed detections.

Acknowledgements:

This work was supported by the German Federal Ministry of Education and Research (BMBF) in the context of the initiative Spitzencluster Medical Valley, project grant Nos. 01EX1012A and 01EX1012E. Additional funding was provided by Siemens AG, Healthcare Sector. The concepts and information presented in this paper are based on research and are not commercially available.

5. REFERENCES


