Deep Learning Assisted Image guided Interventions: a feasibility study

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Editors: Under Review for MIDL 2020

Abstract
We evaluate feasibility of deep learning based tracking for image guided interventions (IGI). Guidewire navigation during real-time IGI currently requires time-consuming manual slice repositioning. Deep learning may increase intervention procedure efficiency by automating this slice repositioning step. We developed a deep learning based pipeline for automated guidewire tracking and steering an MRI scanner. A slice repositioning experiment was successfully conducted on an anthropomorphic blood vessel phantom. We show tracking of a guidewire displacement of 140mm in real-time (121ms) within, on average, a 7mm margin. We conclude that deep learning assisted image guided interventions is feasible, though not yet ready for clinical practice. Further research on model robustness and uncertainty is therefore encouraged in order to push deep learning assisted image guided interventions towards clinical practice.

Keywords: Image guided intervention, MRI, Object detection, Object tracking, Real-time inference

1. Introduction
Deep learning (DL) assisted image guided interventions is a relatively novel field of interest to the medical imaging deep learning community. Current challenges are real-time inference, stricter robustness, and uncertainty requirements (Cleary and Peters, 2010). Image guided interventions (IGI) itself, and especially minimally invasive IGI (MIIGI) are relatively novel fields (Bomers et al., 2020, 2017; Klotz et al., 2019). MIIGI enables minimally invasive procedures that precisely target pathology, while preserving body integrity. Consequently, it has fewer complications than conventional surgical procedures. In comparison to fluoroscopy-, or CT-guidance, the current standard, MRI-guidance avoids harmful radiation to patient and medical personnel and excels in imaging soft tissue pathology (Clogenson and van den Dobbelsteen, 2016; Ahrar et al., 2013).

In this work we focus on MRI-guided endovascular interventions. The current challenge is to track the guidewire tip in the real-time MRI image stream to automate the current time-consuming manual MRI slice repositioning (Clogenson and van den Dobbelsteen, 2016). We aim to utilise deep learning to help reduce the operational complexity of MRI-guided interventions. DL was shown to be capable of detecting and tracking objects in real-time for autonomous systems (Ondruska and Posner, 2016; Wu et al., 2017; He et al., 2018). We propose to develop a DL pipeline that detects and tracks the guidewire tip in an obtained coronal plane image stream in real-time, and autonomously control the MRI scanner to update the spatial position of an imaging scan plane to keep track of the moving guidewire.
2. Methods

![Schematic overview of assessed method.](image)

Figure 1: Schematic overview of assessed method.

2.1. Data

An anthropomorphic blood vessel phantom was used, which is depicted in the left-most image of figure 1 and consists of three interconnected tubular sections encapsulated in a rectangular box, all filled with water.

We performed a simplified MRI-guided vascular intervention procedure on the blood vessel phantom, for which a custom 3-Tesla MRI-compatible guidewire (Nijsink et al., 2020) was inserted in the artificial blood vessels and moved through the tubular sections. This guidewire contained five paramagnetic iron oxide nanoparticle markers to ensure its visibility on a real-time MRI sequence.

MR images with a resolution of $144 \times 144$ pixels and a $2 \times 2$ mm spacing, were acquired from the intervention procedure with a 3-T MRI scanner (Skyra, Siemens, Erlangen, Germany). A coronal plane, through the length of the vessels, and sagittal plane, capturing a cross-section of the vessels, were acquired at a rate of roughly four planes per second using a real-time Gradient Echo (GRE) sequence.

An intervention procedure was performed with different plane locations and orientations. A total of 800 coronal temporal images were used as training data for the object detection network, and 200 coronal temporal planes were used for model validation. Bounding box annotations of guidewire markers were generated semi-automatically using a dedicated image processing pipeline.

2.2. Experiments

The goal of our experiment was to assess feasibility of autonomously tracking a guidewire in real-time during our simplified vascular intervention procedure. We aimed to assess this by enabling DL to continuously retrieve and interpret a fixed coronal plane, and subsequently control the MRI scanner to place a sagittal plane through the tip of the guidewire. An overview of this method is schematically depicted in Figure 1.

After phantom alignment, the MRI scanner continuously acquired a set of coronal and sagittal planes of the phantom. The sagittal plane, depicted with a red border in figure 1, was initialized to intersect at the center of the fixed coronal plane. The coronal plane, depicted with a green border, captured the trajectory of the phantom’s vessels.
We established a bi-directional connection using a dedicated Access-i interface through which our method receives acquired images and sends updated coordinates back to the scanner. The position of the guidewire marker was detected on the coronal planes individually by a YOLO v3 object detection network (Redmon and Farhadi, 2018), trained on the 800 coronal training frames which were upsampled to 416 × 416 pixels and exposed to translation, rotation and noise data augmentation techniques. The position of the guidewire tip was used to derive intersecting sagittal slice acquisition coordinates that were sent to the MRI scanner. The performance was measured in positional error (mm), as a distance (mm) between the predicted and actual marker position, and the inference time (ms).

3. Results and Discussion

A real-time setup shown in figure 2(a) showed feasibility. The mean displacement error was 7 mm (σ = 4). The error is larger during retraction (μ = 10 mm, σ = 3). The actual and predicted displacement over time in the x-direction is shown in figure 2(b). On an Nvidia GeForce GTX 1080, the inference time was 121ms.

Future work involves expanding to more realistic clinical scenarios. Spatio-temporal information may help solve the lagging error issue and allow 3D movement tracking through plane position and orientation estimation. The increased complexity of this information requires efficient tracking architectures to maintain real-time inference. Model uncertainty may reduce unrecoverable tracking mistakes by switching back to manual scanner operation.

Acknowledgments

Acknowledgments withheld.

References

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