Guide wire tracking in interventional radiology


Image Sciences Institute, University Medical Center Utrecht, rm E 01.334, P.O.Box 85500, 3508 GA Utrecht, The Netherlands

A method is presented to aid the extraction and tracking of guide wires during X-ray fluoroscopy guided endovascular interventions. A two-step procedure is utilized, in which first a rigid translation is determined to capture the rough displacement and next a spline optimization is performed for accurate localization of the guide wire. Both the application of subtraction images and filters which enhance line-like structures are investigated. With the optimal settings, the guide wire was tracked successfully in 141 out of 146 frames from 5 image sequences.

Keywords: X-ray fluoroscopy, tracking, matching, interventional radiology

1. INTRODUCTION

A growing interest exists in using endovascular interventions as an alternative for conventional, more invasive, surgical techniques. These interventions require an accurate positioning of the guide wire and the catheter with regard to the vasculature, which is achieved under fluoroscopic control. Owing to the low dose used in fluoroscopy in order to minimize the radiation exposure of the patient and radiologist, the image quality is often limited. This can preclude an accurate localization of the guide wire tip. Therefore, a method is developed to extract and track guide wires during X-ray fluoroscopy guided interventions. The method is constructed so as to deal with the low signal to noise ratio inherent to fluoroscopic images, and motion artifacts as introduced by patient and device motion. The method can be used to improve guide wire visualization, potentially enabling a reduction of radiation exposure. It can also be used to detect the position of the guide wire in world coordinates for registration with preoperatively acquired images as a navigation tool for radiologists.

2. MATERIAL AND METHODS

In order to represent the guide wire we use a spline parameterization. For all experiments in this paper, we used a third order B-spline curve defined by:

\[
C(u) = \frac{\sum_{i=0}^{n} N_{i,3}(u)w_i P_i}{\sum_{i=0}^{n} N_{i,3}(u)w_i}, 0 \leq u \leq 1
\]
where \( P_i \) denote the control points (forming a control polygon), \( w_i \) are the weights and \( N_{i,3}(u) \) are the third degree B-spline basis functions defined on the non-periodic knot vector

\[
U = \{0, \ldots, 0, u_4, \ldots, u_{m-4}, 1, \ldots, 1\}
\]

where \( m \) is the number of knots.

In order to find the spline in frame \( n + 1 \) if the position in frame \( n \) is known, a two-step procedure is applied. First, a rigid translation is determined to approximate the rough displacement of the spline. Next, a spline optimization procedure is performed in which the spline is allowed to deform to capture the shape in the new frame. These steps can be understood as a coarse-to-fine strategy, where the first step ensures a sufficiently good initialization for the spline optimization.

### 2.1. Rigid transformation

In order to obtain a first estimate of the displacement, a binary template is constructed based on the position in the present frame. The best location of this template in the new frame is obtained by determining the highest cross correlation with a certain search region in this image (or features derived from it; see section 2.3).

### 2.2. Spline optimization

If the first step is carried out, the spline is optimized under internal and external forces. The internal constraints are related to the geometry of the curve and influence the length (first derivative of the B-spline) and the bendedness (second derivative of the spline). For the external forces, the image grey values (or a derived feature image, see section 2.3) are used. The spline contains four or five control points and one hundred sample points. The spline is optimized using Powell’s direction set method.

### 2.3. Feature image

In both steps (i.e. obtaining the rigid transformation using cross correlation and spline optimization) a feature image is used to determine the optimal spline position. We compare the use of image intensity, subtraction images and images in which line-like structures are enhanced.

Subtraction images are obtained by subtracting the first frame from frame \( n \). The first frame is used to ensure sufficient guide wire movement so as to make it clearly visible in the subtraction image. In our experiments we used image sequences with a maximum of 49 frames. For longer sequences it will be better to subtract for example frame \( n - 20 \) from the present frame, to limit the effects of background motion. Alternatively, methods for motion correction in subtraction techniques can be used, see [1].

