SMOF: Squeezing More Out of Filters Yields Hardware-Friendly CNN Pruning

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Abstract

For many years, the family of convolutional neural networks (CNNs) has been a workhorse in deep learning. Recently, many novel CNN structures have been designed to address increasingly challenging tasks. To make them work efficiently on edge devices, researchers have proposed various structured network pruning strategies to reduce their memory and computational cost. However, most of them only focus on reducing the number of filter channels per layer without considering the redundancy within individual filter channels. In this work, we explore pruning from another dimension, the kernel size. We develop a CNN pruning framework called SMOF, which Squeezes More Out of Filters by reducing both kernel size and the number of filter channels. Notably, SMOF is friendly to standard hardware devices without any customized low-level implementations, and the pruning effort by kernel size reduction does not suffer from the fixed-size width constraint in SIMD units of general-purpose processors. The pruned networks can be deployed effortlessly with significant running time reduction. We also support these claims via extensive experiments on various CNN structures and general-purpose processors for mobile devices.

1. Introduction

Deep convolutional neural networks (CNNs) have made remarkable breakthroughs on various tasks such as computer vision [5, 12], image processing [6], natural language processing [45], and medical imaging applications [40]. Recently, the rapid development of communication technologies such as Internet-of-Things and 5G [48] provides a vision of the future where edge devices have a crucial role in providing uninterrupted communications and computations every day. Therefore, there will be an explosive increase in applying deep learning on edge devices to address the new challenges and enable more advisable services. However, successful deep CNN architectures such as ResNet [14], DenseNet [18], and EfficientNet [47] typically contain hundreds of layers and tons of parameters, which require a large memory footprint and increased computational power. Therefore, there has been a high demand for reducing the size and FLOPs of CNNs with acceptable compromise on their performance.

In view of this challenge, various neural network pruning strategies have been developed. It has been shown that the redundancy in CNNs mostly lies in their convolution filters [31, 52]. In what follows, we classify pruning methods into two main categories: filter channel pruning and filter weight pruning. Overall, their key idea is to obtain high pruning ratios with acceptable loss in performance [10].

Filter channel pruning approaches are developed by removing the filter channels of a CNN according to certain metrics [27, 35]. These methods will change the network structure in a systematic way and only keep basic network blocks to decrease redundancy. Filter channel pruning can achieve high pruning ratios. However, due to the fixed-size width of the SIMD (single instruction, multiple data) unit in general-purpose processors [19], filter channel pruning may not fully utilize the SIMD unit and may not achieve as much of a latency reduction as its FLOPs reduction.

Filter weight pruning approaches such as [7, 50] focus on optimizing individual filter weights and achieve a sparse network with acceptable performance degradation. In contrast to channel pruning, weight pruning approaches keep the network structure. Since the sparse weights are often randomly distributed in filters, weight pruning approaches usually need an extra record to locate the sparse weights. However, unstructured sparse convolution does not have an efficient implementation on popular hardware architectures (e.g., ARM and x86) and frameworks (e.g., Tensorflow Lite and TensorRT) [19].

In summary, filter channel and weight pruning methods are mostly developed on an algorithmic level without considering the structural constraints of current edge devices. Therefore, we ask, if possible, if not more desirable, to develop a deep CNN pruning method that yields high pruning...
ratios and runtime reduction ratios under hardware limitations. In this work, we propose SMOF to achieve this goal. We summarize our contributions as follows:

1. We develop a hybrid pruning method called Squeeze More Out of Filters (SMOF), which considers both filter weight pruning and channel pruning by reducing the kernel size and the number of output channels.

2. SMOF is hardware-friendly. The pruned network can be deployed effortlessly on common hardware devices without any customized low-level implementations and also enjoy significant runtime reduction. Notably, the pruning effort by kernel size reduction does not suffer from the fixed-size width constraint in SIMD units of general-purpose processors.

3. We demonstrate the efficiency of SMOF on various vision tasks. To evaluate its runtime acceleration, SMOF is compared with several state-of-art pruning methods on general-purpose processors for mobile devices.

2. Related Work

2.1. Filter Channel Pruning

Filter channel pruning approaches are proposed to remove filter channels within each layer based on different measuring metrics or importance scores. Channel pruning keeps the predefined network structure and decreases redundancy at the layer level.

