SATr: Slice Attention with Transformer for Universal Lesion Detection

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Abstract. Universal Lesion Detection (ULD) in computed tomography plays an essential role in computer-aided diagnosis. Promising ULD results have been reported by multi-slice-input detection approaches which model 3D context from multiple adjacent CT slices, but such methods still experience difficulty in obtaining a global representation among different slices and within each individual slice since they only use convolution-based fusion operations. In this paper, we propose a novel Slice Attention Transformer (SATr) block which can be easily plugged into convolution-based ULD backbones to form hybrid network structures. Such newly formed hybrid backbones can better model long-distance feature dependency via the cascaded self-attention modules in the Transformer block while still holding a strong power of modeling local features with the convolutional operations in the original backbone. Experiments with five state-of-the-art methods show that the proposed SATr block can provide an almost free boost to lesion detection accuracy without extra hyper-parameters or special network designs.

Keywords: Universal lesion detection · Slice Attention · Transformer.

1 Introduction

Universal Lesion Detection (ULD) in computed tomography (CT)¹,² plays an essential role in computer-aided diagnosis (CAD)³,⁴, and ULD is a challenging task because different lesions have diverse shapes and sizes, easily leading to false positive and false negative detections. Mainly inspired by the clinical fact that radiologists need several adjacent slices for locating and diagnosing lesions on one CT slice, most existing ULD methods take several adjacent 2D CT slices as the inputs to a 2D network architecture⁵,⁶,¹⁰,¹²,¹⁵,¹⁸ or directly adopt 3D network designs¹⁰ that take 3D volume as input to extract more 3D context information. While both 2D and 3D methods have yielded great
ULD performances, the multi-slice-input based 2D detection methods are much more popular than pure 3D fashion because 2D networks benefit from robust 2D models pretrained from large-scale data whereas publicly available 3D medical datasets are not large enough for robust 3D pretraining.

While achieving success in ULD, the multi-slice-input based 2D approaches have inherent limitations: (i) Weak global context modeling within each slice. Most existing ULD methods are fueled by the successful Convolutional Neural Networks (CNN) pretrained backbones (e.g., DenseNet [31]) which learn local features via convolution operations in a hierarchical fashion (e.g., FPN [32]) as powerful image representations. Despite the strong power of local feature extraction, CNNs show their weakness in dealing with global (long-distance spatial) contexts [33]. As shown in Fig. 1 (a), the single-slice CAMs of two CNN-based ULD backbones contain flocks of redundant and inaccurate activation regions which is due to the limitation of CNN backbones in handling global contexts within each slice for ULD tasks. (ii) Weak inter-slice context modeling. When dealing with the multi-slice input, most ULD methods [4,6–8,10,12,15,18] adopt independent 2D convolutional operations for each slice to extract independent features, and the independent features further go through a 3D convolution for feature fusion. Such convolution-based fusion methods are good at dealing with local features, but they unfortunately deteriorate in handling global features among different slices. To tackle this, some ULD approaches [9,16,17] propose to reshuffle feature channels among different slices which relieves this issue to some degree. But their ability in capturing rich global representations are still weak due to the use of pure convolutional operations. As shown in the CAMs in Fig. 1 with the help of convolution based multi-slice fusion, the number of redundant and inaccurate activation regions can be decreased than single-slice-input based methods; however, these methods still cannot capture rich global contextual information due to the limit of CNN receptive field.

Recently, CNN-transformer hybrid architectures have been introduced to several visual tasks [33,35]. Thanks to the Multihead Self-Attention (MSA) mecha-
To address the above issues, we hereby propose a novel Slice Attention Transformer (SATr) block, which works properly with multi-slice-input and assists can effectively extract the global representations from both each individual slice and multiple adjacent slices. The SATr block can be easily plugged into the popular convolution-based ULD detection backbones to form hybrid network structures, thus reaping the advantages from both Transformer and CNN worlds.

To validate the effectiveness of our method, we conduct extensive experiments on the DeepLesion dataset [36] based on five SOTA ULD methods under all training data settings, and also test the SATr with less training data (25% and 50%) based on two SOTA ULD methods.