In order to enhance elongated structures in the image, the eigenvalues of the Hessian
matrix are calculated at scale \( \sigma \). This Hessian matrix is defined as:

\[
H = \begin{pmatrix}
L_{xx} & L_{xy} \\
L_{xy} & L_{yy}
\end{pmatrix}
\]  

(3)

where \( L_{xx} \) represents the convolution with the scaled Gaussian derivative

\[
L_{xx} = L * \frac{\partial^2}{\partial x^2} G(x, \sigma)
\]

(4)

where \( G(x, \sigma) \) is given as

\[
G(x, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}
\]

(5)

The corresponding eigenvalues are given by:

\[
\lambda_{1,2}(x, \sigma) = \frac{1}{2} \left( L_{xx} + L_{yy} \pm \sqrt{(L_{xx} - L_{yy})^2 + 4L_{xy}^2} \right)
\]

(6)

Let \( \lambda_1 \) denote the largest absolute eigenvalue. On line-like structures \( \lambda_1 \) has a large output. Since we are interested in dark elongated structures on a brighter background, only positive values of \( \lambda_1 \) are considered; negative values of \( \lambda_1 \) are set to zero. The feature image is subsequently constructed by inverting this image since the optimization is based on a minimum cost approach, see Figure 1.

Figure 1. The original image (left) and the feature image computed with the eigenvalues of the Hessian matrix with \( \sigma = 1.5 \) (right).

This feature image can be calculated at multiple scales (\( \sigma \)), (i) to be less sensitive to noise present in the images, (ii) to allow to select the proper scale for the feature (scale selection), and (iii) to enable a coarse-to-fine search strategy.
2.4. Images

The method was applied on five image sequences, three sequences of the thorax and two abdominal image sequences, with a sequence length between 14 and 49 frames. Only J-tipped guide wires were used during the interventions. The image series were acquired on a H5000 (4 sequences) and a H3000 (1 sequence) X-ray fluoroscopy system (Philips Medical Systems, Best, the Netherlands).

3. RESULTS

We compared the performance of the method using the following feature images:
- original image
- subtraction image
- Hessian feature image calculated on the original image using different scales ($\sigma$)
- Hessian feature image calculated on the subtraction image using different scales

Since no ground truth is available, a good criterion for measuring the correctness of the tracking results is difficult. In the evaluation the number of frames in which the spline lies on top of the tip of the guide wire are considered to be tracked correctly.

Table 1 summarizes the results. Results without first applying a rough registration are not listed. These results were worse for every image sequence, which shows the need for a rough initialization before spline optimization.

<table>
<thead>
<tr>
<th></th>
<th>Seq. 1</th>
<th>Seq. 2</th>
<th>Seq. 3</th>
<th>Seq. 4</th>
<th>Seq. 5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intensity</strong></td>
<td>9/14</td>
<td>2/25</td>
<td>28/28</td>
<td>1/30</td>
<td>39/49</td>
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<tr>
<td><strong>Original image</strong></td>
<td></td>
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<tr>
<td>Hessian $\sigma = 1$</td>
<td>12/14</td>
<td>24/25</td>
<td>14/28</td>
<td>28/30</td>
<td>49/49</td>
</tr>
<tr>
<td>$\sigma = 1.5$</td>
<td>12/14</td>
<td>25/25</td>
<td>25/28</td>
<td>30/30</td>
<td>49/49</td>
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<tr>
<td>$\sigma = 2$</td>
<td>9/14</td>
<td>24/25</td>
<td>23/28</td>
<td>29/30</td>
<td>49/49</td>
</tr>
<tr>
<td>$\sigma = 3$</td>
<td>1/14</td>
<td>14/25</td>
<td>9/28</td>
<td>13/30</td>
<td>2/49</td>
</tr>
<tr>
<td><strong>Intensity</strong></td>
<td>14/14</td>
<td>21/25</td>
<td>18/28</td>
<td>26/30</td>
<td>46/49</td>
</tr>
<tr>
<td><strong>Subtraction image</strong></td>
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<tr>
<td>Hessian $\sigma = 1$</td>
<td>9/14</td>
<td>18/25</td>
<td>17/28</td>
<td>23/30</td>
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<tr>
<td>$\sigma = 1.5$</td>
<td>9/14</td>
<td>11/25</td>
<td>20/28</td>
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<td>49/49</td>
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<tr>
<td>$\sigma = 2$</td>
<td>8/14</td>
<td>11/25</td>
<td>22/28</td>
<td>28/30</td>
<td>48/49</td>
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<td>$\sigma = 3$</td>
<td>2/14</td>
<td>1/25</td>
<td>22/28</td>
<td>28/30</td>
<td>48/49</td>
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</table>