Some previous strategies focus on finding better criteria to prune unimportant filter channels. [23] shows the feasibility of using the $\ell_2$-norm of filter weights as a measuring metric. [24, 27, 33] find that the variance of the feature maps could be another choice for this metric. FPGM [16] proposes to measure the geometric information of filters for computing importance scores. In addition, [17] introduce $\ell_1/\ell_2$ regularization to modify network channels during training. [30] adds Lasso regularization on the batch normalization layer to remove the filter channels with small scaling factors. Recently, there is a trend of applying automated machine learning (AutoML) for automatic network compression [3, 8, 15, 39]. The key idea of these methods is to explore the total space of network filter configurations for the best candidate. On the other hand, Amc [15] uses reinforcement learning to sample the structure searching space while retaining accuracy, and LeGR [8] defines a pair of learnable parameters to adjust the important scores across layers, which leads to a global ranking of filters.

However, these methods only develop ranking and removal mechanisms for filter channels without considering the redundancy within the filters. Moreover, arbitrarily pruned filter channels may not be efficiently implemented on edge devices, where the numbers of output channels should align to the fixed-size width of SIMD units.

2.2. Filter Weight Pruning

Filter weight pruning focuses on removing individual filter weights and produce a sparse network. Some methods such as OBProx-SG [7] and SWAT [38] embed the pruning demand into the network training loss and employs a joint strategy of fine-tuning and optimization to learn a sparse CNN. OICSR [25] applies group Lasso regularization to induce sparsity on filter weights. Another recent work [22] enhances the sparsity of weights by adding thresholds to each filter. On the other hand, some other methods focus on converting the network to the spectral domain [13, 32], and utilize sparsity of both filters and feature maps to reduce computational cost. However, for the popular edge device hardware architectures such as ARM and x86, these unstructured sparse convolution computations cannot be implemented efficiently. They require an additional record to locate the sparse weights, which takes extra memory and computational resources.

2.3. Hybrid Filter Pruning

In view of the filter redundancy in both channels and weights, several pruning methods are proposed to account for both dimensions. Some of them attempt to use AutoML to search a compact network structure. [3] and [4] propose to search for a compact structure by shrinking a large network from different dimensions, including number of filter channels and kernel size. However, the training is very heavy in both machine time and human labor. On the other hand, SSL [50] develops a sparsity learning method to regularize filter weights and channels. In addition, some other approaches add extra components or blocks to help the network learn a sparse structure. For example, SWP [35] assigns a learnable matrix to each filter weight to learn its desired kernel shape by stripe-wise pruning\(^1\), and remove a filter channel when all of its stripes are pruned. In PCONV [34] and PatDNN [36], the kernel shapes can be chosen from a predefined set, and the number of remaining filter channels at each layer should be smaller than some predefined threshold. However, allowing various kernel shapes requires customized implementation on the hardware, as most kernel shapes do not fit in the SIMD unit of processors. In summary, both regularization methods and kernel shaping methods require a further customized ASIC design [19] or special low-level implementation to fully utilize the hardware computational capacity. Otherwise, significant runtime reduction ratios cannot be achieved.

3. Proposed Method

In this paper, we propose SMOF for CNN pruning, which Squeezes More Out of Filters by reducing both the kernel size and the number of filter channels at each layer.

\(^1\)See Fig. 1 for the definition of stripe.
At a high level, we assign each convolutional layer a learnable matrix called Filter Skeleton (FS) to learn the kernel shape of filter channels, and another learnable vector called Filter Mask (FM) to learn the importance of individual filter channels. With the same square kernel shape across filter channels at each layer, the pruned network can be deployed effortlessly on popular hardware devices without customized low-level implementations. Notably, the pruning effort by kernel size reduction is not canceled by the fixed-size width of SIMD units in processors.

More specifically, let the weight of a convolutional layer be \( W \in \mathbb{R}^{N \times C \times K \times K} \), where \( K \) is the kernel size, and \( N, C \) are the number of output and input channels, respectively. We say that each filter channel consists of \( K^2 \) stripes of the form \( \mathbb{R}^{C \times 1} \) (see Fig. 1 for an illustration). In order to ensure an efficient implementation of the pruned network on hardware devices, we propose SMOF with a focus on reducing \( K \) and \( N \) in a learnable and coordinated way, see Algorithm 1 for details.

