Parallel Cross Window Attention Transformer and CNN Model for Segmentation of Instrument during Surgery

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Abstract

Precise segmentation of surgical instruments is a fundamental component in the development of computer-aided surgery systems by assisting the surgeons to navigate the patient's body aiming to enhance the surgical precision and patient safety. Though real-time tracking of surgical instruments is critically important in invasive computer-assisted surgeries, it is challenging to achieve a highly sensitive and accurate system in complex surgical environment. Recently, synthetic data for instrument segmentation in surgery (Syn-ISS) challenge using synthetic datasets is organized to develop high performance methods for instrument segmentation. In this work, we present encoder and decoder-based hybrid parallel cross window attention-based transformer during the feature extraction, which consists of the multi-scale channel attention, convolutional layers, and Transformer layers, forming a unified block. Syn-ISS challenge dataset comprised of two tasks. In first task1, they need to develop deep learning-based method for binary instrument segmentation and in second task multiclass instrument segmentation is required. Experiments conducted on Syn-ISS dataset achieved 0.993 F-score for task 1 and 0.993, 0.975, and 0.951 F-score for shaft, wrist, and jaw segmentation respectively for Task 2.

Keywords: Deep Learning, Parallel Cross Window Attention, Transformer, 2D Instrument Surgery segmentation, Dense Net.

1. Introduction

Minimally invasive segmentation using optical imaging systems have gained popularity in modern healthcare due to their advantages, including reduced patient recovery time and lower mortality rates. Optical imaging has enabled the use of robotic platforms such as the da Vinci surgical system by Intuitive Surgery for complex minimally invasive surgeries [1]. Nevertheless, during endoscopic surgical suturing procedures, the presence of surgical instruments can impede surgeons' dexterity due to the confined working space and limited visual field-of-view. These visual obstructions elevate the risk of tissue scars and tears. Therefore, the crucial task is to transparently remove or mask the surgical instruments from the background and subsequently fill the masked region with appropriate background content. Automated segmentation of surgical instruments in MIS is currently a focal point of research due to its significant practical applications [2].

The challenges associated with surgical instrument segmentation are diverse and contingent upon factors such as the source of dataset acquisition, the type of surgical procedure, the specific instruments or tools in use, image resolution, dataset scale, tool characteristics, and challenging conditions like occlusions, rapid appearance alterations, specular reflections, smoke, blur, and blood spatter. Segmentation of surgical instruments has been formulated using both instance segmentation [2] and semantic and segmentation [2].

Recently, Syn- ISS (synthetic data for instrument segmentation in surgery) challenge using synthetic datasets is organized to develop high performance methods for instrument segmentation [3]. Recently, there is a different method has been proposed using medical imaging and signals [4], [5], [6], [7], [8] for classification and segmentation. Based on our previous work on segmentation [6], [7], [8], [9]. We presented encoder-decoder based hybrid transformer and CNN model for instrument segmentation with parallel cross window attention-based transformer block in encoder and 2D Dense Net layer CNN blocks in decoder. The main contribution in this work is:

i. Developed Parallel Cross Window Attention Transformer encoder block for 2D segmentation task.
ii. Proposed 2D Dense Net block at decoder side of proposed model using transformer-based encoder features.
iii. Compare performance on synthetic data for instrument segmentation in surgery for binary and multiclass surgery instrument segmentation.

2. Methodology

2.1. Parallel Cross Window Attention Transformer and CNN model for instrument segmentation

Due to the intrinsic locality of convolution, which is incapable of modelling long-range dependencies. In addition, Transformer generates single scale features with only token wise attention, and it ignores the relationship among channels, thus subpar to tackle situations such as segmenting multi scale lesion regions in medical images. Considering these issues, we introduce the hybrid Transformer block during the feature extraction, which consists of the multi-scale channel attention, convolutional layers, and Transformer layers, forming a unified block. Our proposed model is based on encoder and decoder layers, and we have proposed a hybrid transformer and CNN model for instrument segmentation. Our proposed model consisted of Parallel Cross window attention-based transformer block on the encoder side and 2D Dense Net layer CNN blocks on the decoder side. We have used Dense Net 201 based layers on the decoder side. The proposed model is shown in Figure 1 (a) and Figure 1 (b).

