3D Deformation Simulation for Vascular Tissue with 2D Medical Imaging

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***Abstract*— Ultrasound is a cheap and popular imaging method for localizing vessels in a variety of surgical interventions. Ultrasound-guided robots are increasingly being used to automate vascular access. However, ultrasound being a form of contact imaging, deforms soft tissue, especially vessels. Therefore, for accurate manipulation of vasculature, robots require some form of reasoning that can predict deformations in 3D. While deep learning methods could help, we lack enough 3D training data. Capturing 3D deformation data is a challenging task as ultrasound only provides 2D data in-plane and obtaining 3D deformation data from other forms of imaging such as CT is expensive. To generate more data for training deep learning-based models, we propose the use of realistic FEM simulations with 3D models of vessels built from undeformed 2D tomographic images. In order to match our simulation to our real-world 2D observations, we propose an optimization for material properties by maximizing the IoU of the vessel area from the simulation and the real-world ultrasound images. Post optimization, in matching simulations of deformations to real-world ultrasound observations, we observe the average IoU for compressed vessels to be 0.72.**

I. Introduction

The accurate estimation of deformation is an emerging sub-field within medical robotics and is required for manipulating deformable skin and vascular (vessel) tissue for a variety of tasks. Vascular access through needle insertion is necessary in many surgical interventions such as Resuscitative Endovascular Balloon Occlusion of the Aorta (REBOA), cathether placement etc. Most robots automating this step use ultrasound to guide needle insertion [1] [2]. While ultrasound imaging has several benefits such as high portability, zero ionizing radiation, and low cost, it can be noisy and result in deforming the subject. Ultrasound imaging requires the application of a significant force to maintain contact between the probe and the subject, and in some cases, improve the quality of imaging. An undesirable effect is that the applied force, deforms the elastic tissue and can cause vessel collapses or lateral displacement termed rolling. While an in-plane needle insertion into a vessel under a constant force is feasible with ultrasound, insertions out of the the ultrasound plane run the risk of missing the vessels as the localized vessel centers might shift due to deformations. In such a scenario, having an estimate of the 3D vessel deformation can turn a blind insertion into an informed insertion.

Traditionally, simulators using the Finite Element Method (FEM) have been used to estimate deformations of 3D structures under applied forces. Porting this method to concealed anatomy such as vessels comes with its own set of challenges - 1. The material properties of the tissue are not known exactly; 2. Tissue is typically non-homogeneous material; 3. The 3D shape of the entire vessel cannot be obtained easily; 4. How do we ascertain that the simulation is realistic? Additionally, FEM simulation, even with fast simulators utilizing GPU compute, is time-consuming and cannot be applied in real time for high resolutions.

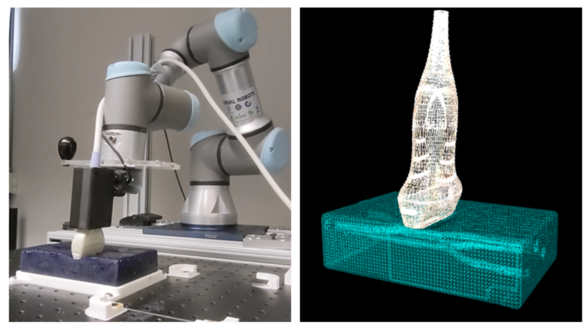

Fig. 1. Left: Our robotic system; Right: The registered simulation setup.

Inference with neural networks can be much faster than FEM simulation [3]. Networks that process 3D representations such as point clouds and meshes can be conditioned on forces to predict deformed shapes [4], effectively mimicking FEM simulation. While such networks may not learn the underlying physics of deformation with the highest precision, they have shown to produce realistic deformations. Few such networks exist in the domain of medical data, perhaps due to the difficulties in obtaining training data from concealed anatomy and using 2D imaging to observe 3D deformations.

