Learning the Complete Shape of Concentric Tube Robots

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Abstract: Concentric tube robots, composed of nested pre-curved tubes, have the potential to perform minimally invasive surgery at difficult-to-reach sites in the human body. In order to plan motions that safely perform surgeries in constrained spaces that require avoiding sensitive structures, the ability to accurately estimate the entire shape of the robot is needed. Many state-of-the-art physics-based shape models are unable to account for complex physical phenomena and subsequently are less accurate than is required for safe surgery. In this work, we present a learned model that can estimate the entire shape of a concentric tube robot. The learned model is based on a deep neural network that is trained using a mixture of simulated and physical data. We evaluate multiple network architectures and demonstrate the model's ability to compute the full shape of a concentric tube robot with high accuracy. We are then able to use the full shape of a concentric tube robot in a motion planner.

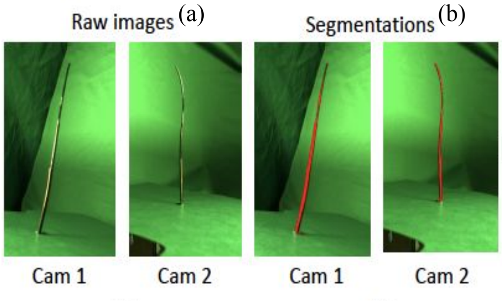
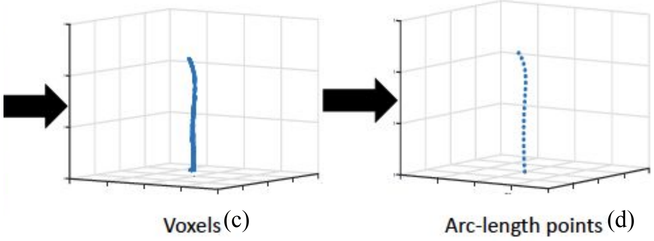


Fig 3. To generate training data from the physical robot. (a) Take an image of the robot's shape with two cameras with known positions relative to the robot.



(b) Use a color thresholding technique to automatically segment out the robot's shape. (c) Apply the shape from silhouette algorithm to generate a set of voxels in 3D space. (d) Generate a set of evenly spaced points that best approximate the set of voxels.

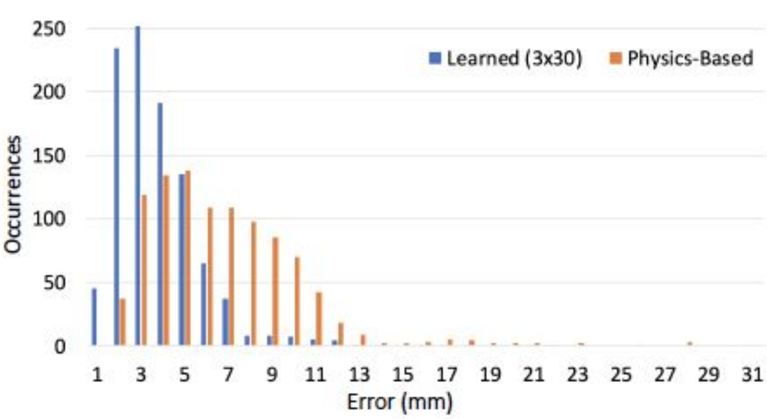


Fig. 4. A histogram of the maximum error along the robot's shaft for the learned model and the physics-based model, for each of the $1,000$ test points. The distribution is shifted to the left in the learned model (Sim+Real 3x30), indicating that it is more likely to produce lower error values.

