Transformer-based Knowledge Distillation for Efficient Semantic Segmentation of Road-driving Scenes

Ruiping Liu, Kailun Yang, Huayao Liu, Jiaming Zhang, Kunyu Peng, and Rainer Stiefelhagen

Abstract—For scene understanding in robotics and automated driving, there is a growing interest in solving semantic segmentation tasks with transformer-based methods. However, effective transformers are always too cumbersome and computationally expensive to solve semantic segmentation in real time, which is desired for robotic systems. Moreover, due to the lack of inductive biases compared to Convolutional Neural Networks (CNNs), pre-training on a large dataset is essential but it takes a long time. Knowledge Distillation (KD) speeds up inference and maintains accuracy while transferring knowledge from a pre-trained cumbersome teacher model to a compact student model. Most traditional KD methods for CNNs focus on response-based knowledge and feature-based knowledge. In contrast, we present a novel KD framework according to the nature of transformers, i.e., training compact transformers by transferring the knowledge from feature maps and patch embeddings of large transformers. To this purpose, two modules are proposed: (1) the Selective Kernel Fusion (SKF) module, which helps to construct an efficient relation-based KD framework, Selective Kernel Review (SKR); (2) the Patch Embedding Alignment (PEA) module, which performs the dimensional transformation of patch embeddings. The combined KD framework is called SKR+PEA. Through comprehensive experiments on Cityscapes and ACDC datasets, it indicates that our proposed approach outperforms recent state-of-the-art KD frameworks and rivals the time-consuming pre-training method.

1. INTRODUCTION

Dense semantic segmentation, assigning pre-defined category-wise labels to each pixel to input images, is an essential task in computer vision and widely used in various real-world applications, such as automated driving, robot navigation, and virtual reality. Driven by deep learning, semantic segmentation enables to unify the perception of surrounding scene elements at the pixel level in an accurate and efficient way, which are desired for robotics and autonomously driving vehicles [1].

The most popular and basic approach leveraged to tackle semantic segmentation task through deep learning based architecture is Fully Convolutional Networks (FCNs) [2] in the past few years. However, a fundamental limitation is that long-range dependency information can’t be well extracted by most FCN-based architectures, which is especially crucial for semantic segmentation of unconstrained scene images [3], [4]. In order to tackle this shortcoming brought by FCNs, the semantic segmentation task can be addressed from another perspective – this task can be treated as a sequence-to-sequence prediction task leveraging transformers due to their excellent capability to preserve long-range dependencies [4], [5]. Vision Transformer (ViT) [5] first applies transformers in computer vision. Then, Segmentation Transformer (SETR) [4] leverages a pure transformer in semantic segmentation. Recently, transformer-based algorithms show comprehensive performance on different benchmarks, e.g., Swin transformer [6] achieves State-of-The-Art (SoTA) on natural image segmentation [7] through using shifted windows during representation extraction. Without making use of positional encoding and complex decoder, the variations of SegFormer [8] are lightweight, which ensures the efficiency while dealing with semantic segmentation tasks.

However, the powerful models for semantic segmentation are heavy with millions of parameters and huge computation costs [2] [3] [6] [9]. In order to achieve model compression and knowledge transfer simultaneously, Knowledge Distillation (KD) [10] has been proposed to transfer information from a cumbersome network (teacher) to a
compact network (student), which is further characterized by the so-called “Student-Teacher” (S-T) learning framework. Response- and feature-based knowledge are leveraged in most knowledge distillation approaches by comparing the outputs of specific layers in the teacher- and the student model. Structured Knowledge Distillation (SKD) [11] calculates the pair-wise similarity between feature maps and utilizes adversarial learning-based method to distill the responses, inspired by generative adversarial networks. Channel Distillation (CD) [12] compares the channel-wise KL-divergence between the responses or feature maps. In contrast to response- and feature-based knowledge distillation, the relationships between different feature maps are further extracted through relation-based knowledge distillation. Knowledge Review [13], a cross-layer knowledge distillation framework, is proposed by Chen et al. to achieve both simplification and efficiency while tackling the knowledge distillation task.

Patch embedding, an essential component in ViT models to encode input images or feature maps into a sequence of embedded patches, plays an important role in improving the performance of visual transformers in numerous research works [5] [6] [8] [14] [15]. Vision transformer equipped with positional embedding shows better performance compared to those without positional embedding, regardless of the form of position embedding, according to the work from Dosovitskiy et al. [5]. Xiao et al. [14] show that the application of a more standard convolutional stem instead of the patchify stem of ViTs enables the use of both AdamW and SGD optimizers, further ensuring faster convergence and the stability of the learning rate and the weight decay. Convolutional stem is widely used in ViT models [4] [6] [8] [16] [17]. We gain inspiration from these works and aim at tackling knowledge distillation from a patch embedding distillation perspective. However, existing works only explore CNN-CNN [11] or CNN-transformer [18] distillation, which cannot fully unlock the potential of transformer architectures.