We present a method to utilize 2D tomographic medical imaging for building and calibrating a simplified FEM simulation of 3D vessel structures. This simulation mimics vessel compression due to forces from an ultrasound probe. We estimate the material properties in calibration by using an optimization for the Young's modulus and Poisson's ratio. This is achieved by maximizing the IoU area between the deformed vessels observed in real-world ultrasound images captured by a robot and vessel cross-section from the simulated deformed model. We propose that our method can be used to generate 3D training data for neural networks being developed to predict deformations. The method is tested on a 3D model of a blue-gel ultrasound phantom created from a high resolution CT (Computed Tomography) scan. We substitute ultrasound imaging with CT for obtaining the initial undeformed shape of vessels. For incorporating real-world data from porcine subjects, we use robot-captured

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ultrasound images at very low forces for generating the 3D model of the vessel/s. This generates a model with some deformation but for the purposes of simulation, we assume this to be the undeformed structure. Our robot setup and the corresponding simulation scene are seen in Fig 1.

II. Related Work

Force data collected from a multi-axial force sensor mounted on the robotic manipulator, and tissue deformation data collected from a stereo camera system are used for estimating mechanical parameters of soft tissue in [5]. The authors of [6] use RGB-D sensing to learn force values in an ex-vivo set up with a da Vinci Surgical System for brain tissue. In [7], a novel approach to simulate the soft-body deformation of an observed object is introduced. The approach tracks an object's movement using an RGB-D sensor and simulates its deformation iteratively. The method could be applied to track skin deformation but since our scope is vessels, RGB-D sensing cannot be applied.

Quite a few studies have explored simulating soft-tissue deformations but few optimize simulations using medical images. In [8], the authors propose a comprehensive pipeline to create patient-specific biomechanical models and optimize deformation predictions in FEM through iteratively updating model parameters by maximizing image similarity between FEM-predicted MR images and the experimentally acquired MR images of a breast. To predict deformations in real-time, in [9] a liver model with biomechanical properties similar to real one is created using FEM and a data set of deformations with different forces is generated. The mechanical behaviour is simulated in real time by a LightGBM regression model trained with the generated data set. Vessels are modeled and deformed in real-time using a tensor-mass method in [10] and the authors perform experiments for determining realism but do not use medical imaging to quantify it and rely on qualitative results. Other papers [11] [12] simulate vessel deformations due to blood flow.

[3] proposes using deep neural networks to learn large deformations occurring in ultrasound-guided breast biopsy as FEM is not real-time. They train a U-Net architecture on a relatively small amount of synthetic data generated in an offline phase from FEM simulations of probe-induced deformations to provide accurate prediction of lesion displacement. 3D-PhysNet, proposed in [4], can predict three-dimensional deformations in solids under applied forces by encoding the physical properties of materials and applied forces in the network, essentially learning the FEM simulation.

III. Data

For building the 3D model of vessel/s, we utilize tomographic imaging to capture the concealed structure of vessels. We show our deformation simulation and calibration on a mesh model of the CAE blue-gel ultrasound phantom built from a CT scan and a porcine femoral vessel built from ultrasound images. Multiple ultrasound sweeps were carried out with varying forces (2, 4, 6, 8 and 10 N) along a predefined trajectory on the live-pig subject. For in-plane comparisons, images from different sweeps were synced using the pose of the ultrasound probe. The ultrasound data was collected using a UR3e manipulator (Universal Robots) with a Fukuda Denshi portable point-of-care ultrasound scanner (POCUS) using a 5-12 MHz 2D linear transducer and a six-axis force/torque sensor (ATI) mounted on the end effector. The IACUC-approved porcine experiments were done with the same robot setup in a controlled lab setting under clinician supervision.