Using the original image for the matching and the optimization step, the J-tipped guide wire could effectively be tracked in only one of the tested image sequences. This sequence had a more or less uniform background with no disturbing structures. In the other images the guide wire was lost. This shows the need for a feature image which contains only the useful information for tracking the guide wire.

A better result was obtained using the feature image computed with the eigenvalues of the Hessian. From Table 1 it can be observed that $\sigma = 1.5$ appears to be the optimal scale.
In only 5 out of the total of 146 frames, the tracking failed. In sequence 1, the failure was caused by line-like structures in the neighbourhood of the guide wire. In sequence 3, motion blur owing to a fast movement of the tip of the guide wire caused a failure in the registration step. However this resulted in a failure in a single frame. In subsequent frames, the guide wire was successfully tracked without manual intervention.

If a smaller $\sigma$ is used, too much noise is present in the eigenvalue image which influences the tracking results, especially the matching step. If a larger $\sigma$ is used in the approach, the guide wire is only partially enhanced and other line-like structures at a larger scale are more enhanced, so that the guide wire is not always detected correctly.

On the subtraction feature image the method was applied partially successfully. Divided over four sequences, 20 out of the 146 frames gave wrong results. The only sequence that could be correctly tracked, was the one that had problems due to guide wire-like structures using the Hessian feature image (sequence 1). These background structures were partially subtracted and therefore correct tracking results were obtained. Note that in this sequence the performance is better than in case of using the original images, indicating the potential merit of utilizing subtraction images. In all the other four sequences several frames caused a mismatch due to too small movements of the guide wire in the beginning of the sequence. Therefore the guide wire itself was partially subtracted and could not be found in the next frame.

If the eigenvalues of the Hessian matrix are calculated for the subtraction image, good results are obtained in the last two sequences, but the tracking failed most of the times in the first three sequences. These sequences are very noisy and by performing digital subtraction, the noise level is amplified. This results in a large output for the eigenvalues of the Hessian on positions without line-like structures. An example of the good tracking results for sequence 4 obtained with $\sigma = 1.5$ is shown in Figure 2.

4. DISCUSSION

There is relatively little literature on tracking guide wires from 2D fluoroscopy images. In [2], guide wire tracking is used to evaluate the possibility of extracting myocardial function from guide wire motion. However, guide wire tracking is only performed in a single frame and not in time. Some work is aimed at the tracking of guide wires during endovascular interventions to control the position of a catheter inside the human body with external devices [3,4], or to reconstruct 3D catheter paths [5]. The presented method is a new approach to improve visualization and localization during endovascular interventions.

Based on the tests in the previous section, a number of conclusions can be drawn. First, the use of the cross-correlation step is helpful, as it supplies a good initialization for the subsequent fitting procedure. It is a known drawback from snake algorithms to be sensitive to the initialization, and using the first rough alignment this is circumvented. Second, the scale parameter with which the feature image was computed was essential. It has to be selected sufficiently large to reduce sensitivity to noise, and sufficiently small to ensure that other line-like structures at a larger scale are not enhanced.
Figure 2. Three frames (frame 4, 11 and 22) of sequence 4, which gives an impression of the tracking result. The method was applied on the feature image in which the eigenvalues of the Hessian matrix were calculated with $\sigma = 1$ on the subtraction images of the sequence.

If the parameters are set correctly, the feature image containing the eigenvalues of the Hessian matrix gave the best overall results. The guide wire was successfully tracked in 141 out of 146 frames from 5 sequences. Subtracting a previous image from the current frame can help if there are elongated structures in the neighbourhood of the spline, but the movement of the guide wire tip has to be large enough to get a good result.

In this work results on tracking J-tipped guide wires were presented. In the future the method will be extended to be able to track straight guide wires.

REFERENCES