In this paper, we propose a framework to perform transformer-to-transformer knowledge distillation, which combines relation-based knowledge and transformer-specific patch embedding knowledge, materialized via the following designs: 1) Our framework to distill feature maps, Selective Kernel Review (SKR), inherits Knowledge Review [13]. Inspired by Li et al. [19], we replace the Attention-Based Fusion (ABF) module with our Selective Kernel Fusion (SKF) module, which is put forward to fuse the feature maps channel-wise and extract their relationships. 2) The Patch Embedding Alignment (PEA) module realizes the dimensional transformation of patch embeddings. The combined framework is called SKR+PEA. Fig. 1 presents the generalized structure of one stage of transformer-based methods, where the knowledge for distillation is from feature maps and patch embeddings.

Finally, the effectiveness of the proposed knowledge distillation framework is analyzed both on a street scene dataset (Cityscapes [20]) and an adverse condition dataset (ACDC [21]), sufficiently verifying the outstanding performance of our methods towards real-world driving applications. Based on our proposed solution, a significant gap is observed between the performance of the distillation framework with PEA and without PEA. Precisely, training with our knowledge distillation model improves SegFormer B0’s performance by 12.72% on Cityscapes.

Here is a summary of the main contributions of our study:

- We are the first to propose a transformer-to-transformer structured knowledge distillation framework in computer vision and to distill the knowledge from transformer-specific patch embeddings by using our Patch Embedding Alignment (PEA) module.
- We put forward an efficient relation-based knowledge distillation framework, Selective Kernel Review (SKR), by replacing the AKF module in Knowledge Review with our Selective Kernel Fusion (SKF) module.
- The performance of the proposed approach, SKR+PEA, is verified on Cityscapes and ACDC datasets and exhibits clear improvement over existing methods.

II. RELATED WORKS

A. Semantic Segmentation

Dense semantic segmentation aims to correspond each image pixel to an item category. Most state-of-the-art methods for semantic segmentation tasks are based on deep CNNs such as FCN [2] and PSPNet [22]. Transformer-based approaches also perform well on semantic segmentation [4] [6] [17], which are always heavy with millions of parameters to reach high accuracy. However, this kind of cumbersome networks is not able to solve the semantic segmentation task efficiently because of high computation costs. Therefore, many recent efforts are made to develop compact variations with similar accuracy, e.g., ResNet18 [9], ESPNet [23], and MobileNets [24]. Transformer-based methods for real-time semantic segmentation have also been proposed, such as SegFormer [8], Trans4Trans [25], and PVT-tiny [17].

B. Vision Transformer

Transformer is the prevalent architecture in Natural Language Processing (NLP). It follows an encoder-decoder architecture, which consists of the following components: stacked self-attention and point-wise, fully connected layers.

Because the transformer shows a satisfactory performance in long-range dependency modeling, researchers investigate it in computer vision. Vision Transformer (ViT) [5] is the first work that successfully trains a transformer on ImageNet [26]. In recent years, transformers demonstrate promising results in semantic segmentation. Segmenter [27] extends ViT to semantic segmentation with a point-wise linear decoder or a mask transformer decoder. Pyramid Vision Transformer (PVT) [17] addresses various pixel-level dense predictions by using a progressive shrinking strategy to control the scale of feature maps. Swin transformer [6], whose key idea is the shift of the window partition between consecutive self-attention layers, performs more robustly than previous state-of-the-art on natural image datasets. Segmentation Transformer (SETR) [4] uses a pure transformer as the encoder
instead of stacked convolution layers. SegFormer [8], a lightweight and efficient semantic segmentation framework, unifies the backbone output feature maps with an uncomplicated multilayer perceptron decoder.

C. Transformer Improvement

As transformers have attracted more and more interests in computer vision, many methods have been proposed to optimize its performance, such as multi-scale networks [6] [8] [17] [28] [29], greater depth [15] [30], knowledge distillation [16] [18], and blending of global and local attention [31] [32]. There are also many efforts to improve the performance of transformer in terms of embeddings. [5] finds that Vision Transformer has much less image-specific inductive bias than CNNs, so it is necessary to adjust positional embedding during the fine-tuning process. Experiments show that there is a large gap between the performance of the models with and without the positional embedding, while the performance of the models with positional embedding in different ways does not vary much. In [14], it is found that ViT models with patchify stem [5] [18] have issues such as sensitivity to learning rate and window dimension, slow convergence, working only with AdamW, and poor performance compared to SoTA CNNs. These issues can be addressed by simply using a minimal convolutional stem [4] [6] [8] [16] [17]. Knowledge Distillation [33] [34] [35] [36] is widely used in natural language processing to accelerate searching and compress the transformer, but there is no transformer-to-transformer distillation framework in computer vision so far.

