Residual Sparsity Connection Learning for Efficient Video Super-Resolution

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Abstract

Lighter and faster models are crucial for the deployment of video super-resolution (VSR) on resource-limited devices, e.g., smartphones and wearable devices. In this paper, we develop Residual Sparsity Connection Learning (RSCL), a structured pruning scheme, to reduce the redundancy of convolution kernels and obtain a compact VSR network with a minor performance drop. However, residual blocks require the pruned filter indices of skip and residual connections to be the same, which is tricky for pruning. Thus, to mitigate the pruning restrictions of residual blocks, we design a Residual Sparsity Connection (RSC) scheme by preserving the feature channels and only operating on the important channels. Moreover, for the pixel-shuffle operation, we design a special pruning scheme by grouping several filters as pruning units to guarantee the accuracy of feature channel-space conversion after pruning. In addition, we introduce Temporal Finetuning (TF) to reduce the pruning error amplification of hidden states with temporal propagation. Extensive experiments show that the proposed RSCL significantly outperforms recent methods quantitatively and qualitatively. Codes and models will be released.

1 Introduction

Video super-resolution (VSR) aims to generate a high-resolution (HR) video from its corresponding low-resolution (LR) observation by filling in missing details. With the popularity of intelligent edge devices such as mobile phones and small drones, performing VSR on these devices is in high demand. Though a variety of VSR networks [42, 48, 17, 27, 22] can perform well, these CNN-based models are usually difficult to deploy on edge devices with limited computing and memory resources. To alleviate this problem, one would want to design a lightweight network for efficient VSR.

Unlike single image super-resolution (SISR), VSR faces the extra challenge to aggregate information from multiple highly-related but misaligned video frames. For example, Kappeler et al. modified SRCNN [8] and extracted features from frames that are aligned by optical flow [18]. TDAN [37] and EDVR [42] adopted deformable alignment modules [6] for aligning and integrating the features from adjacent frames. In addition, by propagating the hidden states of previous steps with the recurrent unit, some works effectively exploited long-range temporal information to improve the reconstruction performance and greatly reduce the inference time. Furthermore, BasicVSR [2] and BasicVSR++ [3] combined optical flow estimation and bidirectional propagation to aggregate the temporal information from the past and the future. Similarly, GOVSR [47] leveraged the VSR output from the past, present, and future. Coming to edge implementations, Xiao et al. designed a space-time knowledge distillation scheme [44] to train lightweight VSR. However, most lightweight VSR methods neglect the sparsity or redundancy of the network, which can be optimized to be more efficient.

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In this paper, we explore a new direction for effective and efficient VSR. To reduce the redundancy of convolution kernels [33, 35, 4, 5] obtaining a more efficient VSR network, we develop a neural network pruning scheme for the VSR task for the first time. Since structured pruning schemes [21, 43, 14, 51] (focusing on filter pruning) can achieve an actual acceleration [43, 38] superior to unstructured pruning schemes [11, 12] (focusing on weight-element pruning), we adopt structured pruning. The proposed method is especially suitable for resource-limited devices, e.g., hand-held devices and small drones. Given a powerful VSR network, we can prune it with a presetting pruning rate and reduce the model to the desired size without seriously compromising performance.