### 3.1. Filter Skeleton (FS) for Kernel Size Reduction

Let \( W^l \in \mathbb{R}^{N^l \times C^l \times K^l \times K^l} \) be the weight of \( l \)-th convolution layer. Inspired by [35], we assign a learnable parameter called Filter Skeleton \( FS^l \in \mathbb{R}^{K^l \times K^l} \) to \( W^l \) to reduce the kernel size \( K^l \). Each element in FS reflects the importance of the corresponding stripe in all of the \( N^l \) filter channels of \( W^l \), and is initialized as 1. Mathematically, the training loss with FS can be written as:

\[
\text{Training loss with FS:} \quad \sum_{(x,y) \in D} \text{loss}(f(x, W \odot FS), y) + \sum_{i=1}^{K^l/2} \sum_{l} \alpha_i \| FS^l_{i,j} \|_g,
\]

where \( K^l \) is the kernel size of the \( l \)-th convolutional layer, and \( FS^l_{i,j} \) denotes the \( i \)-th slice of \( FS^l \) (see Fig. 2), and \( \odot \) denotes the dot product. The penalty term in (1) promotes kernel size reduction. Specifically, the \( \| \cdot \|_g \) norm induces group sparsity on the 4 edges \( FS^l_{i,j} \) (\( i = 1, 2, 3, 4 \)).

\[
\| FS^l_{i,j} \|_g = \sum_{j=1}^4 \| FS^l_{i,j} \|_2.
\]

The \( \| FS^l_{i,j} \|_g \) term induces structured sparsity on the 4 edges \( FS^l_{i,j} \) (\( j = 1, 2, 3, 4 \)) of \( FS^l \), which is inspired from Group Lasso [41, 43]. This type of penalty term has also been applied in other network pruning methods [29, 50].

Kernel size reduction is done in a “peeling” fashion during training, as illustrated in Fig. 2. More specifically, we set a certain ratio \( \rho_{FS} > 0 \) during training. Starting from \( i = 1 \), we consider the 4 edges on the \( i \)-th slice \( FS^l_{i,j} \). If at some iteration during training, the sum of the absolute values of elements on \( FS^l \) on these edges is smaller than \( \rho_{FS} \cdot 4(K^l + 1 - 2i) \), we will prune these elements to 0. After \( FS^l \) is multiplied to \( W^l \), the stripes with positions that correspond to zero values in \( FS^l \) will also be zero, and the kernel size of \( W^l \) is reduced by 2. We repeat this process on the remaining \( FS^l \) elements (i.e., \( i \leftarrow i + 1 \)) to further reduce kernel size. Note that the most central element will not be pruned to 0. To keep current progress, the \( FS^l \) elements that are pruned to 0 will not be updated at later iterations.

In (1), the coefficients \( \alpha_i \) are of the form:

\[
\alpha_i = (K^l/2 + 1 - i) \alpha \quad \text{for some } \alpha > 0.
\]
Figure 2. **Kernel size reduction by FS Pruning.** This FS of size $5 \times 5$ has 2 slices. For each slice, its 4 edges are in solid lines. For the outermost slice with $i = 1$ (in white), its FS elements have been pruned to 0 at some previous iteration. The current kernel size is 3. We now proceed to its inner slice with $i = 2$ (in light blue). During training, if the sum of the absolute values of its FS elements is smaller than $\rho_{FS} \cdot 4(K^l + 1 - 2i)$, these elements will be pruned to 0, and the kernel size is further reduced from 3 to 1. The central element (in dark blue) will never be pruned in SMOF. To prepare for inference, we multiply FS to the weight $W$ and prune the outer stripes of $W$ with zero FS value.

This gives a stronger penalty to the outer slices of $FS^l$, and encourages pruning to start from outer slices.

### 3.2. Filter Mask (FM) for Filter Number Reduction

To further improve pruning ratios, we also reduce the number of filter channels at each layer alongside kernel size reduction. For that purpose, we assign a learnable vector called Filter Mask $FM^l \in \mathbb{R}^{N^l \times 1}$ to the weight $W^l \in \mathbb{R}^{N^l \times C^l \times K^l \times K^l}$. $FM^l$ is multiplied to $W^l \odot FS^l$ during training, which learns the importance of the $N^l$ output channels. The elements of $FM^l$ are initialized as 1.