2.2. *Parallel Cross Window Attention Transformer Block:*

An efficient hybrid segmentation framework consisting of integration of convolutional neural network and learnable global attention heads using Efficient Parallel-Cross Attention module. We use the depth-wise separable convolution as an efficient version of convolution implemented by depth wise conv and pointwise conv, where the depth wise convolution gathers the spatial information while the pointwise convolution gathers along the channel dimension. Furthermore, we have concatenated features from multi-window transformer block with depth wise convolutional layer. In encoder side, we have used transformer-based block aided with cross attention window-based mechanism, however, we have used normal 2DCNN based module at decoder-side. The features are concatenated from window area partition and window partition and further these features are concatenated with depth wise convolutional layer features and then pass these features to next layer of the encoder block.

Unlike the vision transformer (ViT) that computes relationship between tokens at each step of self-attention module, swin transformer is based on computation of attention within partition of non-overlapping local windows of lower resolution feature map and original image. In contrast to the original swin transformer that uses patch merging layer to empower it for pixel level tasks, we used rectangular-paralleled-piped windows to accommodate non-square images using Parallel-Cross Attention approach (window area partition and window partition). To extract different feature maps from each convolutional block with parallel window-based transformer in encoder, each block consists of Parallel Cross Window Attention Transformer block, patch merging and depth wise [7] convolutional layer. The proposed block is shown in Figure 1 (b).

2.3 Convolutional Neural Network (CNN) block:

To better encode spatial location information and inject strong inductive bias, we adopt convolutional block to extract local spatial features. Specifically, given an input feature F_(i-1), we adopt the convolutional block to model local spatial features, which are shown as follows:

$$F_c^i = ConvBlocks_i(F_{i-1}), i \in \{1,2,3,4\} \qquad (1)$$

$where\ F_c^i \in R^{\frac{H}{2^{i+1}}\times\frac{W}{2^{i+1}}\times C_i}$ is the local features, which contains 2D spatial location information, making it possible to encode position information. The convolutional blocks in each decoder stage consisted of DensNet-201 based architecture is shown in Figure 1 (a).

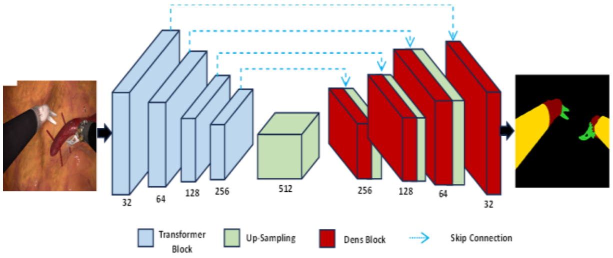


Fig. 1 (a) The proposed model based on hybrid transformer and Dense Net CNN for instrument and instruments parts segmentation

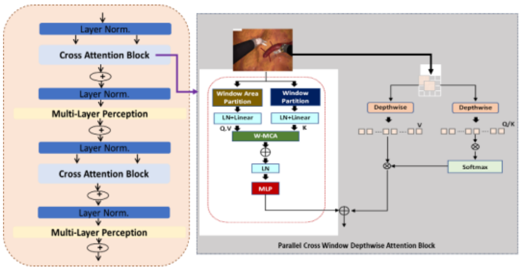


Fig. 1 (b) The proposed Transformer block based on parallel cross window depth wise attention module

In the encoder block, the spatial input size has been reduced with an increasing number of feature maps and on the decoder side, the input image spatial size has been increased using a 2D Conv-Transpose layer. The input features' maps that are obtained from every encoder block are concatenated with every decoder block feature map to reconstruct the semantic information. The spatial size doubled at every encoder block and feature maps are halved at each decoder stage of the proposed model. The feature concatenation has been done at every encoder and decoder block except the last 1x1 convolutional layer. The three-level deep-supervision techniques are applied to get the aggregated loss between ground truth and prediction.

3.0 Experiment

3.1 Dataset

Recently, Syn-ISS challenge [3] is introduce in MICCAI-2023 to develop high performance methods for instrument segmentation. Syn-ISS dataset is synthetic instrument segmentation datasets consist of two main tasks. The task-1 is a binary segmentation to annotate all pixels that contain an instrument and consist of 1200 instances of simulated scene along with computer generated corresponding masks. Task-2 further focuses on segmentation of pixels belonging to different parts of the instrument and consists of 1800 instances.

