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Bleeding Point Detection System For Visualization During Endoscopic Spine Surgery

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UIC NEUROSURGERY

Introduction

Background

Endoscopic Spine Surgery (ESS) offers minimally invasive techniques for spinal procedures and is performed by making a small incision at the desired vertebral level, separating soft tissue from vertebrae to create a cavity for endoscopic instruments, creating a port for the instruments, and continuously filling the cavity with saline to ensure patency of the cavity [1]. Compared to conventional and other minimally invasive techniques, ESS shows advantages in recovery times, tissue damage, and infection rates, but presents challenges such as longer operating times and limited visualization due to bleeding [2]. When a bleed occurs, the field of view becomes compromised.

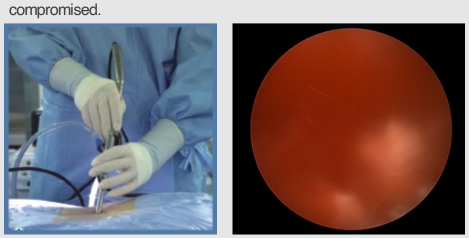

Fig 1. Surgeon with endoscopy apparatus & saline irrigation (left). Occluded surgical bleed (right).

Needs Statement

Neurosurgeons performing endoscopic spine surgery often lose visualization due to bleeding and require a method to maintain a clear visual field and decrease procedure time.

Existing Solutions and their Limitations

Gel immersion endoscopy: facilitates clear visualization by displacing blood during surgeries within the gastrointestinal tract. Not suitable within spinal cavity due to differing anatomy and surgical techniques; dedicated gel not proven safe for use outside of GI tract [3].

Radiofrequency bipolar hemostatic sealer: provides hemostasis by sealing bone and soft tissue. Helps control bleeding and reduce surgical time, but does not assist in detecting bleed point or maintaining clear visual field [4].

Design Objective

Design an effective visualization tool that enhances the surgeon's ability to identify bleeding point(s) in real time during endoscopic spinal surgery.

Most Critical PRDs

Detect bleed point location within 5mm radius.

Indicate location of bleed point within 120 seconds.

Device Design

Bill of materials:

1. MATLAB 2023 license
2. Machine learning toolbox

The semantic segmentation network assigns each pixel in the image a categorical label. Our designed convolutional neural network (CNN) works on an "encoder-decoder" structure, where the encoder down-samples the image and performs non-linear optimization while the decoder uses learnable filters to reconstruct the image. The final product is an image with each pixel labeled either "background" or "bleed".

Device Design Cont'd

Neural Network Design

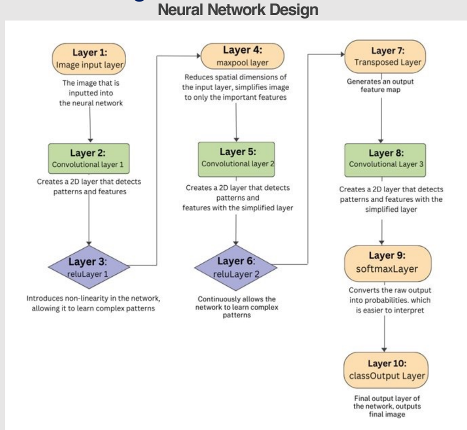

Fig 2. Layers and output of neural network

Neural Network Output

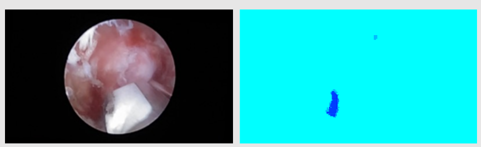

Fig 3. The output of the network which uses the input image (left) and returns the labeled image (right).

= background, = bleed

Verification

We used MATLAB to run the program and tested 20 frames. We marked the actual bleeding points on the 20 test images. We then used ImageJ to set a true scale using the known size of various surgical tools. We then inputted the actual bleeding points in ImageJ from the analyzed frames in MATLAB. Lastly, we found the distance between the true and predicted bleeding point in mm.

Fig 4. Test frame with calibration stick of known length. Actual and analyzed bleeding point shown as 1. 2. (left)

We performed a one-sided T-Test calculation on the two sets of data i.e. the actual bleeding point coordinates and analyzed (calculated) bleeding point coordinates.

