Image Registration between Different Views in Laparoscopic Image

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Abstract

In cancer surgery, reliable intraoperative visualization is still a technological difficulty. Recently, a novel tethered laparoscopic gamma detector was introduced to identify the location of tracer activity to help identify lymph node. However, the location of the probe ('SENSEI®') and the tissue surface it points to will not be clearly indicated. For better tracking of the sensing area of the probe, a miniaturized camera and a structured light will be integrated into the probe. Therefore, the aim of this study is to propose a fast method for image registration between laparoscopic view and an attached miniaturized camera. Meanwhile, the sensing area of probe should be found in the view of laparoscope. We designed a structure to connect the hardware: camera, structured light and probe. A self-supervised convolutional network (AMIRNet) was designed to learn the discriminative features of the images to directly make registration. After that, structured light was used to determine the sensing area of probe in the laparoscopic image.

Introduction

In the past 30 years, laparoscopic surgery has completely changed the concept of minimally invasive surgery [1]. However, clearly distinguishing cancerous and non-cancerous tissues was always difficult for surgeons that once relied on their eyes and sense of touch in traditional laparotomies. To address precise positioning and resection of the labeled cancerous tissue or lymph nodes, gamma probe has been developed by Lightpoint Medical Ltd. called 'SENSEI®'. This probe can complement the preoperative nuclear image, however, it is a visualization challenge in because it is not in direct contact with the tissue in the surgery.

☐ Limitation

Many probe tracking methodologies have been proposed to track the sensing area of the probe in the view of laparoscopic like attaching and detecting the image-based optical pattern [2][3]. However, these methods can just localize the small sensing area in a large laparoscopic view. They can not identify tissue surface and provide better visualization of probe to the surgery.

☐ Solution

For better observing the small area pointed by the probe, the miniaturized camera attached to the probe will provide more detailed information of tissue surface to the surgeons. In order to find sensing area of the probe, the structured light is attached to the probe.

☐ Objectives

1. A connection system is designed to connect structured light, probe and camera.
2. The triangle principle is used to localize the sensing area of probe.
3. A fast self-supervised learning method for image registration between views in laparoscopic image and attached miniaturized camera is built.

Method

☐ Detecting Sensing Area of Probe

- According to the pixel colour, the original image is converted to a binary image
- Based on the binary image, a pattern-localization mask is made to remove unrelated point to improve the accuracy of classification.
- Then, the connected component algorithm is applied to find structured light points.
- The centre point of structured light patterns is labelled and the distance OA away from center of image is calculated.
- The distance OA will change with the height of the camera shot (the higher the height, the larger shooting area, the small OA). Therefore, a linear function can be conducted.

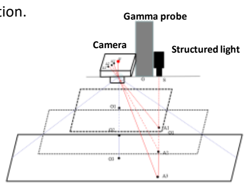

Figure 1 – Principle of measuring distance between structured light and probe

☐ Image Registration

1. ***Make the database:***
   Choose two image (I^A, I^B) from different views ➡ Pick one square region P^B in I^B ➡ Use SIFT to find ground truth (SSIM >0.9)

2. ***Build the network***
   The encoder is build based on Resnet34[5] to learn features from images, the regression part is built to predict the corners of small image in the view of laparoscopic image.

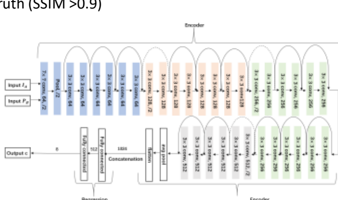

Figure 2 – Network structure

3. ***Loss:***
   a) Least absolute deviations (L1 loss): the ground truth labels and the predicted four corners.
   b) MS-SSIM and L1 loss are combined: rebuilt image by predicted four corners and input small image P^B [4].

$$Loss = \frac{1}{N}\sum_{i=1}^{N}\left|C_{ground\_truth} - C_{predict}\right| + (0.85\mathcal{L}^{SSIM} + 0.15\,\mathcal{L}^{L1})$$

