Autonomous recognition of anatomy and instruments in laparoscopic cholecystectomy surgery

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Introduction

Removal of the gallbladder by keyhole surgery - laparoscopic cholecystectomy (LC) - is one of the most performed general surgery procedures. While a common operation (40,000 annually in Australia), there remains a risk of surgical complication, that includes injury to the bile duct, requiring repeat procedures, prolonged admissions and, in rare cases, death[1].

Artificial intelligence (AI) is a powerful tool with an emerging role in surgical safety, training and quality assurance. AI mimics biological cognitive processes by learning patterns based on prior experience[2]. This pilot project demonstrates the autonomous recognition of anatomy and instruments using an AI algorithm developed with a comprehensive training dataset. Accurate recognition of all structures and instruments is critical to the development of technology that can provide real time guidance, safety mechanisms and feedback to surgeons. To date, other existing LC training datasets do not contain as exhaustive a list of anatomy and instrument labels.

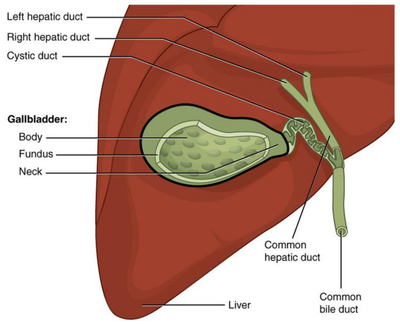

Figure 1: Gallbladder and biliary tree

Aims

1. To develop a pilot training dataset of LC videos using a comprehensive list of instrument and anatomy classes
2. To train an AI algorithm capable of overlying LC video in real time with autonomously identified anatomy and instruments

The primary objective of this software is to mitigate potential risk resulting from a loss of situation awareness. The software can also be employed for coaching and feedback during surgical training.

Methodology

Ethics approval was obtained. Five LC videos were recorded. Individual frames were selected based on a Euclidean distance threshold (approx. 200 per video).

Frames were labelled with 29 anatomy and instrument classes using Darwin V7 labelling software by a surgical trainee. Dataset was expanded using augmentation including colour jitter, random rotation (<30 degrees), random perspective view, random scaling + cropping. Each label has a corresponding RGB colour code.

DeeplabV3+ convolutional neural network (CNN) was trained using training 80% of the data (4 videos) and tested on testing dataset the remaining 20% (5th video).

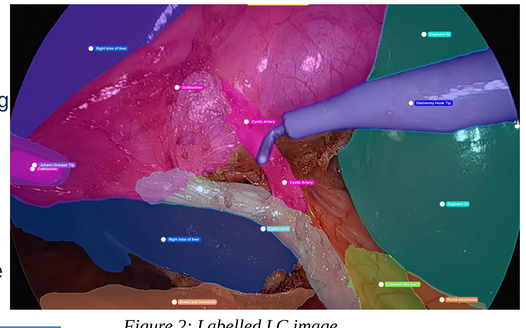

Figure 2: Labelled LC image

Evaluation metrics	
Accuracy	**Intersection over Union (IoU)**
$\frac{\#\text{ correct predictions}}{\text{total }\#\text{ of predictions}}$	Area of overlap between ground truth and prediction

Table 1: Summary of evaluation metrics used in study

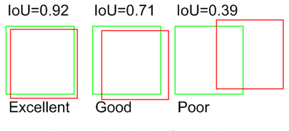

Figure 3: IoU schematic

Results

The network achieved an overall mean accuracy of 83% and mean class weighted IoU of 73%. 90% of classes (26/29) were able to be recognised in the testing dataset. Non recognised and poorly recognized structures were not well represented within the dataset (e.g. Rouviere's sulcus, suction irrigator) or easily confused with other structures or instruments (e.g. grasper, wave grasper, clip applicator)

Class	IoU	Label colour
Gallbladder	0.87	
Diathermy Hook Tip	0.89	
Cholangiogram catheter	0.75	
Johann grasper shaft	0.69	
Johann grasper tip	0.67	
Right lobe liver	0.91	
Segment IV liver	0.89	
Connective Tissue	0.25	
Common Bile Duct	0.32	
Cystic duct	0.42	
Cystic artery	0.22	

Table 2: Classes, intersection over union (IoU) and corresponding class colour (not all classes included)

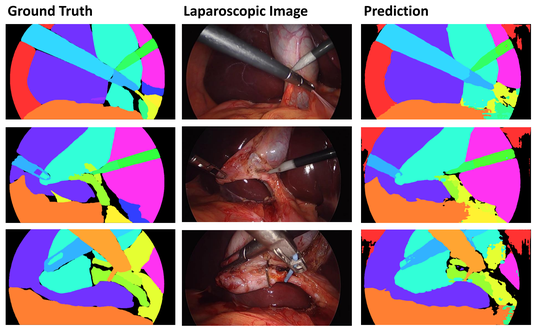

Figure 4: Demonstration of prediction (right) as compared with ground truth (left) on testing dataset

Figure 5 (left): Superimposed labels on LC images (colour coded)

Predictions were also presented in video form mimicking how this technology can be used intraoperatively. Still images are demonstrated in figure 5. The implementation of the technology in real time will require the additional of graphics processing units with the existing laparoscopic video setups in the operating theatre

Conclusions

This pilot trial demonstrates that anatomy and surgical instruments can be accurately detected using AI technology. Using a training dataset with a comprehensive list of classes

The technology can be used to overlay the LC video in theatre, as demonstrated in figure 5 with real time tissue structures autonomously identified, mitigating the potential for injury owing to a loss of situation awareness. Furthermore, the technology can be used as a training and safety tool via:

1. Anatomical mapping for trainee surgeons
2. Recognition of impending iatrogenic injury

Using a limited pilot dataset, we have achieved good results in anatomy and instrument recognition with an extensive class list. By extending and improving our training dataset with additional videos and greater variety of pathological states and surgical approach, we expect the accuracy of our AI algorithms will improve, increasing its utility and a training and safety tool.

Acknowledgments

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