3D Dynamic Roadmapping for Abdominal Catheterizations

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Abstract. Despite rapid advances in interventional imaging, the navigation of a guide wire through abdominal vasculature remains, not only for novice radiologists, a difficult task. Since this navigation is mostly based on 2D fluoroscopic image sequences from one view, the process is slowed down significantly due to missing depth information and patient motion. We propose a novel approach for 3D dynamic roadmapping in deformable regions by predicting the location of the guide wire tip in a 3D vessel model from the tip's 2D location, respiratory motion analysis, and view geometry. In a first step, the method compensates for the apparent respiratory motion in 2D space before backprojecting the 2D guide wire tip into three dimensional space, using a given projection matrix. To counteravail the error connected to the projection parameters and the motion compensation, as well as the ambiguity caused by vessel deformation, we establish a statistical framework, which computes a reliable estimate of the guide wire tip location within the 3D vessel model. With this 2D-to-3D transfer, the navigation can be performed from arbitrary viewing angles, disconnected from the static perspective view of the fluoroscopic sequence. Tests on a realistic breathing phantom and on synthetic data with a known ground truth clearly reveal the superiority of our approach compared to naïve methods for 3D roadmapping.

The concepts and information presented in this paper are based on research and are not commercially available.

1 Introduction

Minimally invasive catheter-guided interventions are common practice in modern hospitals. The aim of such procedures is to navigate a catheter within a vessel system to a region of interest where it can be used for examination and treatment. In abdominal catheterizations, the navigation process is usually supported by fluoroscopic imaging from one view. Here, low-dose X-ray projections are produced, which are acquired in real-time, and display bone structures and a wire which is used to guide the catheter through the vascular system. The guide

Fig. 1. 3D dynamic roadmapping

wire is moving in the image sequence due to respiratory patient motion and the physician's push/pull actions. Since vessel walls and blood have the same radio density as surrounding tissue, vasculature must be made visible in X-ray images by contrast injection. In most hospitals, a high-resolution 2D Digitally Subtracted Angiogram (DSA) is acquired to avoid blind navigation. Using 2D DSAs, the navigation is still difficult at vessel overlays produced by the projection, or at vessel segments that run perpendicular to the image plane.

Thus, 3D angiographic data (CTA/MRA, intra-operative cone-beam reconstructions, 3D DSAs) were introduced into interventional workflow. They can be examined from all possible views, and reveal depth information in regions that are difficult to navigate. However, if they are not related to the current fluoroscopic frame, a necessary user interaction and/or notional fusion of provided data to connect guide wire to 3D vasculature complicates the navigation.

In order to relate 3D high resolution data to the current 2D fluoroscopic frame, systems have been proposed based on 2D-3D registration [1], or C-arm calibration [2]. Atasoy *et al.* [3] also takes breathing motion into account, which is common in abdominal fluoroscopic sequences, by compensating for the apparent motion of the guide wire. Typically, such systems blend a projected 3D vasculature over the current fluoroscopic frame to enhance navigation with a 2D (dynamic) roadmap. While clearly beneficial in terms of vessel visibility, depth perception cannot be increased with these approaches.

We propose a method for *3D dynamic roadmapping* that transfers the 2D navigational procedure to 3D by taking information about 2D guide wire tip location, apparent breathing motion, view and 3D vessel geometry into account

(see Fig. 1). From a vascular model extracted from a 3D scan, and a DSA, we compute the view geometry (projection matrix) of the C-arm device. We relate the DSA to the current fluoroscopic frame by tracking the apparent catheter motion in 2D. From possible guide wire tip locations in 2D, which are automatically detected, we determine candidate 3D locations via backprojection to the 3D vessel model. With the estimates of projection matrix and apparent catheter motion, we automatically derive uncertainties for all these locations and determine the most probable of all 3D candidates using a variable bandwidth kernel estimator for information fusion. With this fusion we make sure, together with information from the previous fluoroscopic frames, that the computation of the 3D location does not fail at overlays of vessel segments, different to a naïve backprojection approach.

