## Identifying tissues for task recognition in training of open inguinal hernia repairs

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**Introduction:** Competency-based medical training requires experts to continually instruct and assess surgical residents. The extra time spent by experts in doing this can be mitigated by introducing a computer-guided training platform to guide residents through procedures and provide them with feedback. In order to provide instruction, we first need to recognize the surgical workflow. In this study, we work towards recognizing workflow tasks of an open inguinal hernia repair. The tasks in this procedure are recognizable based on the interactions of various surgical tools with different tissues. This study thus aims to train a neural network to identify tissues of an IHR phantom as we work towards identifying the tool-tissue interactions needed for task recognition.

**Methods:** Five surgeons performed an open IHR on a synthetic phantom previously developed by Nazari *et al*<sup>1</sup>. They wore headmounted cameras to record the procedure. The phantom represented the male groin region, including the skin, subcutaneous tissue, superficial epigastric vessels, Scarpa's fascia, external oblique aponeurosis, spermatic cord, hernia sac, and nerves. The tissues were segmented throughout 1708 frames from the five videos and each pixel was assigned a class label for a tissue or nothing. The percentage of frames each tissue appeared in can be seen in Figure 1. A U-Net was trained using leave-one-user-out cross validation. The F-scores,

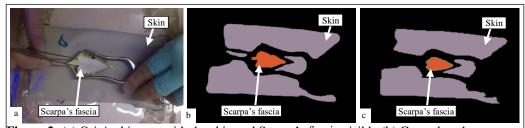
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false positive rates and false negative rates were computed for each tissue to evaluate the U-Net's performance.



**Figure 2:** (a) Original image with the skin and Scarpa's fascia visible (b) Ground truth segmentation of the tissues (c) U-Net correct predictions of the skin and Scarpa's fascia

Results: The U-Net produced higher F-score values for the spermatic cord, skin, and nothing with F-scores of 0.61, 0.69, and 0.97. The U-Net produced slightly lower F-scores for the

subcutaneous tissue, Scarpa's fascia, and external oblique aponeurosis, with values of 0.39, 0.37 and 0.43. The superficial epigastric vessels, hernia sac, and nerves were often not recognized. Figure 2 shows a U-Net prediction in which the skin and Scarpa's fascia were correctly classified.

Conclusions: The U-Net performed better in recognizing nothing, the skin, and the spermatic cord, as these classes were more prevalent in the videos and represented larger portions of the dataset. The U-Net struggled to recognize the hernia sac, vessels and nerves, as they were present in less frames and took up smaller portions of the frames. The Scarpa's fascia and external oblique aponeurosis were often misclassified with each other as they were made of similar materials on the IHR phantom. However, since the videos were recorded at 20 frames/second, the tooltissue interactions last for multiple frames. Thus, misclassifications in individual frames will not be important in task recognition as long as the majority of the classifications for a given interaction are correct. As well, since some tissues are only visible after previous steps, we can mitigate misclassifications by incorporating procedural knowledge. We thus believe our U-Net can sufficiently recognize tissues for workflow recognition. Future studies will look to recognize tool-tissue interactions as we develop a computer-guided IHR training platform.

## **References:**

[1] Nazari, T., Simons, M.P., Zeb, M.H., et al., "Validity of a low-cost Lichtenstein open inguinal hernia repair simulation model for surgical training," Hernia 24, 895–901 (2020).