Content-aware Directed Propagation Network with Pixel Adaptive Kernel Attention

Min-Cheol Sagong, Yoon-Jae Yeo, Seung-Won Jung, Senior Member, IEEE, and Sung-Jea Ko, Fellow, IEEE

Abstract—Convolutional neural networks (CNNs) have been not only widespread but also achieved noticeable results on numerous applications including image classification, restoration, and generation. Although the weight-sharing property of convolutions makes them widely adopted in various tasks, its content-agnostic characteristic can also be considered a major drawback. To solve this problem, in this paper, we propose a novel operation, called pixel adaptive kernel attention (PAKA). PAKA provides directivity to the filter weights by multiplying spatially varying attention from learnable features. The proposed method infers pixel-adaptive attention maps along the channel and spatial directions separately to address the decomposed model with fewer parameters. Our method is trainable in an end-to-end manner and applicable to any CNN-based models. In addition, we propose an improved information aggregation module with PAKA, called the hierarchical PAKA module (HPM). We demonstrate the superiority of our HPM by presenting state-of-the-art performance on semantic segmentation compared to the conventional information aggregation modules. We validate the proposed method through additional ablation studies and visualizing the effect of PAKA providing directivity to the weights of convolutions. We also show the generalizability of the proposed method by applying it to multi-modal tasks especially color-guided depth map super-resolution.

Index Terms—Deep learning, Content-adaptive convolution, Semantic segmentation, Color-guided depth map super-resolution

I. INTRODUCTION

D
EEP learning based on convolutional neural networks (CNNs) has brought remarkable improvement to image processing and computer vision tasks including object detection [1]–[6], classification [7]–[11], image restoration [12]–[16], and generation [17]–[21]. Convolution is a basic element of CNNs, and has been considered as one of the most effective methods to extract and propagate features from images. Due to its weight sharing property, CNNs require less parameters than fully-connected layer and can be efficiently optimized by GPU implementation. However, the learned filters stay fixed after training in traditional convolution, making operation content-agnostic.

Toward content-adaptive convolution, a learnable filter which is generated dynamically conditioned on input features was proposed and showed promising effectiveness through the quantitative and qualitative performance evaluation [2], [22], [23]. In particular, with the marginal increase in the number of network parameters, its adaptive property improves flexibility of the model. Moreover, Su et al. [23] introduced a pixel-adaptive convolution (PAC) which multiplies a spatially-varying kernel with the shared filter weights. It can be ideally used for a wide range of tasks but its effectiveness was shown for only a few image filtering tasks. To further improve flexibility of convolution, a deformable convolution [2], in which spatial sampling locations are augmented with additional learnable offsets, was proposed. This helps CNNs enhance the transformation modeling capability without additional supervision. To focus more precisely on pertinent image regions, the deformable convolution was further reformulated by modulating the input feature amplitudes according to the spatial locations and bins [24]. This modulation can prevent features to be influenced by irrelevant content outside the region of interest.

In this paper, we propose a novel convolutional operation, called pixel adaptive kernel attention (PAKA), which drives the standard convolution to handle a content-adaptive receptive field. Specifically, PAKA modifies the weights of convolution with directional and channel modulations. The directional modulation emphasizes or suppresses features from different kernel directions while channel modulation aggregates the inter-channel relationship. With PAKA, the convolution predicts directions that provide pertinent information in every pixel. We evaluate the efficacy of PAKA with various experiments on multiple tasks. For the semantic segmentation task, we propose a hierarchical module with PAKA which can utilize diverse effective patch sizes. Through the proposed module, the network learns to attend to content-adaptive directions to inherit more information. To visually demonstrate this behavior, we define the modulated receptive field, called propagational field, which is emphasized or suppressed receptive field by the directional modulation. We validate our module by comparing ours with the state-of-the-art information aggregation modules under the same conditions. To demonstrate the generalizability of our method, we also apply PAKA to the joint up-sampling layer for the color-guided depth map super-resolution task. The experimental results indicate that the proposed method not only exhibits superiority on various CNN-based tasks but also has a noticeable potential.

In summary, in this paper we present:

- A novel convolutional operation that provides directivity to the standard convolution to address its limitation which is content-agnostic.
- A novel information aggregation module and extensive experiments to validate the effectiveness of the proposed method on semantic segmentation.
• Application of the proposed method to the joint up-sampling layer and extensive experiments to validate its effectiveness on color-guided depth map super-resolution.