3.2 Network Setting

We adopted data augmentation of horizontal flips, vertical flips, and random rescales. The network is trained for 200 epochs using the Adam optimizer and the weight decay is 0.0001. We have used binary cross-entropy and dice loss used for training and optimization [10], [11]. [12]. The dataset has different spatial size, hence, we resized each image and label sample to 512x512, whereas we resized each sample to original input 2D image size by bilinear interpolation during inference time. The 25-batch size is used during training. The model is training on A6000 GPU machine with 4 GPUs and all model codes are developed from scratch using Pytorch Library.

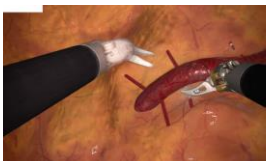
4.0 Result

The training dataset has been divided into 80 percent training and 20 percent validation. We have trained and validated our proposed model using 5-fold cross validation and based on the best validation score, the proposed model has been submitted for task 1 binary segmentation and task 2 multiclass segmentation. We have evaluated the performance using IOU, F-Score, Recall, Precision, and HD. The best score produced by our proposed model based on validation dataset is shown in Table.1 for Task 1 and Task 2.

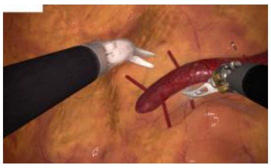
Table 1. The performance analysis of proposed solution for Task1 and Task2.

Algorithms	**Tasks**	**classes**	**IOU**	**F-Score**	**Recall**	**Precision**	**HD**
Proposed model	Task 2	shaft	0.9868	0.9930	0.9923	0.9920	14.23
		wrist	0.9497	0.9753	0.9753	0.9695	10.67
		jaw	0.9086	0.9506	0.9523	0.9357	12.88
Proposed model	Task 1	instrument	0.9868	0.9933	0.9934	0.9909	0

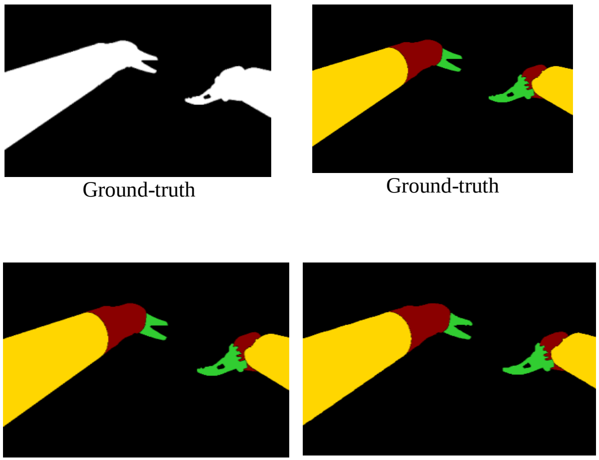
The visualization of validation input image for binary and multiclass segmentation is shown in Figure 2. Our proposed produced similar prediction masks as compared to ground-truth segmentation masks.



input



input



Ground-truth

Ground-truth

Prediction

Prediction

Fig. 2 The input, ground-truth, and predicted segmentation masks. shaft, wrist, and jaws are shown using a yellow, red, and green segmentation mask.

5.0 Conclusion

Ideally, surgical instrument segmentation is used in real time, to identify tools being used as a surgery is being performed. The integration of surgical instrument segmentation into computer-aided surgery systems offers numerous benefits, including real-time guidance, instrument tracking, and improved surgical outcomes. In this work, we presented an encoder and decoder-based hybrid parallel cross window attention-based transformer which consists of the multi-scale channel attention, convolutional layers, and Transformer layers. Experiments conducted on Syn-ISS challenge dataset achieved 0.993 F-score for task-1 and 0.993, 0.975, and 0.951 F-score for shaft, wrist, and jaw segmentation respectively for Task 2.

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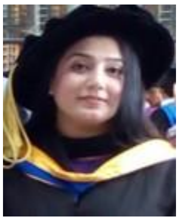

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