Together with FS, we now have the full training loss:

$$
\text{SMOF Training loss with FS and FM:}
\sum_{(x,y) \in D} \text{loss}(f(x, W \odot FS \odot FM), y) + \sum_{l} \sum_{i=1}^{K^l/2} \alpha_i ||FS^l||_g + \sum_{l} \beta ||FM^l||_1,
$$

where $\alpha_i$ is given by (3), and the last term applies $\ell_1$-norm penalty to induce sparsity on $FM^l$. During training, we set a threshold $\delta_{FS} > 0$, and prune the $FM^l$ elements with absolute values smaller than $\delta_{FS}$ to 0. After multiplying $FM^l$ to $W^l \odot FS^l$, any filter channel with a 0 in $FM^l$ is also 0.

For CNNs with special structures, pruning channels at different layers arbitrarily may destroy these structures and cause significant performance degradation. For example, the shortcut connection is a key feature in ResNet [14]. It leads to the superior performance of ResNet over earlier network designs such as GoogleNet [46] and VGGNet [44]. In a simple form, the shortcut connection is given by

$$
y = F(x, \{W^l\}) + x.
$$

When $W^l$ is pruned by $FM^l$, it will have fewer output channels, and a dimension mismatch between $F(x, \{W^l\})$ and $x$ may occur.

To resolve this, we apply a shared FM to all the layers that must have the same output dimension, and prune their output channels at the same time (see Fig. 3). In other words, the shared FM reflects the importance of their output channels altogether. Take ResNet18 as an example, 4 shared FMs are applied for 4 different BasicBlocks.

Figure 3. **Filter channel reduction by FM pruning.** For simplicity, we focus on the case of the simple form of shortcut connection (5) in BasicBlock. FM pruning applies to other structures with shortcut connections as well. The orange blocks denote BasicBlocks with the same structure, in which the shared FM is applied after the FS2 block. The dashed part in shared FM has been pruned to 0. As a result, the corresponding output channels in Conv2 are also pruned to 0. Since the same shared FM is also applied in the previous BasicBlock, the shortcut connection can be applied safely. To prepare for inference, we prune the dashed output channels in the network.

### 3.3. Training and Inference

In order to perform training with the loss function (4), we apply stochastic gradient descent (SGD) on $\{W^l\}$ and...
\( \text{FS}^l \\) and \( \text{FM}^l \). To deal with the nondifferentiable penalty term on \( \{\text{FS}^l\} \), we apply proximal gradient descent [2]. More specifically, the update on \( \text{FS}^l \) is given by

\[
\text{FS}^l_{ij} = \text{Prox}_{\eta_l} \| \cdot \|_2 (\text{FS}^l_{ij} - \eta_l \dot{g}_{ij}^l),
\]

(6)

where \( \eta \) is the learning rate, \( i = 1, 2, \ldots, K/2 \), and \( j = 1, 2, 3, 4 \), \( \dot{g}_{ij}^l \) is a stochastic gradient of the first term in (4) w.r.t. \( \text{FS}^l_{ij} \). The proximal operator \( \text{Prox}_{\eta_l} \| \cdot \|_2 \) has a closed form expression, which is cheap and easy to implement:

\[
\text{Prox}_{\eta_l} \| \cdot \|_2 (x) = \frac{x}{\|x\|_2} \max \{0, \|x\|_2 - \eta_l\}.
\]

(7)

After training is finished, we multiply \( \text{FS}^l \) and \( \text{FM}^l \) to \( W^l \) with zero value in \( \text{FS}^l \), as well as output channels with zero value in \( \text{FM}^l \) (see Figs. 2 and 3). We also need to adjust the zero padding. For example, if the kernel size of \( W^l \) is reduced by 2, its zero padding should be decreased by 1. After this step, the pruned model is ready for inference.

4. Experiments

To validate our proposed approach, we conduct extensive experiments on various deep CNN architectures including VGG [44], ResNet [14] for image classification, and UNet [40] for image denoising.

Hardware Settings We use SNPE (Snapdragon Neural Processing Engine SDK) on Qualcomm Snapdragon SM8250 as our mobile platform. In the following, we test SMOF and other CNN pruning methods on three different general-purpose processors for mobile devices: CPU, GPU, and digital signal processor (DSP). The CPU is a Kryo 585 CPU (ARM V8 Cortex based architecture CPU at 1.8 - 2.84GHz). Our GPU is Adreno 650 GPU with 1.2T FLOPS. Our DSP is Hexagon 698 V66 processor, which is an efficient low power general processor with 15TOPS. These are typical hardware accelerators for deploying CNNs on mobile devices. It is worth noting that the implementation on CPU, GPU, and DSP will try to pad the output channels of Conv layers to be aligned to fixed-size width to fully utilize the SIMD units. For example, the Qualcomm Hexagon DSP V66 processor has a SIMD vector of 1024 bits. All models are trained on a 8 NVIDIA A100 GPUs server using PyTorch.