2 Method

As shown in Fig. 2, The SATr block features two novel modifications of a naive transformer block: i) Enhancement of value vector with key-slice feature. As de-
scribed above, arbitrarily using the all-slice feature causes an opposite effect. Hence we separate the key-slice feature and add it up with the all-slice feature to serve as the value vector. In this way, the key-slice feature is largely preserved and SATr applies more strength to catching global cues between the key-slice’s feature and other slices’ feature. It should be noted that the value vector also entirely contains all-slice feature, therefore SATr is still highly effective in modeling global contexts both within each slice and among different slices. ii) Removal of key-slice feature from the query and key vectors. Experiments show that when using the all-slice feature to generate query and key vectors, SATr is prone to catching feature dependency within the key-slice feature itself (network lazy or overfitting), this is reasonable because the key-slice feature itself should be the main contributor for key-slice lesion detection task, but it completely conflicts with the motivation of introducing multiple adjacent slices to assist ULD. Admittedly, this removal sacrifices the feature dependency learned within the key slice, but it forces the SATr to learn more dependency to better make up the weakness of CNN backbone.

We hereby take the three-slice-input ULD method as a working example to illustrate our method while most SOTA results are reached under 7-slice or 9-slice settings. The SATr blocks are inserted between the feature extractor block (i.e., blocks in backbones) and each feature collector (e.g., FPN) without extra modifications on the original network. Section 2.1 details the common backbone of multi-slice-input ULD methods; Section 2.2 explains the newly introduced SATr block, and Section 2.3 introduces the hybrid network with SATr blocks.

2.1 Multi-slice-input backbone

In the multi-slice-input fashion, the ULD method is trained to localize the lesion in the key slice $I_k$, while the adjacent slices, including the same number of upper slices, $I_u = [I_1^u, ..., I_N^u]$, and lower slices, $I_l = [I_1^l, ..., I_N^l]$, are used to assist the lesion detection for the key slice. Without loss of generality, we set $N = 1$. Hence, the input data can be formulated as $I = [I_u, I_k, I_l] \in \mathbb{R}^{3 \times 1 \times W \times H}$, where $W$ and $H$ are the width and height of the input CT slices, respectively.

Similar to most backbones, the multi-slice-input backbone $F_b$ consists of several continuous CNN blocks $B = [B^0, ..., B^M]$ (e.g, Dense blocks in DenseNet), and further each block utilizes several separate sub CNN blocks $B^m = [B^m_u, B^m_k, B^m_l]$ to deal with the multi-slice input; thus the features from different slices $f = [f_u, f_k, f_l]$ are independent after these blocks. Specifically,

$$f^m = [f_u^m, f_k^m, f_l^m], \quad f^{m+1} = [f_u^{m+1}, f_k^{m+1}, f_l^{m+1}] = [B_u^m(f_u^m), B_k^m(f_k^m), B_l^m(f_l^m)],$$

where $B_k^m$ is the sub-CNN block for the key-slice feature in the $m$-th CNN block $B^m$, and $f^m \in \mathbb{R}^{3 \times C^m \times W \times H}$ is the input (or the output) of $B^m$. $R^m$ and $C^m$ are the downsampling ratio and channel number of CNN block $B^m$.

Afterward, the output feature $f^m \in \mathbb{R}^{3 \times C^m \times W \times H}$ is fed into a 3D convolution $Conv_{3d}$ with $3 \times 1 \times 1$ Kernal to fuse the feature among different slices:

$$f_{fuse} = Unsqueeze(Conv_{3d}(f^m), 0), \quad f_{fuse} = [f_{fuse}^0, ..., f_{fuse}^M],$$
where $f^m_{fuse} \in \mathbb{R}^{C \times \frac{W}{16} \times \frac{H}{16}}$ acts as the $m$-th input layer $l^m_{fpn}$ in FPN $F_{fpn}$:

$$l^m_{fpn} = f^m_{fuse}; \ f_{fpn} = F_{fpn}(l^0_{fpn}, ..., l^M_{fpn}).$$  \hfill (3)$$

The $f_{fpn}$ is the final output of the FPN $F_{fpn}$.

### 2.2 Slice attention transformer

As shown in Fig. 2, the SATr block contains two stages, i.e., patch embedding extraction and slice feature attention.

**Patch embedding extraction.** Motivated by [33][37][38], as shown in Fig. 3, we use the ‘Convolutional + pooling’ manner for single-slice patch embedding extraction. Considering that the extraction is the same among different slices and different CNN blocks $B^m$, we only formulate the extraction processes of key-slice $f_k \in \mathbb{R}^{C \times \frac{W}{16} \times \frac{H}{16}}$ and remove the CNN block index $m$ in this section:

$$f_k^E = \text{AP}(\text{Conv}_2d(f_k), r), \ r = \frac{W}{16} = \frac{H}{16}.$$  \hfill (4)$$

where $\text{Conv}_2d$ denotes a 2D convolution with $\text{Kernel} = (1 \times 1)$ and 384 output channels, the $\text{AP}$ is the average pooling operation with pooling size $r$ and stride $r$. We change the pooling size accordingly to get the fixed size output feature $f^* = [f_u^E, f_k^E, f_l^E] \in \mathbb{R}^{3 \times 384 \times 16 \times 16}$. Now the size of each slice’s patch embeddings $[E_u, E_k, E_l] \in \mathbb{R}^{3 \times 256 \times 384}$ is also fixed after feature reshaping.