II. RELATED WORKS

Content-adaptive filters Recently, several works have explored the idea of utilizing effective content-adaptive filtering techniques such as bilateral filtering [25], [26] and guided filtering [27] as the layers of the CNNs. In the early stages in this direction, some approaches [28], [29] made these filters differentiable to back-propagate the gradients for learning network parameters. Moreover, the learnable layers that play the role of the bilateral filter were applied to superpixels [30]. On the other hand, by reformulating the guided filter as a fully differentiable block, Wu et al. [31] proposed guided filtering layers that can be jointly optimized through end-to-end training. While the aforementioned methods cannot fully replace the standard convolution by their proposed layers, Jampani et al. [32] introduced a sparse high-dimensional convolution that modifies the standard convolution to be content-adaptive. Similarly, Su et al. [23] presented a generalized convolution, called PAC, which can learn adaptive filters and has less computational overhead compared to [32]. In addition, introduced by Jia et al. [22], the dynamic filter network (DFN) directly predicts filter weights using a separate network branch; thus, it can generate adaptive filters corresponding to each input feature.

Attention mechanisms In learning a series of pattern recognition tasks, depending on the characteristic of each task, the network should reflect that given feature maps have different importance along spatial and/or channel direction. To this end, there have been several attempts to adopt the attention modules, which compute the responses for the local part while attending to the global context. Wang et al. [33] introduced a residual attention module which directly generates 3D attention map to refine the intermediate feature map. By using this module, the network performs robustly against noisy labels. Meanwhile, Hu et al. [34] proposed a squeeze-and-excitation module that computes channel attention with global average pooling. Even though the architecture effectively exploits the inter-channel relationships, they did not consider the spatial attention which plays an important role in inferring accurate attention for 3D feature maps. On the other hand, some approaches [35], [36] separately learn both channel attention and spatial attention. By applying the decomposed attention generation, the network showed superior performance than [34] as well as much less parameter overhead than [33].

Information aggregation modules In recent years, many researches have explored information aggregation for scene understanding. Zhao et al. [37] proposed PSPNet which adopts the pyramid spatial pooling (PSP) module [38] to reduce the feature maps into different scales. PSPNet utilizes various local context including the global information. On the other hand, Deeplab methods [39]–[41] introduced atrous spatial pyramid pooling (ASPP) which applies sampling with different rates for information aggregation. Fu et al. [42] and Yuan et al. [43] adopted the self-attention mechanism [44] to aggregate long-range spatial information, while Zhang et al. [45] utilized context encoding module (CEM) which contains the global pooling to capture the global context and highlights the class-dependent feature maps.

III. PROPOSED METHOD

Fig. 1 illustrates the modified convolution in which PAKA is applied. The proposed method produces kernel attention from input feature through two separate branches, i.e., channel modulation branch and directional modulation branch. In this section, we describe details of PAKA.

A. Pixel Adaptive Kernel Attention

Formally, convolution for each location \( p \) on the output feature map \( y \in \mathbb{R}^{H \times W} \) and input feature maps \( x \in \mathbb{R}^{N \times H \times W} \) can be expressed as follows:

\[
y(p) = \sum_{j=1}^{N} \sum_{k=1}^{K} x(p + p_k, j) \cdot w(k, j),
\]

where \( w(k, j) \) denotes the weight for the \( k \)-th location and the \( j \)-th channel, and \( p_k \) is the pre-specified offset for the \( k \)-th location. \( N \) and \( K \) are the numbers of channels and sampling locations, respectively. For instance, \( K = 9 \) and \( p_k \in \{(−1, −1), (−1, 0), \ldots, (1, 1)\} \) correspond to \( 3 \times 3 \) convolution with dilation 1. \( (1) \) indicates that the weights only depend on pixel and channel positions; thus, the standard convolution is content-agnostic. To cope with this problem, we designed PAKA which provides directivity to weights along pixel contents. With PAKA, \( (1) \) becomes

\[
y(p) = \sum_{j=1}^{N} \sum_{k=1}^{K} x(p + p_k, j) \cdot w(k, j) \cdot A_{k,j}(p),
\]

where \( A_{k,j} \) is learnable kernel attention for the \( k \)-th location and the \( j \)-th channel. The attention lies in the bounded range by applying the activation function to the combination of directional and channel modulations, which are denoted as \( m_k \in \mathbb{R}^{K \times H \times W} \) and \( n_j \in \mathbb{R}^{N \times H \times W} \), respectively. Each modulation is obtained by individual branches that apply multiple learnable layers to the same input feature maps \( x \). By combining two decomposed modulations, PAKA can conduct attention mechanism in an efficient and effective manner. In particular, we apply element-wise summation with the tensor broadcast to combine them for efficient gradient flow [8]. As a result, the kernel attention can be expressed as

\[
A_{k,j} = 1 + \tanh(m_k + n_j).
\]