4.1. ResNet56 and VGG16 on CIFAR-10

Models and Dataset We test on the CIFAR-10 dataset [21], which contains 50K training images and 10K test images for 10 classes. For the training set, we apply standard data augmentation procedures, including random crop and random horizontal flip. For this dataset, we apply two popular CNNs: VGG16 [44] and ResNet56 [14].

Parameter Settings For ResNet56 and VGG16, we start pruning from pretrained models. We train for 180 epochs, where the initial learning rate is 0.1 and is divided by 10 at the 90th and 135th epoch. The training algorithm is SGD with a momentum of 0.9, a batchsize of 128, and a weight decay of 1e−4. During the first 90 epochs, we apply parameter settings listed in Tables 1 and 2. After the 90th epoch, we set \( \alpha = \beta = \rho_{\text{FS}} = \delta_{\text{FM}} = 0 \), which stops the pruning process and fixes the obtained network structure.

For ResNet56, we also set a certain percentage (denoted by \( r \)) of FM values to be learnable at each convolution layer, while the rest are always 1. This avoids pruning of all of the channels in one layer and therefore makes training easier1.

Discussion of ResNet56 Results In Table 1, we present a pruning ratio and runtime comparison between our SMOF and other pruning strategies. Our baseline model has an accuracy of 93.18%. SMOF achieves a higher pruning ratio than HRank [27] and Global Ranking [8], while enjoying a 0.39% accuracy gain. SMOF also saves much more GPU and DSP runtime than HRank [27] and Global Ranking [8]. We speculate that this is because these two strategies only focus on filter channel pruning, while for processors with longer SIMD (e.g., 1024 bit for the DSP processor we used

\footnote{If we set \( r = 1 \), then for certain layers of ResNet56, the elements of FM are very similar during training, and all the channels are pruned nearly at the same time. By fixing some FM elements to be 1, we keep the corresponding channels and allow channel pruning for the rest.}

Table 1. ResNet56 pruning with CIFAR-10. The baseline ResNet56 model has a CPU runtime of 616(ms), a GPU runtime of 5.7(ms), and a DSP runtime of 0.845(ms). All DSP runtime are averaged over 20 runs. SMOF achieves the most runtime reduction with an accuracy gain of 0.39%. More results and comparisons can be found in Sec. 5.
Table 2. VGG16 pruning with CIFAR-10. The baseline of SMOF has an accuracy of 93.95%. The baseline of HRank [27] and GAL-0.1 [28] has an accuracy of 93.96%. The baseline of Zhao et al. has an accuracy of 93.25%.

| Method      | Params % ↓ | FLOPs % ↓ | Accuracy |
|-------------|------------|-----------|----------|
| SMOF: \(r = 1\) \[\alpha = 1e-6, \rho_{FS} = 0.31, \beta = 1e-8, \delta_{FM} = 0\] | 80.8 | 50.1 | 93.88 |
| SMOF: \(r = 1\) \[\alpha = 1e-6, \rho_{FS} = 0.31, \beta = 1e-8, \delta_{FM} = 0.025\] | 80.9 | 58.0 | 93.50 |
| HRank [27]  | 82.9 | 53.3 | 93.43 |
| GAL-0.1 [28]| 82.2 | 45.2 | 93.42 |
| Zhao et al. [51] | 73.3 | 39.1 | 93.18 |

Discussion

In Tables 3 and 4, we present a pruning ratio and runtime comparison between our SMOF and other pruning strategies. The SMOF-1 model has smaller pruning ratios and a higher accuracy compared with SMOF-2. Although they have higher FLOPs reduction ratios, their CPU and GPU runtime are similar to SMOF, and their DSP runtime are worse. This is because the aligned processing mentioned at the beginning of Sec. 4 cancels some of their channel pruning efforts, especially on the DSP processor with a longer SIMD unit of 1024 bits. Moreover, the data padding/cropping itself costs extra latency.

We provide structure of pruned ResNet18 in appendix.