As for the all-slice patch embedding extraction, we utilize a 3D convolution $\text{Conv}_3d$ to fuse features among different slices which is the same with the fusion manner in the backbone.

$$f_{all}^E = \text{Conv}_3d(f).$$  \hfill (5)$$

Differently, the $\text{Conv}_3d$ is with $\text{Kernel} = (3 \times r \times r)$ and stride $r$, so the $f_{all}^E$ shares the same shape with single-slice patch embeddings, and the all-slice patch embeddings $E_{all} \in \mathbb{R}^{256 \times 384}$ can be also generated after feature reshaping.
It is worth noting that all patch embeddings, including single- and all-slice embeddings, are with the same spacial size to fit the followed transformer block.

**Slice feature attention.** Within the slice feature attention, we still follow the ‘<q, k, v> head-MSA-MLP’ design as in the naive transformer block, but we modify the input of q,k&v according to the ULD multi-slice-input scene.

As for the query head $H_q$ and key head $H_k$, we concatenate the patch embedding of all adjacent slices ($E_u$&$E_l$) to act as the input:

$$f_q = H_q([E_u; E_l]), f_k = H_k([E_u; E_l]),$$  \hspace{1cm} (6)

where $f_q$ and $f_k$ are the q value and k value, respectively. As for the value head $H_v$, the sum of key-slice and all-slice patch embedding is the input:

$$f_v = H_v(E_{all} + E_k),$$  \hspace{1cm} (7)

where $f_v$ is the v value and ‘+’ denotes the element-wise sum.

The afterward design follows the naive Transformer block including MSA $F_{msa}$ and MLP $F_{mlp}$:

$$f_{msa} = F_{msa}(f_q, f_k, f_v), \quad f_{mlp} = F_{mlp}(f_{msa} + f_v), \quad f_{tr} = f_{mlp} + f_{msa}. \hspace{1cm} (8)$$

The generated output feature $f_{tr} \in \mathcal{R}^{256 \times 384}$ will be interpolated and reshaped to the original size to get the final output of our proposed SATr,

$$f_{SATr} = \text{ReShape}(\text{Interpolate}(f_{tr})), \hspace{1cm} (9)$$

where $f_{SATr} \in \mathcal{R}^{C_m \times \frac{W}{16} \times \frac{H}{16}}$ is the output of the SATr.

### 2.3 Hybrid network

The proposed SATr $F_{SATr}$ can be easily implemented into convolution-based detection backbones to form hybrid network structures:

$$f_{SATr}^m = F_{SATr}(f_{fuse}^m), \quad \hat{f}_{fuse} = \text{Conv3d}(\{f_{SATr}^m; f_{fuse}^m\}), \hspace{1cm} (10)$$

where $\text{Conv3d}$ denotes a 3D convolution with $Kernel = (2 \times 1 \times 1)$, the outputs of ‘SATr’ $f_{SATr}^m$ and the original backbone $f_{fuse}^m$ will be concatenated and further fused by $\text{Conv3d}$ to serve as the $m$-th input layer $f_{fpn}^m$ of FPN:

$$l_{fpn}^m = \hat{f}_{fuse}^m, \quad f_{fpn} = F_{fpn}(l_{fpn}^0, ..., l_{fpn}^M). \hspace{1cm} (11)$$

### 3 Experiments

#### 3.1 Dataset and setting

Our experiments are conducted on the ULD dataset DeepLesion [36]. The dataset contains 32,735 lesions on 32,120 axial slices from 10,594 CT studies of 4,427 unique patients. Most existing datasets typically focus on one type of lesion,
Table 1. Sensitivity (%) at various FPPI under full training dataset settings on the testing dataset of DeepLesion [36].