Channel modulation branch Each pixel in feature maps contains information from different contents (e.g., pixels from the object and background). As each channel tends to respond to a specific feature, we drive PAKA to exploit inter-channel relationship from every single pixel by channel modulation. We use a multi-layer perceptron including two \( 1 \times 1 \) convolutional layers followed by a batch normalization layer to estimate channel modulation.
Details of PAKA. Given the intermediate feature map $x$, PAKA computes the channel modulation $n_j$ and directional modulation $m_k$ through the two separate branches in every pixel. Both branches contain a couple of convolutional layers, the batch normalization, and ReLU. The two modulations are combined with the tensor broadcast and generate the kernel attention by the activation function. Since the kernel attention is different in every pixel, the proposed convolutional layer can learn the content-adaptive directivity.

**Directional modulation branch** Pixels corresponding to the same object can be surrounded by different objects (e.g., pixels in the center and around boundary of objects). However, since the standard convolution applies shared weights across every pixel, a trained network propagates information from the same directions for different pixels in an image. To solve this problem, the directional modulation $m_k$ is acquired to emphasize or suppress information from different directions. Specifically, it infers which kernel direction among the pre-specified offsets should be focused on every pixel. By adopting multiple convolutional layers with PAKA, each pixel can take information propagated from different fields. We design the directional modulation branch using a $3 \times 3$ convolutional layer followed by a $1 \times 1$ convolutional layer. In particular, the $3 \times 3$ layer is designed to have the same kernel size, dilation, and stride as the shared convolution layer such that they have the same receptive field. In addition, batch normalization is applied at the end of convolutional layer for a scale adjustment.

**B. Hierarchical PAKA Module**

With PAKA, we propose our hierarchical PAKA module, or HPM, as illustrated in Fig. 2. On the top of the module, we apply a $1 \times 1$ convolutional layer with BN and ReLU to squeeze the number of channels before feeding into the convolutional layers with PAKA. The HPM employs a series of dilated convolutional layers with PAKA to deal with the hierarchical pyramid architecture. In the last of HPM, we concatenate the Globally pooling input and every output feature maps from PAKA with different dilation rates.

**C. Understanding and Analysis**

Several existing convolution operations perform position-specific modifications as explained in Section II. In DFN [22], since an auxiliary network generates filters for every offset and channel, a large number of parameters are needed. In addition, DFN requires an elaborate architecture design because all position-specific filter weights have to be predicted without sharing. Unlike DFN, PAKA allows efficient learning by position-specific attentions and shared weights. Liu et al. [46] and Cheng et al. [47] propose spatial propagation networks by learning affinity. Although they utilize the directivity to propagate the information, they target the guide learning or refinement to learn affinity matrices. On the contrary, PAKA can be self-directed because it only specifies the direction to focus on each pixel.

The deformable convolution [2], [24] employs position-specific modification by altering the grid of convolutional kernel to apply different sizes of receptive fields on different targets. It augments the spatial sampling location with the learnable offsets and modulation scalars. However, since the offset vectors have a high degree of freedom, it is very challenging to reach an optimal solution. In addition, the deformable convolution cannot explicitly consider the channel-wise attention because it only modifies the spatial sampling
Fig. 2. An architecture of HPM. We apply the bottleneck layer to reduce the channel of input feature maps before feeding into the first PAKA layer. The module contains several PAKA layers with different dilation rates. We indicate PAKA layers’ output channel with c and dilation rate with d. We concatenate the input and output features of each PAKA layer to utilize various receptive fields.

Fig. 3. Toy example for multiple convolutional layers with PAKA on different locations. With PAKA, the convolution propagates the information from different directions depending on the local contents.

IV. EXPERIMENTAL RESULTS

The proposed method is evaluated on the ADE20K [48] dataset for the semantic segmentation task. The ADE20K dataset contains very challenging 150 classes including 35 stuff classes and 115 discrete object classes. The dataset is divided into 20,210 images for training, 2,000 and 3,352 images for validation and testing, respectively. For evaluation, class-wise intersection over union (mIoU) and pixel-wise accuracy (PixAcc) are used.