4.3. U-Net for Image Denoising

We evaluate SMOF on U-Net for image denoising, and compare with five state-of-the-art pruning approaches (DHP [26], Factor-SIC2 [49], Group [37], LeGR [8], and HRank [27]). We train on the DIV2K [1] dataset and evaluate on the BSD68 dataset.

Parameter Settings

To ensure a fair comparison, we apply the same network hyperparameters as in the original network training strategy [40]. We use SGD with momentum=0.9, fixed learning rate of \(1e - 4\), a batchsize of 256, and a weight decay factor of \(5e - 5\). We also apply the same procedures for data preprocessing, filter weights initialization, and the same noise level of images (70). To compare these model compression methods, we measure their performance in six metrics, including the number of parameters, FLOPs, Peak Signal-to-Noise Ratio (PSNR), and runtime on CPU, GPU, and DSP.

Discussion

We evaluate two models pruned by SMOF for different purposes: one for computational efficiency (SMOF-1) and the other one for high PSNR (SMOF-2). We report pruned network structure in Figure 4 and summarize the test results in Table 4. The procedures for obtaining these pruned models can be found in the appendix.

Compared with LeGR [8] and HRank [27], SMOF-1 saves more runtime and has a similar PSNR. Besides, we notice that SMOF-1 achieves the similar PSNR and complexity reduction as Group [37], but with less run-time on CPU and DSP. This might due to the inefficient implemen-
Table 3. **ResNet18 pruning with ImageNet.** The pruned models SMOF-1 and SMOF-2 are obtained with parameters and procedures described in Sec. 4.2. The baseline ResNet18 model has a CPU runtime of 566(ms), a GPU runtime of 24.3(ms), and a DSP runtime of 4.96(ms). * denotes our independent test. All DSP runtime are averaged over 20 runs.

| Network | Method | Params % ↓ | FLOPs % ↓ | CPU(ms) | GPU(ms) | DSP(ms) | Accuracy % |
|---------|--------|------------|-----------|---------|---------|---------|-------------|
| UNet    | DHP [26] | 58.25      | 58.06     | 0.12    | 163.9   | 9.85    | 0.71        |
|         | Factor-SIC2 [49] | 67.65 | 64.22 | 0.23 | 828.7 | - | 31.80 |
|         | Group [37] | 73.45 | 56.30 | 0.11 | 294.4 | - | 19.80 |
|         | LeGR* [8] | 53.09 | 58.65 | 0.13 | 393.7 | 29.20 | 1.44 |
|         | Hrank* [27] | 56.96 | 57.77 | 0.15 | 157.3 | - | 0.85 |
|         | SMOF-1 | 74.74 | 52.79 | 0.11 | 134.7 | 4.60 | 0.54 |
|         | SMOF-2 | 58.89 | 44.28 | 0.05 | 152.9 | 8.47 | 0.56 |

Table 4. **Comparison of several model pruning methods for image denoising.** The noise level of training and testing images is 70. All the methods are tested on BSD68 dataset and FLOPs is reported for a $128 \times 128$ image. SMOF achieves significant runtime reduction on different general-purpose processors of mobile devices. * denotes our implementation.

| Network | Method | Params % ↓ | FLOPs % ↓ | PSNR | CPU(ms) | GPU(ms) | DSP(ms) |
|---------|--------|------------|-----------|------|---------|---------|---------|
| UNet    | DHP [26] | 58.25      | 58.06     | 0.12 | 163.9   | 9.85    | 0.71    |
|         | Factor-SIC2 [49] | 67.65 | 64.22 | 0.23 | 828.7 | - | 31.80 |
|         | Group [37] | 73.45 | 56.30 | 0.11 | 294.4 | - | 19.80 |
|         | LeGR* [8] | 53.09 | 58.65 | 0.13 | 393.7 | 29.20 | 1.44 |
|         | Hrank* [27] | 56.96 | 57.77 | 0.15 | 157.3 | - | 0.85 |
|         | SMOF-1 | 74.74 | 52.79 | 0.11 | 134.7 | 4.60 | 0.54 |
|         | SMOF-2 | 58.89 | 44.28 | 0.05 | 152.9 | 8.47 | 0.56 |

5. Ablation Study

In this section, we demonstrate the advantage of adaptive group sparsity term (2) over the usual $\ell_1$-norm. Trade-off curves of SMOF and HRank [27] are also presented.