With our proposed system, we successfully bring abdominal guide wire navigation to 3D, thus solving the problems of blind navigation and lack of depth perception. Ambiguities that arise from backprojection in a one view scenario are resolved, providing the first dynamic roadmapping technique for non-biplane C-arm systems that is fully automatic, operates in 3D, and is not aided by external tracking devices. Moreover, special care is taken of patient movement during fluoroscopic image acquisition in abdominal regions.

2 Method

In this section, we present our method for predicting the 3D position of a 2D guide wire tip. First, we describe the necessary input data and preprocessing steps, then we give a detailed description of the algorithm.

2.1 Data and Preprocessing

The data sets that form the basis to our method are a fluoroscopic image sequence $\mathcal{S}$, a high resolution DSA with the same projection parameters as the fluoroscopic sequence, and a 3D angiographic scan from which we extract a 3D vessel model $\mathcal{V}$ as described in [4].

To determine the 3D position $\mathbf{X}$ of the guide wire tip, we need to know its position $\mathbf{x}$ within the current 2D fluoroscopic image frame $\mathcal{S}_i$. Despite the high level of noise in these images, the unbiased line detector proposed by Steger [5] can be successfully applied to compute the curvilinear structures of the guide wire, and hence extract its tip.

Another important input is the projection matrix $\mathbf{P}$ that aligns the 3D scan with the DSA image. Different vessel contrast in 3D and 2D image, as well as motion blur caused by breathing, are typical issues of abdominal 2D/3D registration that we solve using an approach by Groher *et al.*, which is robust to deformations and has a high capture range [1].

To countervail apparent respiratory motion, we compute the 2D motion in-between frames using the template based approach proposed in [3]. A template $\mathcal{T}$ containing parts of the guide wire is selected in the fluoroscopic image frame $\mathcal{S}_0$,

the non-contrasted frame used for DSA computation. It is matched to every other frame $\mathcal{S}_i$ by evaluating the cross correlation similarity measure, $CC(\mathcal{T}, \mathcal{S}_i, d)$, where d is a global 2D translation vector displacing $\mathcal{T}$ w.r.t. its initial position. The final approximation of the respiratory motion d_i between frame $\mathcal{S}_0$ and frame $\mathcal{S}_i$ is defined as $d_i = \arg \max_d CC(\mathcal{T}, \mathcal{S}_i, d)$.

2.2 3D Guide Wire Tip Localization

Our method fuses all gathered information to compute the 3D correspondence of the guide wire tip location for every image frame, assuming a given uncertainty connected to each input parameter. In a first step, we subtract the respiratory motion displacement d_i of image frame $\mathcal{S}_i$ from guide wire tip location $\mathbf{x}$ to obtain the tip location with respect to image frame $\mathcal{S}_0$, denoted by $\mathbf{x}_0$. This is advantageous, since we can then use the pseudo-inverse of $\mathbf{P}$ to backproject the guide wire tip into 3D space. However, a simple backprojection of $\mathbf{x}_0$ will not always yield a satisfactory solution. First, ambiguities can arise if the backprojection ray intersects the vessel model multiple times. Second, the estimate of the guide wire tip location in 2D is prone to error caused by detection and motion compensation. We solve these problems with a statistical approach that is based on the creation of possible 2D guide wire tip candidates and the evaluation of their registration accuracy.