A. Implementation Details

As a backbone network for feature extraction, we use a pretrained ResNet [8] model with the dilated network strategy [39], [49]. The size of the feature maps is 1/8 of the size of the input image. We adopt convolutional layers and bilinear up-sampling layer to generate the final prediction map. We apply the cross-entropy loss to train the proposed network. Following the previous researches [37], we integrate the auxiliary loss in stage 4 of the ResNet backbone.

For the training, we normalize the input in the range $[-1, 1]$. We also apply data augmentation including random horizontal flipping, random Gaussian filtering, and scaling with random factors of $[0.5, 2.0]$ to avoid overfitting. Last, we randomly crop the input image into the fixed size of $256 \times 256$ pixels. The pioneering researches [37], [45] mention that the larger the crop size, the better the semantic segmentation performance. However, we use the same patch size of $256 \times 256$ for all compared methods considering our hardware resource. Although it is smaller than the size used in the original papers, whole conditions are unified for fair validation of the information aggregation modules.

During the training phase, we employ the stochastic gradient descent algorithm with a poly learning rate policy, $\gamma = \gamma_0 \times \left(1 - \frac{N_{\text{iter}}}{N_{\text{total}}}\right)^p$, where $N_{\text{iter}}$ and $N_{\text{total}}$ represent the current iteration number and total iteration number, respectively, and $p = 0.9$. We set the initial learning rate $\gamma_0$ as 0.01, momentum as 0.9, weight decay as 0.0001, and batch size as 16. We train the model for 150K iterations.
B. Evaluation for Semantic Segmentation

Ablation Study for HPM

To demonstrate the superiority of our PAKA and HPM, we conduct the experiments with several different settings containing the conventional information aggregation modules, which are PSP [37], ASPP [40] and, Self-Attention [44], as shown in Table I.

First, we evaluate performance of our baseline model. The baseline consists of ResNet for the backbone network and the last convolutional layers followed by a up-sampling layer. It results in 36.28% in terms of mIoU and 76.84% in terms of PixAcc. We adopt this model as our baseline to compare the performance of the information aggregation modules. We list our evaluation results of different information aggregation modules in Table I. Note that we reimplement the conventional methods using the same condition for fair comparison. As can be seen in the table, the proposed method shows the best result in terms of both mIoU and PixAcc. With our HPM, the baseline model is significantly improved by 4.87% and 2.86% in terms of mIoU and PixAcc, respectively. Fig. 6 shows several semantic segmentation results obtained by the baseline and HPM, demonstrating the effectiveness of information aggregation by HPM.

In order to demonstrate the validity of the proposed modulations, we conducted ablation experiments by eliminating each modulation from PAKA. Table II shows that the PAKA without any modulation exhibits inferior performance compared with the original PAKA and both modulations are essential for the performance improvement. To support the effectiveness of PAKA and the necessity of HPM, we have conducted ablation studies by switching the standard convolution and PAKA in ASPP and HPM. As shown in Table III, simple replacement of the standard convolution by PAKA improves the performance of ASPP. In addition, it shows that PAKA is more effective with HPM compared to ASPP. We consider this is because a cascade structure with PAKA can utilize diverse propagational fields as illustrated in Fig. 3. However, ASPP adopts a parallel structure that cannot fully take advantage of PAKA. Therefore, we designed HPM including a cascade structure with PAKA to fully exploit its effectiveness. Moreover, to show the computational cost of PAKA, we present the number of parameters and
TABLE I
SEGMENTATION RESULTS ON THE ADE20K VALIDATION SET IN COMPARISON WITH DIFFERENT INFORMATION AGGREGATION MODULES.

| model                      | mIOU  | pixAcc |
|----------------------------|-------|--------|
| ResNet-50 (Baseline)       | 36.28 | 76.84  |
| ResNet-50 + PSP            | 38.34 | 77.79  |
| ResNet-50 + Self-Attention | 39.16 | 78.58  |
| ResNet-50 + ASPP           | 40.37 | 79.39  |
| ResNet-50 + HPM (Proposed) | 41.15 | 79.70  |
| ResNet-101 (Baseline)      | 39.03 | 78.60  |
| ResNet-101 + PSP           | 40.12 | 79.55  |
| ResNet-101 + Self-Attention| 41.84 | 80.08  |
| ResNet-101 + ASPP          | 42.08 | 80.07  |
| ResNet-101 + HPM (Proposed)| 42.21 | 80.38  |

TABLE II
ABLATION STUDY DEMONSTRATING THE EFFECTS OF CHANNEL MODULATION AND DIRECTIONAL MODULATION.