| Methods     | data slices | 0.5 | 1   | 2   | 4   | Avg. [0.5,1,2,4] |
|-------------|-------------|-----|-----|-----|-----|-----------------|
| Faster R-CNN [39] | 100%        | 57.17 | 68.82 | 74.95 | 82.43 | 70.85          |
| Faster R-CNN+cBM [17] | 100%        | 59.32 | 70.68 | 79.09 | 84.34 | 73.86          |
| Faster R-CNN+SATr | 100%        | 62.52 (5.35↑) | 73.91 (5.09↑) | 82.43 (1.107↑) | 88.90 (0.927↑) | 77.67          |
| Faster R-CNN+SATr | 100%        | 64.38 (5.06↑) | 75.55 (4.87↑) | 82.43 (1.40↑) | 88.90 (0.927↑) | 77.67(4.25↑)   |
| Faster R-CNN+cBM+SATr | 100%        | 67.41 (2.04↑) | 78.02 (1.71↑) | 82.43 (1.40↑) | 88.90 (0.927↑) | 79.19(1.52↑)   |
| Faster R-CNN+cBM+SATr | 100%        | 69.77 (2.34↑) | 79.31 (1.97↑) | 82.43 (1.40↑) | 88.90 (0.927↑) | 79.19(1.52↑)   |
| MVP-Net [7] | 100%        | 70.07 | 78.77 | 84.91 | 87.33 | 80.27          |
| MVP-Net+cBM [17] | 100%        | 72.34 (2.27↑) | 82.27 (1.50↑) | 86.11 (1.20↑) | 88.21 (0.88↑) | 81.73(1.46↑)   |
| MVP-Net+SATr | 100%        | 73.65 | 81.41 | 87.22 | 89.37 | 82.76          |
| MVP-Net+cBM+SATr | 100%        | 74.11 (1.14↑) | 82.31 (0.90↑) | 86.14 (0.92↑) | 89.13 (0.76↑) | 83.67(0.91↑)   |
| MVP-Net+cBM+SATr | 100%        | 75.68 (2.38↑) | 84.36 (1.44↑) | 90.21 (1.14↑) | 92.37 (0.96↑) | 85.21(1.34↑)   |
| 3DCE [6] | 100%        | 77.20 | 84.36 | 88.91 | 92.31 | 85.73          |
| 3DCE+cBM [17] | 100%        | 78.98 (1.78↑) | 85.62 (1.44↑) | 90.21 (1.14↑) | 93.27 (0.96↑) | 87.07(1.34↑)   |
| 3DCE+SATr | 100%        | 79.17 | 85.71 | 89.80 | 92.65 | 86.83          |
| 3DCE+cBM+SATr | 100%        | 79.98 (0.81↑) | 86.96 (0.65↑) | 90.22 (0.42↑) | 92.39 (0.34↑) | 87.07(0.36↑)   |
| A3D [16] | 100%        | 81.27 | 88.94 | 92.94 | 96.41 | 88.31          |
| A3D+cBM [17] | 100%        | 84.27 | 88.27 | 92.39 | 96.41 | 88.31          |
| A3D+SATr | 100%        | 81.03 (1.79↑) | 86.64 (1.69↑) | 90.70 (1.55↑) | 93.30 (0.59↑) | 87.92(1.38↑)   |
| A3D+SATr | 100%        | 81.03 (1.79↑) | 86.64 (1.69↑) | 90.70 (1.55↑) | 93.30 (0.59↑) | 87.92(1.38↑)   |

while DeepLesion contains a variety of lesions with large diameter range (from 0.21 to 342.5mm). The 12-bit intensity CT is rescaled to [0,255] with different window range settings used in different frameworks. Also, every CT slice is resized and interpolated according to the detection frameworks’ setting. We follow the official split, i.e., 70% for training, 15% for validation and 15% for testing. To further test our method’s performance on a small dataset, we also conduct experiments based on 25% and 50% training data. The number of false positives per image (FPPI) is used as the evaluation metric. For training, we use the original network architecture and settings.

3.2 Lesion detection performance

Five state-of-the-art ULD approaches [6, 7, 9, 16, 17] and one natural image [39] detection method are compared to evaluate SATr’s effectiveness.

Full training dataset results. As shown in Table 2 our method brings promising detection performance improvements for all baselines with full training dataset. The improvements of Faster R-CNN [39], 3DCE, 3DCE w/ cBM and MVP-Net are more pronounced than those of AlignShift [9] and A3D [16]. This is because AlignShift and A3D introduce channel-fusion mechanism among different slices in backbone, thus the v value enhancement design in SATr brings less advances. Anyway, SATr still endows A3D and AlignShift with strong global dependency catching power to provide notable improvements. Meantime, the A3D w/ SATr reached the SOTA result.