The accuracy of the 2D tip location in frame $\mathcal{S}_i$ depends on the detection and apparent motion estimation. We take errors from both estimation steps into account by randomly modifying the computed d_i in a range of $[\pm 10, \pm 10]$ pixels to generate n 2D tip candidates around $\mathbf{x}_0$, denoted by $\mathbf{x}_k$ where $k = 1..n$. We backproject each $\mathbf{x}_k$ using the pseudo-inverse of $\mathbf{P}$, compute the closest point on the vessel model $\mathcal{V}$ to the resulting ray, and define it to be a 3D correspondence candidate $\mathbf{X}_k$. Next, we compute an uncertainty connected to each $\mathbf{X}_k$ that is introduced by the uncertainty of the pose parameters Θ from $\mathbf{P}$. We randomly modify the registered pose Θ m times within an interval of $[\pm 5, \pm 5]$ mm for the translational, and $[\pm 5, \pm 5]^\circ$ for the rotational parameters. This results in m different poses Θ_j , which yield n sets of m 3D points: $\{\mathbf{X}_{k_j}\}$, $k = 1..n$, $j = 1..m$. We assign a weight r_j to each $\mathbf{X}_{k_j}$, where r_j is computed as the reciprocal of the cost function used for 2D-3D registration [1], evaluated for pose Θ_j , and normalized such that $r_j \in [0; 1]$. The uncertainty of each $\mathbf{X}_k$ can be represented as its weighted covariance matrix (visualized by green spheres in Fig. 1)

$$C_k = \frac{1}{\sum_{j=1}^m r_j} \sum_{j=1}^m r_j (\mathbf{X}_{k_j} - \bar{\mathbf{X}}_k)(\mathbf{X}_{k_j} - \bar{\mathbf{X}}_k)^T, \quad (1)$$

where $\bar{\mathbf{X}}_k = \frac{1}{\sum_{j=1}^m r_j} \sum_{j=1}^m r_j \mathbf{X}_{k_j}$ is the weighted mean.

In a final step, we fuse this uncertainty information to obtain an estimate for the 3D guide wire tip location. An approach to fuse such information is

the Variable-Bandwidth Density-Based Fusion algorithm (VBDF), proposed by Comaniciu in [6]. It is robust to outliers, which occur as 3D correspondence candidates on a wrong vessel branch in our scenario, and involves the uncertainties of the measurements. In this approach, we estimate a density function from all measurement means $\bar{\mathbf{X}}_k$ and define its most significant mode to be the estimated 3D guide wire tip location. For Gaussian kernels, mean shift is an iterative, hill-climbing approach, that moves a given point $\mathbf{X}$ towards a location with an equal or higher density in a local neighborhood, and converges to a location with zero gradient. We use variable-bandwidth to keep the algorithm nonparametric and improve the kernel estimator by adapting the scale of the kernel. The bandwidth of the algorithm is based on the covariance matrix of each measurement, and on a scaling factor α . It is defined as the bandwidth matrix

$$H_k = H(\bar{\mathbf{X}}_k) = C_k + \alpha^2 I, \quad (2)$$

where I is the identity matrix. Based on (2), we define our sample point density estimator as

$$f_v(\mathbf{X}) = \frac{1}{n(2\pi)^{d/2}} \sum_{k=1}^n \frac{1}{|H_k|^{1/2}} \exp\left(-\frac{1}{2}D^2(\mathbf{X}, \bar{\mathbf{X}}_k, H_k)\right), \quad (3)$$

where $D^2(\mathbf{X}, \bar{\mathbf{X}}_k, H_k)$ is the squared Mahalanobis distance between measurement $\bar{\mathbf{X}}_k$ and point $\mathbf{X}$. The variable-bandwidth mean shift vector that moves $\mathbf{X}$ towards the most significant mode of f_v is defined as

$$m_v(\mathbf{X}) \equiv \left(H_h(\mathbf{X}) \sum_{k=1}^n w_k(\mathbf{X}) H_k^{-1} \bar{\mathbf{X}}_k \right) - \mathbf{X}. \quad (4)$$

H_h is the data-weighted harmonic mean of the bandwidth matrix and reads as

$$H_h(\mathbf{X}) = \left(\sum_{k=1}^n w_k(\mathbf{X}) H_k^{-1} \right)^{-1}. \quad w_k \text{ is a weight that is based on the covariance}$$

of the associated measurement, and satisfies the condition $\sum_{k=1}^n w_k(\mathbf{X}) = 1$.