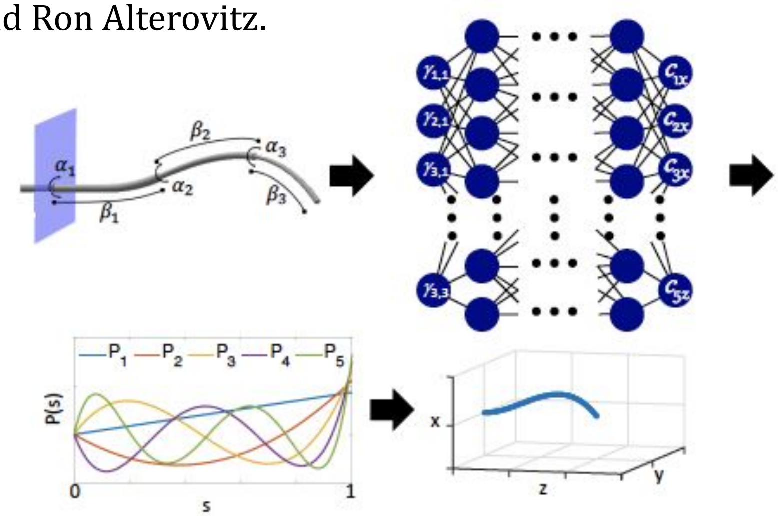


Fig. 1. Given a concentric tube robot configuration defined by the translations and rotations of the tubes (upper left), our neural network (upper right) outputs coefficients for a set of polynomial basis functions (lower left) that are combined to model the backbone of the robot's 3D shape (lower right).

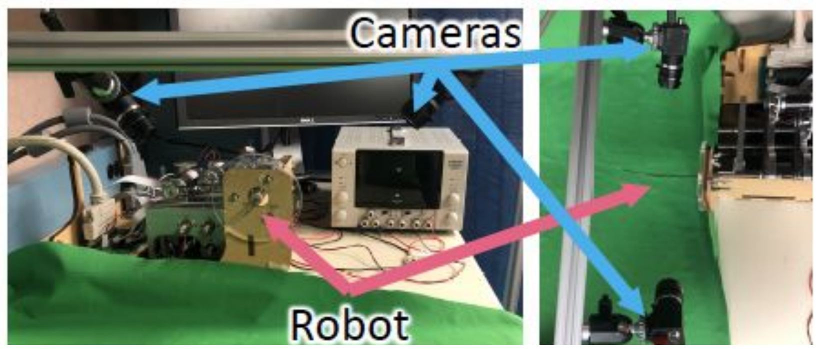


Fig. 2. We train the neural network using data from a physical robot. By taking images from multiple cameras (blue arrows), the shape of the robot's shaft (pink arrows) can be reconstructed in 3D using shape from silhouette.

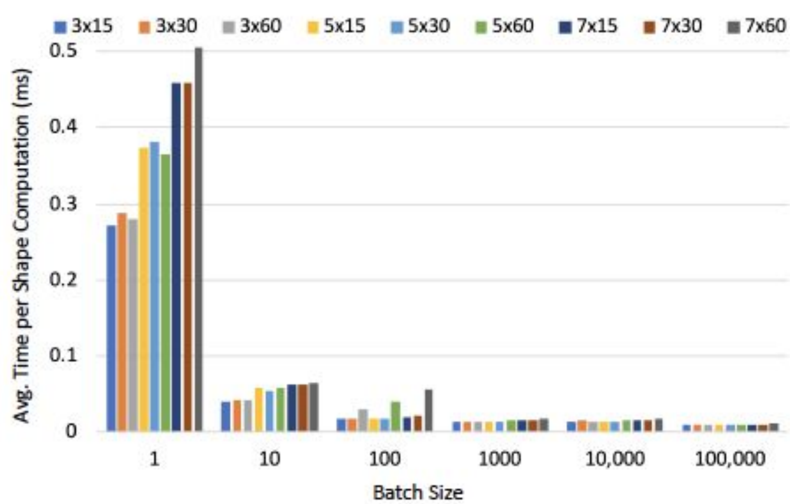


Fig. 5. The average time taken to compute the shape of the concentric tube robot at a specified configuration, for 20 evenly spaced points along its backbone. We present the average for each network topology (Sim+Real), for varying batch sizes. For comparison, the physics-based model averages 1.73ms per shape computation.