D. Knowledge Distillation

Hinton et al. [10] introduce the concept of KD, which aims to transfer the knowledge from a cumbersome model to a compact one. These two models behave like a teacher and a student. The KD strategy is widely used in computer vision. In this paper, we focus on investigating and designing a KD framework for semantic segmentation.

According to Gou et al. [37], KD frameworks are divided into three categories based on the form of knowledge: response-based KD [11] [12] [38] [39], feature-based KD [11] [39] [40] [41] [42] [43], and relation-based KD [13] [44] [45]. Liu et al. [11] first introduce the concept of structured knowledge distillation, where adversarial learning is used to align the segmentation map generated by the compact network with that from the cumbersome network. Knowledge Review (KR) [13] proposes cross-stage connection paths for knowledge distillation for the first time. Double Similarity Distillation (DSD) [44] transfers both detailed spatial dependencies and global category correlations. In contrast to previous works devoted to distillation of spatial-wise knowledge, some recent works focus on channel-wise distribution. Intra-class Feature Variation Distillation (IFVD) [39] transfers the intra-class feature variation between networks. Channel Distillation (CD) [12] focuses on the soft distributions of channels and pays attention to the most salient parts of the channel-wise maps. Inter-channel correlation knowledge distillation (ICKD) [41] aligns the diversity and homology of the student network’s feature space with that of the teacher network. These previous works dedicate to developing CNN-to-CNN or CNN-to-transformer
distillation frameworks. Differently, we explore knowledge distillation in a novel transformer-to-transformer fashion.

III. METHODS

As mentioned before, there are previous methods [5] [14] working on patch embedding to enhance the performance of transformers, so patch embedding contains important knowledge, such as location information [5] [4] [18]. Besides, transformer-to-transformer knowledge distillation is explored in natural language processing on embeddings, hidden states, and attention matrices [33] [34] [35] [36]. As vision transformers do not have hidden states, we prefer to distill knowledge from feature maps converted from attention matrices. Thus, our work distills knowledge from patch embeddings and feature maps by using our Patch Embedding Alignment (PEA) module and Selective Kernel Review (SKR) relation-based knowledge distillation framework.

We propose a novel knowledge distillation framework for transformers, SKR+PEA, as shown in Fig. 2. This framework is divided into two parts: knowledge distillation of (1) patch embeddings and (2) feature maps. The distillation losses obtained from each stage are added to the original cross-entropy loss \( L_{CE} \) during the training process. The overall KD loss can be formulated as:

\[
L = L_{CE} + \sum_{m=1}^{M} \alpha_m L_{embd}^m + \sum_{m=1}^{M} \beta_m L_{fm}^m \tag{1}
\]

where both students and teachers have \( M \) stages. \( L_{embd}^m \) and \( L_{fm}^m \) are the patch embedding loss and feature map loss between the \( m \)-th stage of the teacher and the student. \( \alpha_m \) and \( \beta_m \) are the \( m \)-th elements of \( \alpha \) and \( \beta \), which control the weights of patch embedding loss and feature map loss from each stage, respectively. \( \alpha \) and \( \beta \) are set as [0.1, 0.1, 0.5, 1] and [1, 1, 1, 1].

A. Patch Embedding

To perform the Patch Embedding Alignment (PEA), the loss between the patch embedding is calculated by MSE loss at each stage, as depicted in Eq. (2):

\[
L_{embd}^m = MSE(E^S_m W_e, E^T_m) \tag{2}
\]

where \( E^S_m \) and \( E^T_m \) are the patch embeddings at the \( m \)-th student and teacher stages. A learnable matrix \( W_e \) is applied to align the mismatch number of channels between the student and teacher patch embeddings.

B. Feature Map

The framework we propose to distill feature map knowledge, Selective Kernel Review (SKR), inherits the distillation framework from Knowledge Review (KR) [13], which proposes the attention based fusion (ABF) module to fuse feature maps and the hierarchical context loss (HCL) to calculate the loss between the output of each fusion module and the teacher feature map. Inspired by the Selective Kernel (SK) unit [19], we propose a fusion module Selective Kernel Fusion (SKF) to replace ABF. The basic idea of SK unit is to use gates to control the information flows from multiple branches carrying different scales of information into neurons in the next layer. We treat the output feature map of the fusion module as a branch of the feature map of the previous stage. The structure of SKF is shown in Fig. 3.