Results

☐ For Hardware

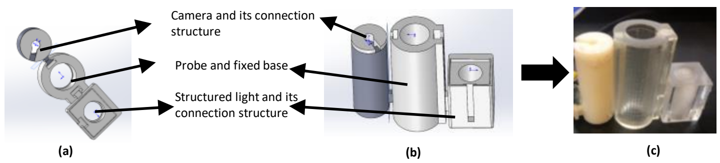

Figure 3 – (a) Top view of 3D model (b) Front view of 3D model (c) Front view of real model

☐ For Detecting Sensing Area

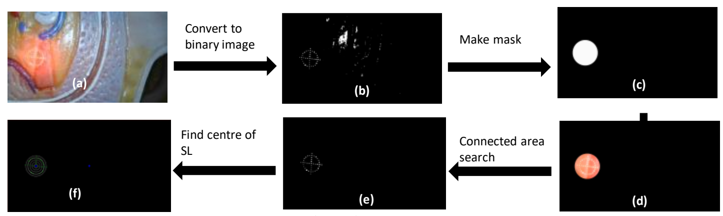

Figure 4 – The flow of detecting structured light position

The conducted formulation based on distance and height: $H = -0.00758D + 9.985$

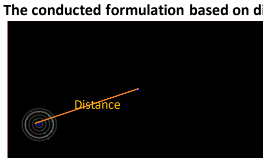

Figure 5 – The example detecting result (height in 5cm)

Table 1: Test results

Ground truth depth(cm)	Distance(pixel)	Measured depth (cm)	Error (cm)
4.2	777.185	4.19cm	0.01
4.4	740.401	4.46cm	0.06
5	685.85	4.85cm	0.15
5.6	581.129	5.59cm	0.01

☐ For Image Registration

For database, 38719 images were made for training and 4000 images were used for validation. After training, 2560 images were tested.

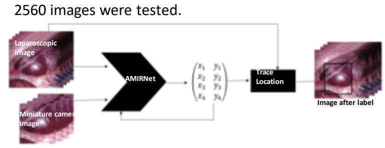

Figure 6 – The workflow of image registration framework

Table 2: Test results

	Corners error (pix)	Test time(s)	Unable test image
Our method	2.8506	0.000834	0
Brisk	685.85	0.26	919
Orb	4e30	0.011	1038

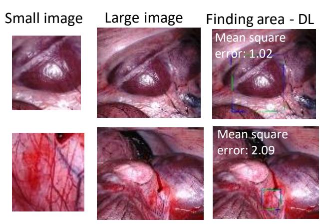

Figure 7 – The test results from Endovis database

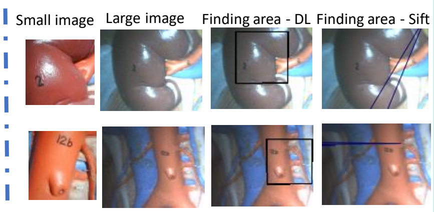

Figure 8 – The test results for real data

Discussion

1. We have designed a 3D model to connect the components for the experiment, and the model has been printed and used successfully.
2. The structured light can be detected now and the depth of probe away from the plane has been calculated.
3. The Affine-Svd-Sift method is tried for image registration. However, the speed of it is too slow about the 60s for each pair. Therefore, deep learning is designed. The database is made and the AMIRNet is built and trained successfully. The result of deep learning is better than the traditional feature-based method. It has achieved a faster speed smaller than 1s for each pair.

Future work

1. According to the depth, the sensing area should be found out. Present depth estimation is just suitable for the perpendicular plane, another structured light should be tried for a more complex condition.
2. Based on the new structured light, a new connected component should be designed and printed for experiment.
3. The present database is based on the Endovis database, therefore, it still has some errors used in real data. Therefore, a new database should be collected and made for training the network. And the network can be improved in the future.

References

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