For the initial iteration we assign a sufficiently high value for α to achieve a density function with a single mode. The highest mode of the current iteration is used as an initial value for $\mathbf{X}$ in the next iteration and α is decreased until a scale factor of zero. The detected mode of this last iteration is declared to be the most significant mode of the density function, i.e. the estimated 3D location of the guide wire tip. For a more accurate and robust result, we modify the original weights w_k from [6] to fit our requirements. We involve information about the 3D location that was computed from the previous fluoroscopic image frame. The idea is to weigh the measurements $\bar{\mathbf{X}}_k$ dependent on their distance to the estimate of the previous frame. This is justified by the fact, that the guide wire will probably not move dramatically between successive image frames. Assuming

statistical independence, we add the probabilistic term v_k to the original weights by multiplication,

$$w_k(\mathbf{X}) = v_k \frac{\frac{1}{|H_k|^{1/2}} \exp\left(-\frac{1}{2}D^2(\mathbf{X}, \overline{\mathbf{X}}_k, H_k)\right)}{\sum_{k=1}^n \frac{1}{|H_k|^{1/2}} \exp\left(-\frac{1}{2}D^2(\mathbf{X}, \overline{\mathbf{X}}_k, H_k)\right)}, \quad (5)$$

where v_k is the reciprocal of the length of the path in $\mathcal{V}$ between the orthogonal projection of $\overline{\mathbf{X}}_k$ on $\mathcal{V}$ and the estimated $\mathbf{X}$ of the last frame, divided by the sum of reciprocal lengths of all k . To ensure the 3D guide wire to be inside a vessel, we pick the closest point on $\mathcal{V}$ to the computed $\mathbf{X}$ and define this point to be the final 3D guide wire tip position.

3 Experiments and Results

To test our method, we ran four studies on synthetic data, and two studies on a realistic breathing phantom, all with a known ground truth.

3.1 Testing on Synthetic Data

For our tests, we create a synthetic DSA and a fluoroscopic image sequence.

To generate the DSA, we subtract two successive fluoroscopic image frames and use the result as a background image. The vessel system is simulated by projecting a 3D vessel model, extracted from patient CTA data, onto the background image with a projection matrix typical to an interventional C-arm setting. Disks that are proportional to the vessel diameter are drawn at each projected centerline point, and low intensities are assigned to the inside of large disks, higher intensities to small ones to simulate contrast propagation (compare Fig. 2(a)).

For the fluoroscopic sequence, we use a real fluoroscopic background image (960×960 pix) and add the guide wire using a 10 pixel wide B-Spline curve whose control points are obtained by projecting 3D vessel centerline points that we consider to be our ground truth. For subsequent fluoroscopic frames, we move a predefined path in the 3D vasculature to simulate the catheter movement inside the vessel. Additionally, we translate the projected points by a displacement vector of ± 30 pixels in y , and ± 2 in x direction to simulate apparent breathing motion. An overview of the test scenario and the generated data sets are visualized in Fig. 2(a)-2(c).

We compare our approach with a naïve backprojection algorithm of the catheter tip disobeying uncertainty information from 2D-3D registration and motion compensation. For particular test cases (visualized as colored circles in Fig. 2(b)), which are chosen to be at regions with vessel overlay, we compute a target error ϵ , which is defined by the mean of Euclidean distances between computed 3D point and ground truth in mm . ϵ , together with its standard deviation σ are additionally evaluated for each coordinate axis separately. The results are summarized in Tab. 1 and clearly point out the benefit of our approach. The target error is always considerably smaller than the error obtained by the naïve