Specifically, we first conduct \( 1 \times 1 \) convolution to implement the channel-wise transformation of the input feature map \( U_{in}^m \) and conduct interpolation to implement the spatial-wise transformation of the feature map \( U_{mid}^{m+1} \) from the next fusion module. Their height and width are the same as the feature map of this \( m \)-th stage \( U_{in}^m \). The resulting \( U_{in}^m \) and \( U_{mid}^{m+1} \) are element-wise summed:

\[
U_m = U_{in}^m + U_{mid}^{m+1}, \tag{3}
\]

The following steps are the same as the SK unit. The global information is embedded with global average pooling, where \( s_c \) denotes the channel-wise statistics:

\[
s_c = \mathcal{F}_{gp}(U_m) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} U_m(i, j), \tag{4}
\]

then a compact feature \( z \in \mathbb{R}^{d \times 1} \) in Eq. (5) is generated for precise and adaptive selections.

\[
z = \mathcal{F}_{fc}(s_c) = \delta(B(\phi(s_c))), \quad d = \max(C/r, L), \tag{5}
\]

where \( \delta \) denotes the ReLU function, \( B \) denotes Batch Normalization, and \( \phi \) denotes \( 1 \times 1 \) convolution. \( d \) is the dimension of vector \( z \), which is controlled by a reduction ratio \( r \). \( L \) is chosen to be the minimum value of \( d \).
Soft attention across channels is used to adaptively select information from different branches:

\[
a_c = \frac{e^{A_c z}}{e^{A_c z} + e^{B_c z}}, \quad b_c = \frac{e^{B_c z}}{e^{A_c z} + e^{B_c z}},
\]

\[
U_{m,c}^{mid} = a_c \cdot \tilde{U}_{m}^{in} + b_c \cdot \tilde{U}_{m+1}^{mid}, \quad a_c + b_c = 1,
\]

where \( A, B \in \mathbb{R}^{C \times d} \) are two learnable matrices, \( A_c, B_c \in \mathbb{R}^{1 \times d} \) are the \( c \)-th elements of them, \( a_c, b_c, \) and \( U_m^{mid,c} \) are the \( c \)-th elements of \( a, b, \) and \( U_m^{mid} \). \( a \) and \( b \) denote the soft attention vector for \( U_m^{in} \) and \( U_m^{mid+1} \), respectively. Further, we conduct \( 3 \times 3 \) convolution to convert \( U_m^{mid} \) to \( U_m^{out} \), which has the same dimension as the teacher’s feature map.

After feature fusion by SKF, HCL [13] is applied as the loss function between the outputs of the fusion modules and the teacher stages. Each feature map is separated into \( N \) levels’ context information via spatial pyramid pooling. \( p_n \) is the pool-size of the \( n \)-th level (we obtain multi-level features at \( \{1/4, 1/2, 1 \} \) of the original feature resolution in our experiments). At each stage, \( L_2 \) distances are utilized to distill knowledge between levels. HCL between feature maps at \( m \)-th stage is formulated as:

\[
L_{fm}^m = \frac{1}{1 + \sum_{n=1}^{N} \frac{1}{2^{n}} MSE(U_{m,n}^{out}, U_{m,n}^{T})},
\]

IV. EXPERIMENTS

A. Datasets and Metrics

Cityscapes [20] is a large-scale dataset, which contains stereo video sequences recorded in street scenes from 50 different cities. Cityscapes consists of 2975 training- and 500 validation images with annotation and 1525 test images. It is known to assess the performance of vision algorithms for urban semantic understanding. For the evaluation metric, we use the mean Intersection over Union (mIoU) score, which is averaged across 19 semantic classes.

ACDC [21], the Adverse Conditions Dataset with Correspondences, addresses semantic segmentation under adverse conditions, e.g., fog, nighttime, rain, and snow. Each adverse condition includes 400 training, 100 validation, and 500 test images, except for the nighttime condition which includes 106 validation images. Tougher and more comprehensive situations, are considered in the ACDC dataset, with the aim to ensure robust semantic segmentation performance in adverse conditions for safety-critical automated driving. ACDC has the identical label set of 19 classes as Cityscapes.

We use mean Intersection over Union (mIoU) over all classes as the evaluation metric in all experiments. Further, we also study IoU values of several methods for each class in Cityscapes, and each condition in ACDC. To study computation complexity, the Multiply–Accumulate Operations (MACs) value of each method is measured with a fixed image resolution of 512 × 1024.

B. Implementation Details

For all semantic segmentation knowledge distillation experiments, we apply the pre-trained SegFormer B2 as the teacher and SegFormer B0 without pre-training as the student. When evaluating the performance of knowledge distillation frameworks on the Cityscapes dataset, we resize the image to 512 × 1024, and on the ACDC dataset, to 512 × 910. According to the structure of SegFormer in [8], the height and width of the output and target are all rescaled with ratio 1/4 compared with the input image. The performance of the baseline models of SegFormer has a slight reasonable decay due to a smaller size chosen for the input image. The models in our work are trained using the AdamW optimizer with a batch size 2 for \( K \) iterations on both datasets with the learning rate initialized as \( 6 \times 10^{-5} \) and adjusted by a polynomial learning rate decay scheduler with a factor of 1.0 by default. Besides, the number of channels of the feature maps in the SKF fusion module \( C \) is set to 64. The HCL [13] divides the feature map into \( N = 3 \) contextual information levels and the pool-sizes are \( p = [4, 2, 1] \).