IV. Methods

A. 3D Model Generation

Slices of the CT volume of the phantom are segmented through pixel thresholding in 3DSlicer [13] for labeling vessels. The vessel labels are manually rectified and propagated through the length of the CT volume to obtain a hollow triangular mesh. This mesh is uniformly downsampled with Blender [14] to ensure vertices are uniformly distributed with low distances between vertices. FEM simulations could fail with meshes that have sparse vertices placed far apart. This downsampled mesh is then converted to a volumetric tetrahedral mesh using Gmsh [15], with the vessel region not having any connectivity. The tetrahedral connectivity is only for the region of the phantom that mimics tissue.

For the porcine subjects, we employ a UNet-based segmentation model with a weak supervision data augmentation technique to obtain masks for vessels from ultrasound images [16]. These masks are then stacked by robot pose to create a solid volume of the vessel. This volume is processed through marching cubes to obtain a hollow mesh which is then fused with an artificially-added outer mesh that represents tissue. The resulting mesh is tetrahedralized for results similar to the phantom model. Fig 2 shows the medical image data and the generated 3D models of the phantom and the porcine vessels.

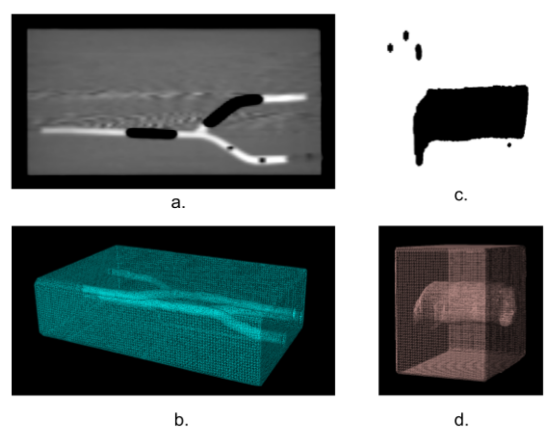

Fig. 2. a. The CT volume of the blue-gel phantom; b. The tetrahedral mesh of the blue-gel phantom; c. The stacked ultrasound volume of a pig vessel; d. The tetrahedral mesh of the pig vessel

B. Simulation

We use the SOFA library [17] for our simulations and parameterize the simulation in a simplistic manner. We assume that material density, Young's modulus E and Poisson's ratio ν are the primary factors affecting the response of a model to applied forces. After defining the correct transformations that register our simulation frame to the robot frame, we load our

3D tetrahedral model for simulation. We define downward gravity and define all the points at the base of the model as fixed. By defining simulation parameters such as material properties, force and application direction, we simulate the probe-phantom interaction resulting in vessel deformations.

C. Calibration with IoU

In our setup, we assume that the exact material properties of the subject are unknown. While the material properties for the phantom are known as it is a standard equipment, this information has to be estimated for the tissue of every new subject that we would want to perform deformation simulation for. It then becomes necessary to apply some form of per-subject estimation. In our case, we have done this through an optimization for E and ν of the material by maximising the overlap of the vessel area between the ultrasound images and the corresponding cross-sections from generated simulations. This is performed for the model of the phantom for which the material density was known.

The idea is that since the simulation frame is registered to the robot, the cross section from the deformed model at a given pose p and force f, along the image plane, should resemble the vessel anatomy seen in the ultrasound image collected by the robot at p and force f. We use the IoU between vessel regions to determine the overlap and use it as a reward in a Cross-Entropy Maximization method.

V. Experiments and Results

We apply the iterative Cross Entropy Maximization method [18] for optimization with 8 agents, sampling values for E and ν from known ranges for the gel material of the phantom. 2 agents are purely exploratory and the ranges are 60-850 kPa [19] and 0.47-0.49 for E and ν. The optimization was considered converged when the standard deviation was lower than 5 and 0.005 for E and ν respectively. With the addition of scattering agents to the polymers used for manufacturing the blue-gel phantom, we expect a slight deviation from the expected 600 KPa and 0.48 values for two the parameters. We perform the optimization at two poses with 3 different force values (6, 8 and 10 N) and average over them for obtaining the final calibrated material properties. All 6 optimizations converged within 10 epochs.