Table 1. Results of target errors ϵ and standard deviations σ in *mm*

Synthetic (Fig. 2(b))		ϵ_x	ϵ_y	ϵ_z	ϵ	σ_x	σ_y	σ_z	σ
Case 1 (dark blue)	New	0.44	0.58	2.57	2.79	0.58	0.72	4.52	4.54
	Naïve	0.72	0.79	4.59	4.89	0.76	0.79	6.85	6.82
Case 2 (orange)	New	0.15	0.27	0.17	0.38	0.17	0.35	0.23	0.42
	Naïve	0.21	0.39	2.08	2.36	0.16	0.29	4.49	4.37
Case 3 (light blue)	New	0.23	0.47	0.27	0.63	0.25	0.48	0.48	0.68
	Naïve	0.26	0.50	2.13	2.46	0.24	0.29	6.01	5.92
Case 4 (green)	New	0.44	0.51	0.47	0.92	0.40	0.33	0.41	0.49
	Naïve	0.25	0.60	0.79	1.16	0.19	0.36	1.26	1.20
Phantom (Fig. 2(f))		ϵ_x	ϵ_y	ϵ_z	ϵ	σ_x	σ_y	σ_z	σ
Case 5 (yellow)	New	1.78	2.51	1.96	3.98	1.55	1.00	1.10	1.44
	Naïve	2.70	4.97	24.39	26.59	1.38	2.94	43.41	42.58
Case 6 (red)	New	0.89	1.90	1.13	2.66	0.71	1.74	0.67	1.58
	Naïve	1.35	2.71	19.38	20.75	1.59	3.82	37.27	36.87

Fig. 2. Overview of test scenarios: (a) Synthetic DSA. (b) Synthetic test scenarios where the guide wire path is circled dark blue (case 1), orange (case 2), light blue (case 3), and green (case 4). (c) Fluoroscopic image of case 1 with overlaid 3D vessel model, showing the advantage of a modified viewing angle. The arrow points to the estimated guide wire tip location in 3D. (d) Breathing phantom. (e) Rendered 3D volume of phantom with arrows marking the path of case 5 (yellow), case 6 (red). (f) Phantom fluoroscopy showing tubes and guide wire. The circles mark the same paths as arrows in (e).

approach. The relatively large error in case 1 is a result of the guide wire mainly moving in the direction orthogonal to the viewing plane. In this case, the missing depth information cannot be totally compensated by statistical evaluations. Still, we achieve a significant improvement.

3.2 Testing on Breathing Phantom

We use a phantom including a vessel system, which is formed by a set of connected plastic tubes fixed in liquid wax (Fig. 2(d)). The breathing motion is simulated by an electronic pump that is attached to the phantom, yielding apparent in-plane displacements of up to 14 pixels (in 1024×1024 images). The image data is acquired with a Siemens AXIOM Artis dBA, a calibrated bi-plane C-arm device. It allows us to grab two fluoroscopic sequences (Fig. 2(f)) from which we can compute the guide wire tip's 3D ground truth position. The vessel model $\mathcal{V}$ is extracted from a rotational run under contrast agent. For testing our algorithm, we used only one of the projection sequences, where two particular overlay cases are evaluated (see arrows in Fig. 2(e)). The DSA for registration was created from a second, contrasted sequence. Again, errors and associated standard deviations are shown in Tab. 1. Please note that the error especially in ray direction (ε_z) can be reduced significantly using our method.

4 Conclusion

In this work we propose an algorithm, which robustly facilitates 3D navigation of guide wires in abdominal catheterizations using fluoroscopic images from a monoplane C-arm system. By statistically involving results from 2D-3D registration, catheter tip detection, and motion compensation within the process of backprojection, we considerably improve the accuracy of the system. Encouraged by the good results from synthetic and phantom tests, we will proceed with an extensive patient study. Further ideas are aiming at a feedback system for physicians in cases where the C-arm configuration is not optimal with respect to the desired operation situs, or where the system's prediction is too ambiguous.

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