C. Evaluation on the Cityscapes Dataset

In order to evaluate the effectiveness of our knowledge distillation framework, we compare its performance with several other distillation models on the Cityscapes dataset.

- Knowledge Distillation (KD) [10]: logits-based distillation model is leveraged. The soft target is generated via a softmax transform on the teachers’ responses. The objective function – the sum of traditional training loss and Kullback–Leibler (KL) divergence loss between the soft target and the probability distribution of student, is to be minimized.
- Structured Knowledge Distillation (SKD) [11]: two structured knowledge distillation schemes are proposed in this work, which are pair-wise distillation (PA) and holistic distillation (HO). The similarities between pixels of student and teacher are calculated from their features respectively and leveraged to formulate the pair-wise similarity distillation loss with MSE. For holistic distillation, the discriminator in generative adversarial network is utilized to learn the holistic embeddings of segmentation maps.
- Channel-wise Knowledge Distillation (CD) [12]: KL divergence is used to align the channel-wise probability maps of the two networks.
- Knowledge Review [13]: It proposes a new review mechanism in knowledge distillation. The feature map fusion module ABF aggregates different stage’s student feature maps with attention maps. HCL calculates the difference between the student and the teacher’s feature maps with pyramid pooling.

Here we perform knowledge distillation experiments with the optimizer and poly-scheduler for training SegFormer. However, the SGD optimizer is employed with a learning rate of 0.0004 for the SKD [11] discriminator training. The number of parameters to be compared in Tab. I is the sum of the number of the parameters of the student network and the necessary information transformation layers, e.g., the feature map fusion module and the linear alignment layer. After the
Fig. 4. Qualitative segmentation results on Cityscapes [20]. The pre-trained SegFormer B2 [8] and B0 without pre-training are applied as the teacher- and student model, respectively. The performance of our knowledge distillation framework SKR+PEA is compared with recent relation-based knowledge distillation framework, Knowledge Review (KR) [13] and Channel-wise Knowledge Distillation (CD) [12].

| Network       | Params (M) | MACs (G) | mIoU (%) |
|---------------|------------|----------|----------|
| Teacher (B2)  | 27.36      | 113.76   | 76.49    |
| Student (B0)  | 3.72       | 13.65    | 55.86    |
| +Pre-train    | 3.72       | 13.65    | 69.75    |
| +KD [10]      | 3.72       | 13.65    | 56.45    |
| +CD [12]      | 3.72       | 13.65    | 61.90    |
| +SKD (PA) [11]| 3.85       | 13.72    | 58.05    |
| +SKD (HO) [11]| 3.85       | 13.72    | 59.00    |
| +Knowledge Review [13]| 4.35   | 16.14    | 63.40    |
| +SKR (ours)   | 4.37       | 16.14    | 65.94    |
| +SKR+PEA (ours)| 4.56      | 16.44    | 68.58    |

Distillation procedure, only the original student network is used for semantic segmentation.

Tab. I presents the performance of our distillation frameworks in comparison with the results of students with and without ImageNet pre-training and other knowledge distillation frameworks. It can be seen that training SegFormer B0 with our distillation framework, SKR+PEA, achieves a 12.72% improvement in mIoU, which outperforms other distillation frameworks by wide margins, and it is only slightly inferior to the pre-trained model. Compared to traditional logits-, feature-, and relation-based knowledge distillation, the combination of traditional distillation and patch embedding knowledge distillation greatly improves the effectiveness of transformer-to-transformer distillation. Our relation-based knowledge distillation SKR shows a clear performance improvement of 2.5% in contrast to Knowledge Review by replacing the original AKF with SKF.

We list per-class IoU evaluation results of our method, SKR+PEA, and the other two recent proposed methods, CD [12] and Knowledge Review [13] in Tab. II. CD and Knowledge Review are the best-performing response-based and relation-based knowledge distillation frameworks we have tested, respectively. Our method outperforms the other two methods in almost all classes, small objects in particular, such as pole, traffic light, traffic sign, person, and rider, which are especially safety-relevant for self-driving applications. Compared with other methods, our knowledge distillation framework performs satisfactorily when segmenting small scene elements and occluded vehicles according to the visualization results presented in Fig. 4. The quantitative results in Tab. II and the first two control groups of the qualitative results in Fig. 4 both demonstrate that our approaches behaves well in semantically segmenting challenging less regular classes like bus and truck.

D. Ablation Studies

1) Effect of Replacing the Feature Map Fusion Module and the Feature Map Loss: The Knowledge Review distillation framework is a relation-based method that fuses feature map information with the ABF module and further divides the feature map into different levels of context information with spatial pyramid pooling. MSE is leveraged for loss calculation between different levels.

