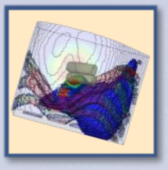

Development of a Real Time Augmented Reality RoboPatient Platform with Haptic Feedback using a 3D Surrogate Model

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Introduction

Medical examination procedures, such as abdominal palpation is highly challenging for medical trainees. They require many years of experience to sharpen their skill to effectively assess the patient's condition. Simulation-based systems, e.g. manikins and virtual reality platforms are used in training but they lack the ability to provide realistic feedback (e.g. haptics and visual) [1]. Thus, we are developing a robotic patient training platform which incorporates haptic feedback informed by real-time visualisation of stress contours on internal organs for more effective training. **We developed a surrogate model from high-fidelity finite element model (FEM) simulations, and train it using a machine learning algorithm to render tissue deformation given the palpation location and force by the user.** Here, we **demonstrate the surrogate model construction and machine learning outcome to be incorporated with the robotic hardware platform.**

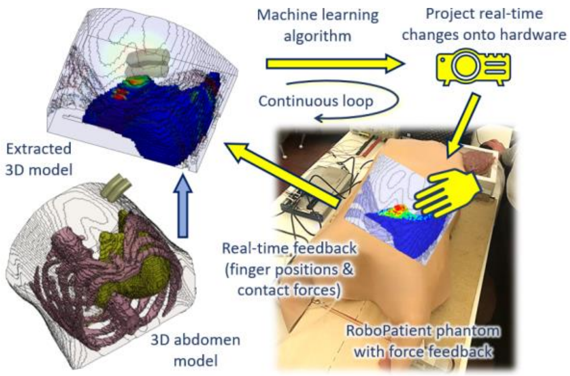

Figure 1 - Overview of the real-time internal abdomen visualisation with respect to haptic feedback from the robotic patient platform.

Method

A high fidelity model of the abdomen is obtained from an abdominal CT scan using the XCAT program, segmented and meshed to construct a finite element model (FEM) (Fig 2a). The full model is simplified in LS Dyna to a lumped abdomen model with liver and ribs, using material properties from the GHBMC model [2] for the flesh and ribs, and the Ogden parameters in [3] for the liver. A dummy finger is added for contact with the abdomen. The surrogate model consists of 25 simulations sets performed with 15mm finger indentation into the abdomen at different locations above the region of interest (ROI) which in this study is the liver edge. The element stresses in the ROI and the fingers contact force are recorded.

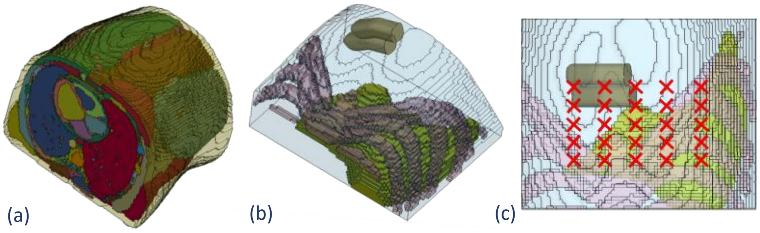

Figure 2 – a) High fidelity abdomen model, b) simplified model for simulations in surrogate model construction, c) top view of model showing simulated finger positions (red crosses)

The finger positions and contact forces are fed into the neural network as training inputs, with element stresses as outputs. The neural network (Fig 3) has 4 hidden layers which use 'tanh' activation functions, and the final hidden layer uses a linear function. The model is then tested with a random finger position and contact force outside the training input and validated by an FEM simulation using the same parameters.

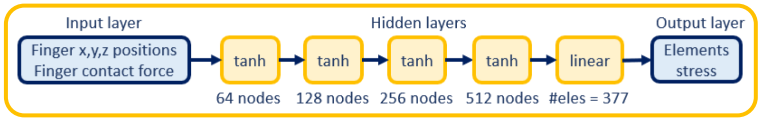

Figure 3 – Machine learning algorithm for the surrogate model training.