Partial training dataset results. As shown in Table 2 under the 25% and 50% training data settings, our method brings more improvements than that in the full training data scene. Although the bigger performance improving space plays a huge role, we can also attribute this to our value removal design. When
Table 2. Sensitivity (%) at various FPPI on the testing dataset of DeepLesion [36] under 25% and 50% training data settings.

| Methods            | data slices | @0.5 | @1 | @2 | @4 | Avg [0.5,1,2,4] |
|--------------------|-------------|------|----|----|----|----------------|
| AlignShift         | 25%         | 25%  | 7  | 52.17 | 62.17 | 69.50 | 75.24 | 64.77 |
| AlignShift+cBM     | 25%         | 7    | 56.84 | 64.96 | 71.86 | 81.08 | 68.69 |
| AlignShift+cBM+SATr| 25%         | 7    | 62.31 (5.47↑) | 70.18 (5.17↑) | 76.79 (4.83↑) | 81.17 (0.09↑) | 72.60 (3.13↑) |
| A3D                | 25%         | 7    | 55.67 | 65.39 | 73.35 | 79.31 | 68.43 |
| A3D+SATr           | 25%         | 7    | 59.99 (4.32↑) | 68.05 (2.66↑) | 74.67 (1.32↑) | 81.09 (0.22↑) | 70.45 (2.02↑) |
| AlignShift         | 50%         | 7    | 68.69 | 76.73 | 82.25 | 86.54 | 78.55 |
| AlignShift+cBM     | 50%         | 7    | 73.20 (2.53↑) | 81.32 (1.59↑) | 88.51 (1.47↑) | 90.08 (1.66↑) |
| AlignShift+cBM+SATr| 50%         | 7    | 73.53 (3.23↑) | 81.60 (1.75↑) | 88.50 (1.54↑) | 90.17 (1.76↑) |
| A3D                | 50%         | 7    | 72.52 | 80.27 | 86.14 | 90.15 | 82.27 |
| A3D+SATr           | 50%         | 7    | 75.24 (2.72↑) | 82.19 (1.92↑) | 88.99 (0.85↑) | 90.96 (0.81↑) | 83.85 (1.58↑) |

Table 3. Ablation study of our method at various FPs per image (FPPI).

| A3D [16] w/o fusion | Naive transformer block | Enhancement of value vector | Removal of key-slice feature | FPPI=0.5 | FPPI=1 |
|---------------------|-------------------------|-----------------------------|-----------------------------|----------|-------|
| ✓                   | ✓                       | ✓                           | ✓                           | 72.47    | 81.35 |
| ✓                   | ✓                       | ✓                           | ✓                           | 72.91 (0.44↑) | 81.68 (0.33↑) |
| ✓                   | ✓                       | ✓                           | ✓                           | 73.85 (0.94↑) | 82.48 (0.80↑) |
| ✓                   | ✓                       | ✓                           | ✓                           | 74.68 (0.83↑) | 83.17 (0.69↑) |

the training data is limited, SATr forces the network to learn more dependency to avoid overfitting. Besides, our experiments also show some results contradicted with the full-training dataset experiment, e.g., AlignShift outperformed A3D.

Classification activation maps results. We showcase CAMs (based on [40] [41]) of two SOTA ULD methods to evaluate the global context modeling power of SATr. As shown in [1] SATr helps model useful dependency within single slice (a₁v.s.A₁ and a₂v.s.A₂) and among different slices (b₁v.s.B₁ and b₂v.s.B₂). More cases are included in Suppl. Material.

3.3 Ablation study

An ablation study is provided to evaluate the importance of the two key designs: (i) Enhancement of value vector with key-slice feature and (ii) Removal of key-slice feature from the query and key vectors. Adding naive transformer block for baseline, the performance is increased by 0.44%, enhancing the value vector with the key-slice feature, we obtain a 0.94% improvement over the naive transformer block. Further removing the key-slice feature from the query and key vectors accounts for another 0.83% improvement and give the best performance. Ablation study for different SATr blocks, which is included in Suppl. Material, shows that all SATr blocks is important.

4 Conclusion

Multi-slice-input based ULD methods using CNN backbones have inherent limitations in capturing the global contextual information within individual slice
and among multiple adjacent slices. To address this issue, we propose a slice attention transformer (SATr) block that can be integrated with conventional CNN backbones to obtain better global representation. Extensive experiments using several SOTA ULD methods as baselines show that the proposed can be easily integrated with many existing methods to boost their performance without extra hyperparameters or special network designs.
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