H_0: $\mu \geq 5$ mm

H_A: $\mu < 5$ mm

Results

The model correctly labeled the bleeding point in 16 out of the 20 test frames. We defined cases that qualitatively categorize the verification results:

Case A: Only the correct region labeled.
Case B: Multiple regions labeled (including the correct region).
Case C: Correct region NOT labeled.
Case D: No regions labeled; or the region is a straight line.

12 of the 16 frames correctly labeled frames were Case A, whereas in the other 4, the model also labeled one or more incorrect regions in addition to the correct one (Case B).

The model labeled the bleeding point within 5mm from the center of the true bleeding point with statistical significance (Fig. 4, p = 9.74E-09 < 0.05, from t = -9.21 < 2.086). The average error across all frames was 1.9423mm. The average error across Case A frames only was 1.247mm.

We normalized the prediction centroid to the true centroid in cartesian coordinates and plotted the mean x and y coordinates to determine if there was a directional bias. Our finding suggests that the model may overshoot along the positive y-axis and x-axis.

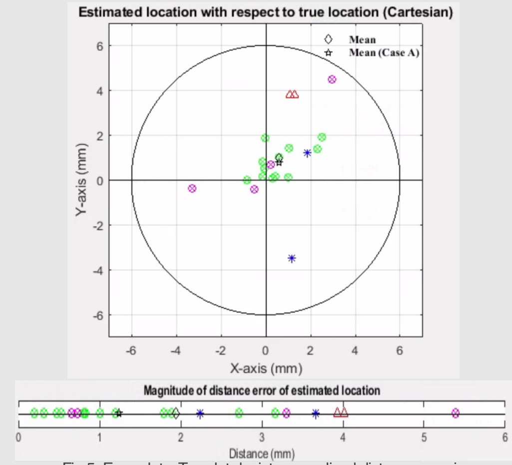

Fig 5. Error plots. Top plot depicts normalized distance error in cartesian format. Each point represents the centroid of the predicted location of the bleeding point normalized to the centroid of the true bleeding point. Bottom plot depicts magnitude. The far left represents the centroid of the true bleeding point (i.e., zero error).

Conclusion and Next Steps

The use of neural network models to identify bleeding endoscopic surgery shows promising results. Our verification method indicated that the model can correctly identify the bleeding point in vast majority of test frames. However, the model has room for improvement, as it occasionally labels non-target regions or fails to identify the relevant region entirely. The significance of this project lies in its potential to shorten surgical time and enhance patient recovery through better detection of the bleed. This project highlights how combining cutting-edge computing with medical expertise can tackle major health challenges.

Moving forward, the project will aim to incorporate a wider range of endoscopic video footage from diverse patient groups. We have recently demonstrated the model's ability to analyze an entire video and predict the center of the bleeding point based on a fast retrospective analysis of the persistence of blood in each pixel in the frame (Fig. 6). Additionally, we intend to conduct validation testing in a controlled, simulated environment to compare the performance of the model against traditional methods of bleed point detection.

Upon completion of the testing phase, we will collaborate with clinicians to receive feedback on the usability of the model in a live surgical setting and adjust the user interface accordingly. We will explore the integration of the model into existing endoscopic systems to test its functionality in real-time during surgeries. Lastly, we will investigate the model's scalability to other types of surgeries.

Fig. 6 Overlayed label indicating the bleeding point during the video of model simulation (left). The neurosurgeon also has the option of pressing a physical button that toggles an arrow to further assist in identifying the bleeding point (right).

References

[1] H. Kwon *et al.* (2023, Mar.). "The Role and Future of Endoscopic Spine Surgery: A Narrative Review."
[2] L. Pan *et al.* (2014, May). "Comparison of tissue damages caused by endoscopic lumbar discectomy and traditional lumbar discectomy: A randomised controlled trial."
[3] T. Yano *et al.* (2021, Jun.). "Development of a gel dedicated to gel immersion endoscopy."
[4] Medtronic, "Electrosurgical Products - Aquamantys Bipolar Sealers."

Acknowledgements

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