Results

Using the neural network shown in Fig 3, the surrogate model was trained to predict the maximum principle stress of the elements in the ROI when the fingers are in contact with the abdominal tissue (Fig 4a). **The performance of the algorithm is evaluated using Eq. (1), with an outcome of 89.92%.**

$$\text{Fit} = 1 - \sqrt{\sum(y_i - \hat{y}_i)^2 / \sum(y_i - \bar{y})^2} \tag{1}$$

where $y, \hat{y}$ and $\bar{y}$ are the actual, estimated and average stress value in testing stage respectively. FEM simulation with the same parameters used to test the neural network was performed in LS Dyna (Fig 4b). **The simulation shows comparable stress distribution onto the liver edge**, with elements stress shown up to 2e-6 GPa. As the model does not take into account the effect of the indentation experienced by the ribs and its contact with the liver, the internal stresses caused by the ribs are neglected in the neural network testing stage.

The input to the neural network will be replaced by real-time force and position readings from force sensors incorporated on the abdominal phantom platform (Fig 5). The changes in the internal element stresses within the ROI will be projected onto the abdominal platform for real –time visualization during user training.

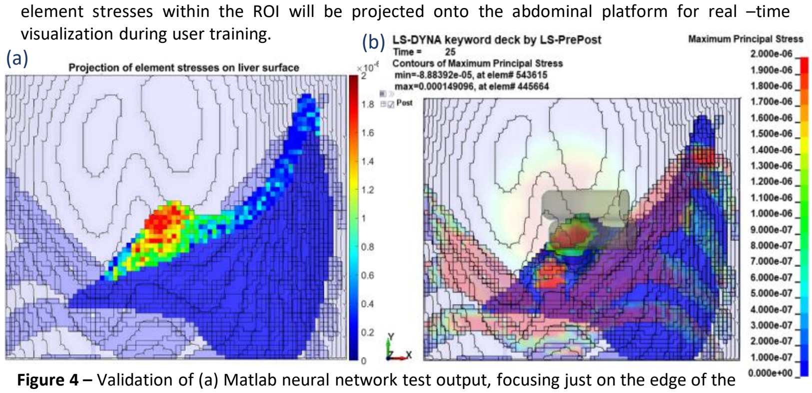

Figure 4 – Validation of (a) Matlab neural network test output, focusing just on the edge of the liver with simulation performed in LS Dyna (a) with same input conditions. (Note that the colormap in Matlab is not exactly the same as that in LS Dyna.)

Discussion

With the surrogate model constructed using the FEM simulations results, we were able **to train the surrogate with neural network using the simulation data to quickly predict desired real-time output to be projected onto the hardware**. This allows us to bypass performing FEM simulations which are computational heavy and time-consuming for each input.

We are currently implementing the trained network with an abdominal phantom equipped with a force sensing platform with four Robotous RFT80-6A01 force sensors (Fig 5) at each corner for real-time force input based on the finger positions of and contact forces exerted by users onto the hardware platform.

We hypothesize that training on the robotic phantom with visual feedback of the organs (e.g. liver stresses) will enhance touch sensitivity in trainees compared to training without the visual feedback, hence providing a more effective training experience. User studies on both the training scenarios will be performed to verify the hypothesis. Our future work includes adding respiratory cycle into the simulations, training and hardware for more realistic organs and abdomen motions during training.

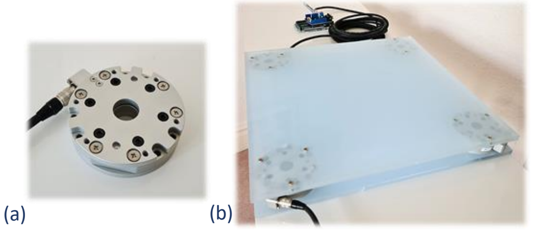

Figure 5 – (a) Robotous RFT80-6A01 force sensor, b) force sensing platform used with the phantom for real time force feedback.

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