From Fig. 6 we can see that SMOF has a better trade-off curve than HRank. Compared with using the plain $\ell_1$-norm penalty as in [35], adaptive group sparsity term (2) have a clear advantage as it applies stronger group penalty on the outer edges, which encourages pruning in the “peeling” fashion as described in Fig. 2. On the other hand, the $\ell_1$-norm penalty applies uniform penalty on all the stripes, which is unnecessary for stripes on the inner edges. Finally, when FM(Filter Mask) pruning is disabled, SMOF applies less pruning with the same FS parameters, the same happens for SMOF without FS pruning.
6. Conclusions and Future Work

In this work, we propose a hardware-friendly CNN pruning framework called SMOF. The key idea is to Squeeze More Out of Filters by reducing both the kernel size and filter channels at each layer. SMOF learns the importance of stripes and channels. It prunes the unimportant stripes and channels in a coordinated way, such that the kernel size and number of channels can be reduced while preserving the network structure. The efficiency of SMOF is demonstrated on popular CNNs and general-purpose processors without any customized low-level implementations.

There are still open problems to be addressed. For instance, can we allow additional kernel shapes other than just squares? A direct extension to this would be rectangle kernels with different zero padding applied along the x and y directions. In addition, the performance of SMOF enables us to conclude that kernel size reduction is a direction worth pursuing. Therefore, is it possible to combine it with other channel pruning strategies such as [8] and [11]? We believe that this would lead to even higher pruning ratios and run-time reduction.
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A. SMOF Pruning for U-Net

**SMOF pruning procedures for U-Net** First, we keep all the elements in Filter Masks to be 1 \((\beta = 0, \delta_{FM} = 0,\) and \(r = 0)\) and set \(\alpha = 1e - 6, \rho_{FS} = 0\) for 50 epochs. Then, we either 1) keep \(\alpha = 1e - 6\) and set \(\rho_{FS} = 0.30, \beta = 3e - 4, \delta_{FM} = 0.02,\) and \(r = 1\) for another 50 epochs, or 2) set \(\alpha = 2e - 6, \) and \(\rho_{FS} = 0.35,\) keep \(\beta = 0, \delta_{FM} = 0,\) and \(r = 0\) for 50 epochs. We call the obtained models SMOF-1 and SMOF-2, respectively. Next, we stop pruning and fix their network structures by setting \(\alpha = \rho_{FS} = \beta = \delta_{FM} = 0,\) and apply Adam optimizer \([20]\) with learning rate \(= 1e - 4\) with for 100 epochs.

B. Structure of Pruned ResNet18

In this section, we provide the structure of the structure of a pruned ResNet18. Specifically, we provide a comparison of the original ResNet-18 (FLOPs = 1842.78M) with the SMOF-1 in Sec. 4.2 (FLOPs = 1271.17M).

| Layer               | ResNet18 | SMOF-1 |
|---------------------|----------|--------|
| conv1               | (64, 7)  | (64, 5) |
| layer1.0.conv1      | (64, 3)  | (64, 1) |
| layer1.0.conv2      | (64, 3)  | (64, 3) |
| layer1.1.conv1      | (64, 3)  | (64, 3) |
| layer1.1.conv2      | (64, 3)  | (64, 3) |
| layer2.0.conv1      | (128, 3) | (128, 3)|
| layer2.0.conv2      | (128, 3) | (128, 1)|
| layer2.0.downsample_conv | (128, 1) | (128, 1)|
| layer2.1.conv1      | (128, 3) | (128, 3)|
| layer2.1.conv2      | (128, 3) | (128, 3)|
| layer3.0.conv1      | (256, 3) | (256, 3)|
| layer3.0.conv2      | (256, 3) | (256, 3)|
| layer3.0.downsample_conv | (256, 1) | (256, 1)|
| layer3.1.conv1      | (256, 3) | (256, 3)|
| layer3.1.conv2      | (256, 3) | (256, 3)|
| layer4.0.conv1      | (512, 3) | (512, 3)|
| layer4.0.conv2      | (512, 3) | (512, 3)|
| layer4.0.downsample_conv | (512, 1) | (512, 1)|
| layer4.1.conv1      | (512, 3) | (512, 3)|
| layer4.1.conv2      | (512, 3) | (512, 1)|

Table 5. Comparison of (output channels, kernel size) of the Conv layers in ResNet18 and SMOF-1. Note that SMOF only reduces the kernel sizes for ResNet18.