In Tab. III, the feature map fusion module and loss function of Knowledge Review are replaced respectively and it is combined with the PEA module. In this experiment, we distill the patch embeddings with equal weights, i.e., $\alpha = [1, 1, 1, 1]$.

Little effect on the results is indicated by utilizing spatial-wise KL divergence, channel-wise KL divergence, or spatial pyramid pooling plus MSE as the loss function. In contrast, based on our proposal, adding PEA or replacing ABF with SKF considerably improves the effectiveness of the relation-based distillation framework, denoted as Selective Kernel Review (SKR). Combining all phases of PEA results in a 4.86% increase in the performance of Knowledge Review. Better performance of SKR has been shown when combining only one stage of PEA. Still, when combining all stages of PEA with equal weights, it is more unstable than Knowledge Review due to excessive constraints despite obtaining lower validation loss.

2) Effect of PEA by stages: Since not all transformer-based methods have 4 stages and too many constraints can make knowledge distillation ineffective occasionally, in this study, patch embedding is distilled by stages shown in Tab. IV. When distilling only one stage of patch embedding, the patch embedding loss is directly added to the loss function of the relation-based knowledge distillation, Knowledge...
TABLE II
PER-CLASS IOU OF OUR PROPOSED KNOWLEDGE DISTILLATION FRAMEWORKS COMPARED WITH OTHER TWO TYPICAL STRUCTURAL KNOWLEDGE TRANSFER METHODS ON THE VALIDATION SET OF CITYSCAPES [20].

| Method               | mIoU (%) | road    | sidewalk | building | wall    | fence   | pole    | traffic light | traffic sign | vegetation |
|----------------------|----------|---------|----------|----------|---------|---------|---------|--------------|--------------|------------|
| CD [12]              | 61.90    | 96.84   | 76.10    | 87.68    | 39.32   | 38.90   | 47.57   | 51.70        | 61.77        | 89.07      |
| Knowledge Review [13]| 63.40    | 97.09   | 78.07    | 88.26    | 37.55   | 44.12   | 46.55   | 53.15        | 60.96        | 89.39      |
| SKR+PEA (ours)       | 68.58    | 97.47   | 80.29    | 89.71    | 47.13   | 48.25   | 53.78   | 56.24        | 65.82        | 90.74      |

| Class                |          | terrain | sky      | person   | rider   | car     | truck   | bus      | train       | motorcycle | bicycle   |
|----------------------|----------|---------|----------|----------|---------|---------|---------|----------|-------------|------------|-----------|
| CD [12]              | 54.84    | 91.22   | 65.96    | 36.72    | 89.10   | 42.19   | 58.49   | 56.71    | 29.08       | 62.77      | 63.40     |
| Knowledge Review [13]| 57.74    | 92.34   | 65.26    | 40.58    | 89.83   | 50.92   | 64.30   | 44.29    | 40.79       | 63.40      | 63.40     |
| SKR+PEA (ours)       | 60.63    | 93.05   | 71.92    | 45.76    | 91.84   | 66.02   | 74.01   | 63.31    | 39.60       | 67.54      | 67.54     |

We also compare the relation-based knowledge distillation with Knowledge Review and SKR combined with PEA, respectively. SKR improves 1.2% to 2.5% over Knowledge Review when not combined or combined with a phase of PEA, verifying the superiority of our approach. When the relation-based knowledge distillation frameworks combine PEA at all stages with weights of $\alpha_m = 1$. We can see that distillation of patch embedding at any stage is effective. Typically, the deeper the stage, the more channels of patch embedding are used and the better the distillation effect the framework can provide.

TABLE III
ACCURACY ANALYSIS ON REPLACEMENT OF FUSION MODULE AND LOSS FUNCTION.

| Feature Map Fusion | Norm | Divergence | PEA | mIoU (%) |
|--------------------|------|------------|-----|----------|
| ABF                |      |            |     |          |
| Pyramid            | MSE  | None       |     | 63.40    |
| Pyramid            | MSE  | 4th stage  |     | 66.52    |
| Pyramid            | MSE  | All stages |     | 68.26    |
| Channel            | KL   | All stages |     | 67.93    |
| Spatial            | KL   | All stages |     | 68.15    |
| SKF                |      |            |     |          |
| Pyramid            | MSE  | None       |     | 65.94    |
| Pyramid            | MSE  | 4th stage  |     | 67.73    |
| Pyramid            | MSE  | All stages |     | 67.75    |

E. Evaluation on the ACDC Dataset

To verify the semantic segmentation effectiveness of our distillation framework in adverse conditions, we also conduct experiments on the ACDC dataset. Our distillation framework is optimized jointly in all four conditions compared to Knowledge Review [13] and Channel-wise Distillation (CD) [12] and improves SegFormer B0 by about 12% in all conditions, which confirms that our approach generalizes well to adverse scenes, beneficial for enhancing the robustness of semantic surrounding understanding of self-driving in the real world. Adding the PEA increases SKR’s performance moderately by 1.59% in the fog condition and significantly by about 3% in the other three adverse conditions. Our approach outperforms the counterparts when segmenting small- and remote traffic objects, e.g., traffic light and traffic sign, and the persons faraway, according to the qualitative segmentation results displayed in Fig. 5. Our knowledge distillation framework helps the compact student network to recognize small objects at a distance, which are always ignored by the student network without using any knowledge distillation under adverse conditions.