| Channel Directional | mIOU  | pixAcc |
|---------------------|-------|--------|
|                     | 39.85 | 78.43  |
| ✓                   | 40.41 | 79.68  |
| ✓                   | 40.85 | 79.65  |
| ✓ ✓                 | 41.15 | 79.70  |

TABLE III
ABLATION STUDY REPLACING STANDARD CONVOLUTION WITH PAKA FOR ASPP AND REPLACING PAKA WITH STANDARD CONVOLUTION FOR HPM.

| Backbone   | ResNet-50 | ResNet-101 |
|------------|-----------|------------|
| Aggregation module | ASPP | HPM |
| PAKA       | ✓         | ✓         |
| # parameters | 56.0M | 90.7M | 36.1M | 40.8M |
| average runtime | 138ms | 187ms | 124ms | 136ms |
| mIOU       | 40.37 | 40.71 | 39.85 | 41.15 |

We also evaluate the combined model of HPM and the conventional modules. As mentioned in Section III-C, HPM learns direction to propagate the context information. Since HPM plays a different role compared to other modules, combining HPM with the other existing modules can yield further improvement. As indicated in Table IV, the combined module produces better results than a single module.

Comparison with state-of-the-art methods We compare the proposed method with other state-of-the-art methods to demonstrate effectiveness of the proposed method. For this experiment, we use the same patch size as the conventional methods (480 × 480) for training and utilize the combined model of ASPP and HPM. Similar to the compared methods [37], [40], [50], [51], we average the predictions from multiple scaled and flipped inputs to further improve the performance. We use the scale factors of {0.5, 0.75, 1.0, 1.25, 1.5} for the multi-scale testing strategy. As shown in Table V, the proposed method outperforms recent state-of-the-art methods although our proposed method is trained with simple up-sampling layers for image reconstruction.

V. JOINT DEPTH SUPER-RESOLUTION WITH PAKA
In order to demonstrate superiority over other content-adaptive convolution, i.e., pixel-adaptive convolution (PAC), and generalizability of PAKA, as a case study, we apply PAKA for the color-guided depth map super-resolution task, which generates a high-resolution depth map with help of its corresponding high-resolution color image. Early studies adopt content-adaptive filtering techniques such as joint bilateral filtering [56] and guided image filtering [27]. The common

TABLE IV
PERFORMANCE IMPROVEMENTS BY COMBINING HPM WITH THE CONVENTIONAL MODULES. THE EVALUATION METRIC IS mIOU(%). △ INDICATES THE ABSOLUTE DIFFERENCE.

|       | PSP | Self-Attention | ASPP |
|-------|-----|----------------|------|
| w/o HPM | 38.34 | 39.16 | 40.37 |
| w/ HPM  | 41.48 | 41.02 | 41.47 |
| △      | +3.14 | +1.86 | +1.10 |

Fig. 6. Qualitative comparisons with the baseline and HPM on the ADE20K validation dataset. Propagation of the related context information by PAKA helps to understand the scenes, resulting in a significantly performance improvement over the baseline.
TABLE V
QUANTITATIVE EVALUATION ON THE ADE20K VALIDATION SET IN COMPARISON WITH STATE-OF-THE-ART METHODS.

| Method   | Backbone | mIOU | pixAcc |
|----------|----------|------|--------|
| EncNet [45] | ResNet-50 | 41.11 | 79.73 |
| PSPNet [37] | ResNet-50 | 42.78 | 80.76 |
| ACNet [50] | ResNet-50 | 43.01 | 81.01 |
| CFNet [52] | ResNet-50 | 42.87 | -     |
| CPN [51] | ResNet-50 | 44.46 | 81.38 |
| Proposed | ResNet-50 | 44.75 | 81.29 |

characteristic of them is that they determine filter weights to up-sample the target (i.e., low-resolution (LR) depth map) from the guide content (i.e., HR color image). Consequently, the surrounding pixels that have higher content similarity to the center have greater influence in filtering. We notice that PAKA can be used as a learnable and generalized model of such conventional filtering methods.

A. Joint up-sampling layer with PAKA

To conduct the color-guided depth map super-resolution task, we design a joint up-sampling layer with PAKA. Fig. 7 illustrates the proposed joint up-sampling layer with PAKA. The proposed joint up-sampling layer receives low-resolution (LR) target feature maps and high-resolution (HR) guide feature maps as input. We obtain the kernel attentions from the guide feature maps by employing both channel modulation branch and directional modulation branch in the same manner as the original PAKA. The each kernel is multiplied with the shared weights to generate sub-pixels of the upsampled feature maps. With the kernel attention from PAKA, the proposed joint up-sampling layer is driven to concentrate more on important directions (e.g., edge) to inherit the information from the guide features.

