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Towards using SOFA to train a controller for neurovascular catheter interventions

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1 Introduction

Neurovascular catheters are thin flexible tubes used for the treatment of strokes and other vascular diseases. During the procedure, the catheter instrument is navigated through the blood vessels of the patient to a target site in the brain where the surgeon performs the intervention (e.g., a mechanical thrombectomy) by feeding instruments or drugs through the catheter. Navigating catheters through tortuous blood vessels to the brain is challenging due to their small size and flexibility, which often lead to unexpected and unintuitive catheter motions. Thus, a number of researches have proposed robotic assistance to aid the surgeon in the control of such catheters [1].

In previous work, we proposed a closed-loop control system for the navigation of catheter instruments based on Deep Reinforcement Learning (DRL) [2]. The system uses the SOFA framework - specifically, the BeamAdapter (BA) plugin [3] - to generate training data for a neural network-based controller. By means of simulations, we showed that this approach is feasible for a simplified vessel phantom.

Here, we present our ongoing work on the development of said control system. We show that a DRL-based controller trained only in a simulated environment (SOFA + BA plugin) can successfully be transferred to a physical test bench.

2 Methods and Materials

Our setup consists of the controller (DRL-Agent), a simulated environment created in SOFA and a physical test bench (Fig. 1). The simulation in SOFA is used to generate training data for our DRL-Agent. Once training has been finished, we transfer the controller to the test bench for evaluation.

For training the controller, we use the Deep Reinforcement Learning framework ‘Nervana Systems Coach’. The Deep Deterministic Policy Gradient (DDPG) algorithm along with Hindsight Experience Replay (HER) are used to train the artificial neural networks of our controller. Catheter instruments – here, only the guidewire - are simulated in SOFA with the help of the BeamAdapter plugin. Our SOFA scene consists of a rigid phantom with evacuated lumen and a single beam instrument with a curved tip (i.e., the guidewire) that is moved through the lumen. The geometric and material parameters of the simulated instrument were set to loosely resemble its physical counter

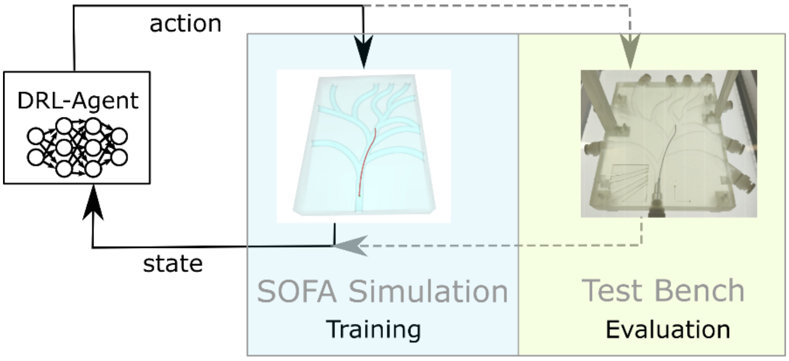

Fig. 1. System overview showing the interface between the DRL framework, the SOFA simulation and the physical test bench. Training is performed only in the simulated environment.

part. The test bench consists of a custom-made robotic manipulator (two degrees of freedom), a 3D-printed vessel phantom and a camera for tracking the position of the guidewire in the vessel phantom. The robotic manipulator is used to translate and rotate the guidewire according to the controller commands it receives. For real-time tracking of the guidewire in the phantom, we use MeVisLab (MeVis Medical Solutions AG, Bremen). The communication framework OpenIGTLink [4] is used to exchange information between the DRL framework and the simulation and test bench, respectively.

Our training routine consists of the DRL-Agent sending motion commands (‘action’, i.e., velocity, direction, travel distance) to the SOFA simulation, which computes the resulting pose of the instrument. The coordinates of the instrument tip (‘state’) are then sent back to the DRL-Agent. The goal of the training is for the guidewire tip to reach a specified target in the vessel phantom. During the training, this target is moved gradually to areas in the phantom that are intuitively harder to reach, for example, further away from the starting position. Thereby, the difficulty of the task is increased during the training.

In our first experiments, we consider the controller to be sufficiently trained once no significant improvement in its performance can be observed. The trained controller is then transferred to the test bench where it is tasked to steer the guidewire to randomly chosen points in the phantom. No additional training on the test bench is performed.

3 Results and Discussion

Our first qualitative results show that our DRL-based controller yields a success rate of about 90-95 % in both the simulated and the physical environment. Although so far only qualitative results have been obtained, transfer from simulated to physical environment did not require further training of the controller. However, when changing the

3D-printed phantom we noticed a drop in the success rate. This is likely due to differences in the surface roughness between the two vessel phantoms caused by manufacturing tolerances. We were able to reproduce our initial results by adjusting material parameters in the SOFA simulation and then repeating parts of the training procedure.

Training the controller in the simulated environment took approximately one day on a computer with an AMD Ryzen 7 2700X, GPU GeForce RTX 2070 and 48 GB RAM.

Simulating the guidewire using SOFA together with the BeamAdapter plugin proved sufficiently accurate for our use case. Apart from a few minor adjustments to the BeamAdapter code, the software could be used ‘out of the box’ for our purposes.

4 Conclusion

In this ongoing work, we present first promising results of our DRL-based catheter controller trained using SOFA. We are able to demonstrate that a controller trained only in SOFA with the BeamAdapter plugin can reliably navigate a guidewire through a simple 3D-printed vessel phantom.

In the future, we plan to expand on this work by successively increasing the complexity of our simulation and test bench with the goal of approximating the real world application better.

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