TABLE V
ACCURACY ANALYSIS ON THE ACDC DATASET [21].

| Network       | Fog | Night | Rain | Snow | All-ACDC |
|---------------|-----|-------|------|------|----------|
| Teacher (B2)  | 75.26 | 51.14 | 49.26 | 72.09 | 69.34    |
| Student (B0)  | 52.10 | 33.33 | 45.79 | 48.38 | 46.26    |
| CD [12]       | 57.07 | 40.82 | 51.37 | 52.15 | 52.56    |
| Knowledge Review [13] | 59.83 | 42.38 | 52.30 | 55.69 | 54.90    |
| SKR (ours)    | 62.15 | 41.51 | 54.22 | 57.04 | 55.35    |
| SKR+PEA (ours) | 63.74 | 44.63 | 57.16 | 60.30 | 58.56    |

V. Conclusion

To enhance efficient semantic segmentation of road-driving scenes in robotics and self-driving applications, we propose a practical relation-based knowledge distillation framework, Selective Kernel Review (SKR), and provide a new perspective of performing transformer-to-transformer knowledge distillation in patch embedding. This work designs the Patch Embedding Alignment (PEA) module to distill the patch embeddings at various stages. There is a big gap between the performance of distillation frameworks with and without distillation of patch embeddings, and the superiority of our framework compared to other knowledge distillation frameworks is verified on Cityscapes and ACDC datasets spanning a wide variety of urban and adverse road-driving scenes. Since training the transformer by our approach is on par with the time-consuming pre-training method, it is further possible to develop a knowledge distillation framework comparable to the pre-training process by adjusting the balance between patch embedding and feature map knowledge distillation, or develop a module that can distill the knowledge in patch embeddings more efficiently. Furthermore, since compact models are also often applied to indoor mobile devices, such as domestic assistant robots, the performance of the proposed knowledge distillation methods will be evaluated on indoor datasets in our future work.
Fig. 5. Qualitative semantic segmentation results on ACDC [21] (Fog, Night, Rain, and Snow). The performances of our knowledge distillation framework, SKR+PEA, are compared with Channel-wise Knowledge Distillation (CD) [12] and Knowledge Review (KR) [13].

REFERENCES

[1] K. Yang, X. Hu, H. Chen, K. Xiang, K. Wang, and R. Stiefelhagen, “DS-PASS: Detail-sensitive panoramic annular semantic segmentation through SwatNet for surrounding sensing,” in CVPR, 2020.

[2] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in CVPR, 2015.

[3] Y. Liu, X. Chen, and J. Wang, “Object-contextual representations for semantic segmentation,” in ECCV, 2020.

[4] S. Zheng et al., “Rethinking semantic segmentation from a sequence-to-sequence perspective with transformers,” in CVPR, 2021.

[5] A. Dosovitskiy et al., “An image is worth 16x16 words: Transformers for image recognition at scale,” in ICLR, 2021.

[6] Z. Liu et al., “Swin transformer: Hierarchical vision transformer using shifted windows,” in ICCV, 2021.

[7] B. Zhou et al., “Semantic understanding of scenes through the ADE20K dataset,” in IJCV, 2019.

[8] E. Xie, W. Wang, Z. Yu, A. Anandkumar, J. M. Alvarez, and P. Luo, “SegFormer: Simple and efficient design for semantic segmentation with transformers,” in NeurIPS, 2021.

[9] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in CVPR, 2016.

[10] G. Hinton, O. Vinyals, and J. Dean, “Distilling the knowledge in a neural network,” in arXiv preprint arXiv:1503.02531, 2015.

[11] Y. Liu, K. Chen, C. Liu, Z. Qin, Z. Luo, and J. Wang, “Structured knowledge distillation for semantic segmentation,” in CVPR, 2019.

[12] C. Shu, Y. Liu, J. Gao, L. Xu, and C. Shen, “Channel-wise knowledge distillation for dense prediction,” in ICLR, 2021.

[13] P. Chen, S. Liu, H. Zhao, and J. Jia, “Distilling knowledge via knowledge review,” in CVPR, 2021.

[14] T. Xiao, M. Singh, E. Mintun, T. Darrell, P. Dollár, and R. Girshick, “Early convolutions help transformers see better,” in NeurIPS, 2021.

[15] D. Zhou et al., “DeepViT: Towards deeper vision transformer,” arXiv preprint arXiv:2103.11886, 2021.