B. Implementation Details

We build the network architecture motivated by the pioneering method [57] of joint depth map super-resolution, which is simple yet efficient. We provide the details of the network in Fig. 8. Following the common training procedure [57], [58], we use MPI Sintel depth dataset [59] and Middlebury dataset [60] (including 2001, 2006 and 2014 datasets). In the training phase, we crop the images into $128 \times 128$ patches with overlapping for all scaling factors (i.e., $\times 8$ and $\times 16$) to reduce the training time.

C. Evaluation for depth map super-resolution

Table VI shows the numeric results of the proposed and conventional methods in case of 8 times and 16 times super-resolution, respectively. We compare the performance in terms of root mean squared error (RMSE) and peak signal-to-noise ratio (PSNR). As can be seen in the table, our proposed joint up-sampling network with PAKA outperforms the conventional state-of-the-art methods [23], [58], [61]. For further study, we test the conventional methods in conjunction with PAKA. As can be seen in Table VII, PAKA contributes to further performance improvements of the conventional models. Fig. 9 shows visual comparisons of the state-of-the-art methods and the proposed method. The proposed method generates more sharp object boundaries than other methods. It indicates that PAKA can help to learn accurate directivity to up-sample the features than the conventional methods.

VI. CONCLUSION

In this paper, we propose a novel convolutional operation called PAKA that learns the directivity to effectively propagate information. PAKA emphasizes or suppresses information from different directions with two decomposed branches, which predict channel and directional modulations. We validate superiority of PAKA with visualization of its propagational fields and the extensive experiments. We also demonstrate that PAKA is applicable in many vision tasks...
including semantic segmentation and joint depth map super-resolution. Since PAKA can directly replace the standard convolutional layers, we think that PAKA has a notable potential to leverage various CNN-based tasks.

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Min-Cheol Sagong received his B.S. degree in Electrical Engineering from Korea University in 2018. He is currently pursuing his Ph.D. degree in Electrical Engineering at Korea University. His research interests are in the areas of digital signal processing, computer vision, and artificial intelligence.

Yoon-Jae Yeo received his B.S. degree in Electrical Engineering from Korea University in 2017. He is currently pursuing his Ph.D. degree in Electrical Engineering at Korea University. His research interests are in the areas of image processing, computer vision, and deep learning.

Seung-Won Jung (S’06-M’11-SM’19) received the B.S. and Ph.D. degrees in electrical engineering from Korea University, Seoul, Korea, in 2005 and 2011, respectively. He was a Research Professor with the Research Institute of Information and Communication Technology, Korea University, from 2011 to 2012. He was a Research Scientist with the Samsung Advanced Institute of Technology, Yongin-si, Korea, from 2012 to 2014. He was an Assistant Professor at the Department of Multimedia Engineering, Dongguk University, Seoul, Korea, from 2014 to 2020. In 2020, he joined the Department of Electrical Engineering at Korea University, where he is currently an Associate Professor. He has published over 70 peer-reviewed articles in international journals. He received the Hae-Dong young scholar award from the Institute of Electronics and Information Engineers in 2019. His current research interests include image processing and computer vision.

Sung-Jea Ko (M’88-SM’97-F’12) received his Ph.D. degree in 1988 and his M.S. degree in 1986, both in Electrical and Computer Engineering, from State University of New York at Buffalo, and his B.S. degree in Electronic Engineering at Korea University in 1980. In 1992, he joined the Department of Electronic Engineering at Korea University where he is currently a Professor. From 1988 to 1992, he was an Assistant Professor in the Department of Electrical and Computer Engineering at the University of Michigan-Dearborn. He has published over 210 international journal articles. He also holds over 60 registered patents in fields such as video signal processing and computer vision.

Prof. Ko received the best paper award from the IEEE Asia Pacific Conference on Circuits and Systems (1996), the LG Research Award (1999), and both the technical achievement award (2012) and the Chester Sall award from the IEEE Consumer Electronics Society (2017). He was the President of the IEIE in 2013 and the Vice-President of the IEEE CE Society from 2013 to 2016. He is a member of the National Academy of Engineering of Korea. He is a member of the editorial board of the IEEE Transactions on Consumer Electronics.