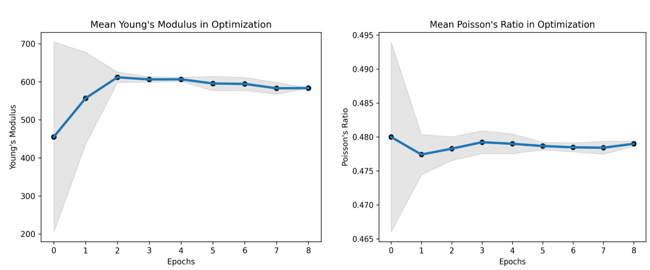

Fig. 3. The mean E (left) and ν (right) values (with standard deviations in grey) after each epoch of the optimization for pose 1, force 8 N.

The graph showing the convergence of the optimization for the blue-gel phantom model is shown in Fig 3. The average converged values for Young's Modulus and Poisson's Ratio are 592.5433 $\pm$ 20.13 kPa and 0.482 $\pm$ 0.003. The highest IoU at the poses where the optimization was applied was 0.76. The simulation and optimization results for the blue-gel phantom showing the contours from the cross section of the deformed mesh progressively aligning better with the vessel masks from the ultrasound data are seen in Fig 4.

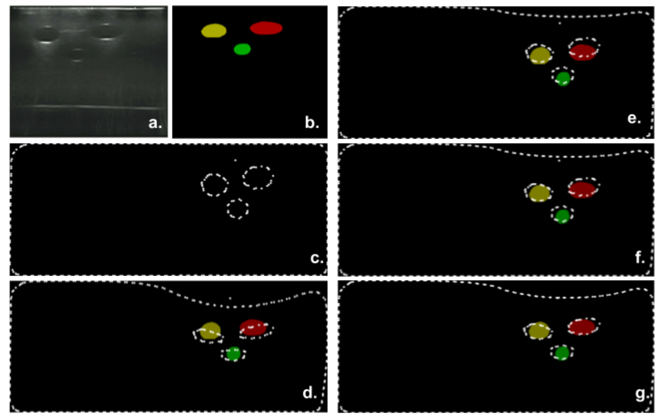

Fig. 4. a. The ultrasound image captured by the robot at pose 1 with force 6 N; b. Vessel masks identified in the ultrasound image by our segmentation model; c. The cross-section contours from the undeformed mesh at pose 1. d-f. Cross-sections from the deformed phantom model with the registered vessel masks at pose 1. The cross-sections were generated with applied force 6 N, simulated with material properties estimated in epochs 0, 2, 6 and 8 of the optimization respectively.

VI. Discussion and Conclusion

We observe that after optimization, the highest IoU score in simulations across all the poses at three different forces is 0.79 with the average being 0.72. This shows that our parameter estimates work uniformly at all poses over the homogeneous phantom. The gap in the IoU from the perfect score of 1 can be attributed to some of the assumptions made in our simplified model and to discrepancies arising from obtaining vessel masks in both CT and ultrasound data. We do not simulate fluid inside the vessels and assume that the Young's Modulus and Poisson's Ratio are sufficient to model soft tissue properties. The vessel masks obtained either through thresholding or segmentation are prone to noise in the data and to the robustness of the segmentation model.

In this work, we show a method to use tomographic medical images (CT and ultrasound) of vessels to build models for deformation simulations. Additionally, we show how to use these medical images to approximate the material properties of tissue. While we have reconstructed vessel structures from porcine subjects and processed them successfully to work with our simulation pipeline, we are yet to try the optimization for these models and are in the process of collecting more real-world data for this purpose. Currently, the optimization process is lengthy, given that multiple simulations have to be run to find optimal material properties. While using low resolution models and GPU compute can speed this process, our method is still slow for real-time applications, taking 40 mins for a single epoch. However, data generation through our method is feasible and currently, our group is using this method to generate training data for force-conditioned 3D flow estimation networks.

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