[16] B. Graham et al., “LeViT: A vision transformer in ConvNet’s clothing for faster inference,” in ICCV, 2021.

[17] W. Wang et al., “Pyramid vision transformer: A versatile backbone for dense prediction without convolutions,” in ICCV, 2021.

[18] H. Touvron, M. Cord, M. Douze, F. Massa, A. Sablayrolles, and H. Jegou, “Training data-efficient image transformers & distillation through attention,” in ICMIL, 2021.

[19] X. Li, W. Wang, X. Hu, and J. Yang, “Selective kernel networks,” in CVPR, 2019.

[20] M. Cordis et al., “The cityscapes dataset for semantic urban scene understanding,” in CVPR, 2016.

[21] C. Sakaridis, D. Dai, and L. V. Gool, “ACDC: The adverse conditions dataset with correspondences for semantic driving scene understanding,” in ICCV, 2021.

[22] H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia, “Pyramid scene parsing network,” in CVPR, 2017.

[23] S. Mehta, M. Rastegari, A. Caspi, L. Shapiro, and H. Hajishirzi, “ES-PNet: Efficient spatial pyramid of dilated convolutions for semantic segmentation,” in ECCV, 2018.

[24] A. G. Howard et al., “MobileNets: Efficient convolutional neural networks for mobile vision applications,” in arXiv preprint arXiv:1704.04861, 2017.

[25] J. Zhang, K. Yang, A. Constantinescu, K. Peng, K. Müller, and R. Stiefelhagen, “Trans4Trans: Efficient transformer for transparent object and semantic scene segmentation in real-world navigation assistance,” arXiv preprint arXiv:2108.09174, 2021.

[26] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and F.-F. Li, “ImageNet: A large-scale hierarchical image database,” in CVPR, 2009.

[27] R. Strudel, R. Garcia, I. Laptev, and C. Schmid, “Segmenter: Transformer for semantic segmentation,” in ICCV, 2021.

[28] C.-F. Chen, Q. Fan, and R. Panda, “CrossViT: Cross-attention multi-scale vision transformer for image classification,” in ICCV, 2021.

[29] H. Fan et al., “Multiscale vision transformers,” arXiv preprint arXiv:2104.11227, 2021.

[30] H. Touvron, M. Cord, A. Sablayrolles, G. Synnaeve, and H. Jégou, “Going deeper with image transformers,” in ICCV, 2021.

[31] X. Chu et al., “Twins: Revisiting the design of spatial attention in vision transformers,” in NeurIPS, 2021.

[32] W. Wang et al., “CrossFormer: A versatile vision transformer hinging on cross-scale attention,” in ICLR, 2022.

[33] V. Sanh, L. Debut, J. Chaumond, and T. Wolf, “DistilBERT, a distilled version of bert: smaller, faster, cheaper and lighter,” arXiv preprint arXiv:1910.01108, 2019.

[34] X. Jiao et al., “Tinybert: Distilling bert for natural language understanding,” in EMNLP, 2020.

[35] W. Wang, F. Wei, L. Dong, H. Bao, N. Yang, and M. Zhou, “MinimLM: Deep self-attention distillation for task-agnostic compression of pre-trained transformers,” in NeurIPS, 2020.

[36] C. Dong, G. Wang, H. Xu, J. Peng, X. Ren, and X. Liang, “EfficientBERT: Progressively searching multilayer perceptron via warm-up knowledge distillation,” in EMNLP, 2021.

[37] J. Gou, B. Yu, S. J. Maybank, and D. Tao, “Knowledge distillation: A survey,” IJCV, 2021.

[38] Q. Guo et al., “Online knowledge distillation via collaborative learning,” in CVPR, 2020.

[39] Y. Wang, W. Zhou, T. Jiang, X. Bai, and Y. Xu, “Intra-class feature variation distillation for semantic segmentation,” in ECCV, 2020.

[40] Z. Wu, Y. Jiang, C. Cai, Z. Yang, X. Xue, and H. Qi, “Spirit distillation: Precise real-time semantic segmentation of road scenes with insufficient data,” arXiv preprint arXiv:2103.15733, 2021.

[41] L. Liu et al., “Exploring inter-channel correlation for diversity-preserved knowledge distillation,” in ICCV, 2021.

[42] Y. Zhu and Y. Wang, “Student customized knowledge distillation: Bridging the gap between student and teacher,” in ICCV, 2021.

[43] A. Douillard, Y. Chen, A. Dapogny, and M. Cord, “Tackling catastrophic forgetting and background shift in continual semantic segmentation,” arXiv preprint arXiv:2106.15287, 2021.

[44] Y. Feng, X. Sun, W. Diao, J. Li, and X. Gao, “Double similarity distillation for semantic image segmentation,” TIP, 2021.

[45] S. An, Q. Liao, Z. Lu, and J.-H. Xue, “Efficient semantic segmentation via self-attention and self-distillation,” T-ITS, 2022.