Although structured neural network pruning has been explored in image classification, it is hardly transferred to VSR directly. Therefore, we specially develop Residual Sparsity Connection Learning (RSCL). (1) Residual blocks are crucial components, extensively used in state-of-the-art VSR networks to ease the training (e.g., BasicVSR [2] has 60 residual blocks). As shown in Fig. 1 (a), it is difficult to prune the residual blocks because the skip and residual connections ought to share the same indices [21]. Thus, as shown in Fig. 1 (b), many structured pruning algorithms for classification simply do not prune the last convolution layer in the residual blocks, which restricts the pruning space and limits the pruning performance. As shown in Fig. 1 (c), ASSL [51], a structured pruning scheme for SISR, attempted to enforce the pruned filter indices between the skip and residual connections to be the same, which again restricts the pruning space. Hence, as shown in Fig. 1 (d), our Residual Sparsity Connection (RSC) preserves all channels of the input and output feature maps but selects the important channels for convolution and addition. Compared with the above pruning schemes, our RSC liberates the pruning space of the last convolution in the residual blocks without adding extra calculations. (2) The upsampling network accounts for 22% of the total calculations in BasicVSR [2], which has to be pruned. However, since the pixel-shuffle [34] in VSR networks converts the channels to space, pruning the pixel-shuffle without any restrictions will cause this channel-space conversion to fail. To address the problem, we take four consecutive filters as the pruning unit for $2 \times \times$ pixel-shuffle. (3) The recurrent unit widely used in VSR takes the previous hidden state as input, the error of which will accumulate with propagation steps increasing after pruning. To address the issue, we further introduce Temporal Finetuning (TF). Overall, our main contributions are threefold:

- We propose the RSCL for efficient VSR. To the best of our knowledge, the design of structured pruning for optimizing VSR networks has received little attention so far.

- We propose the RSC and pixel-shuffle pruning scheme for VSR. Moreover, we introduce Temporal Finetuning to reduce the propagation error after pruning.

Figure 1: Illustration of different schemes for residual block pruning. (a) Structure of the residual block in the VSR network. (b) The residual block pruning schemes [21, 7, 40] do not prune the last convolution. (c) ASSL [51] prunes the same indices on skip and residual connections to keep channel alignment. (d) Our RSC can prune the first and last convolutions without restrictions.
Extensive experiments show that our RSCL significantly outperforms state-of-the-art pruning schemes as well as lightweight VSR methods with the same or even less computational cost.

2 Related Work

2.1 Video Super-Resolution

VSR can be considered an adaptation of SISR that exploits additional information from neighboring low-resolution frames [16, 9, 26, 45, 46, 49, 50, 3]. Earlier VSR methods [1, 36, 46] estimate the optical flow between low-resolution (LR) frames and perform spatial warping for alignment. Later methods resort to a more sophisticated approach of implicit alignment. Instead of image-level motion alignment, TDAN [37] and EDVR [42] work at the feature level. TDAN [37] first adopted Deformable Convolution [6] in VSR to align the features of different frames. EDVR [42] extended TDAN by introducing coarse-to-fine deformable alignment and a new spatio-temporal attention fusion module. RSDN [16] adopted a recurrent detail-structural block and a hidden state adaptation module to reduce the effect of appearance changes and error accumulation. Recently, BasicVSR [2] found that bidirectional propagation coupled with a simple optical flow-based feature alignment can further improve performance. Similarly, Yi et al. [47] used the bidirectional propagation framework to exploit LR frames and estimated hidden states from the past, present, and future. To compress the VSR model, Xiao et al. designed a space-time knowledge distillation scheme [44].

2.2 Network Pruning

Network pruning [33, 35, 4, 5] is widely used to remove a set of redundant parameters for network acceleration. Pruning methods can be divided into two branches, structured pruning [21, 43, 14, 10] and unstructured pruning [11, 12]. Structured pruning methods prune the network at the level of filters, channels, and even layers, which can obtain regular sparsity after pruning. This is beneficial for acceleration. In contrast, unstructured methods focus on pruning weights, leading up to irregular sparsity. This is beneficial for compression but tends not to yield an actual acceleration [43, 38]. Specifically, Li et al. [21] applied the \( L_1 \)-norm to measure the importance of different filters and then removed the less important ones. Afterward, Liu et al. [28] added a sparsity-inducing penalty term on scaling factors of the batch normalization layers to enforce the channels with lower scaling factors to be the less informative ones. Recently, Zhang et al. [51] utilized aligned structured sparsity learning for structured pruning of residual blocks. In addition, Luo et al. [30] developed a residual block pruning scheme for image classification using the convolutions on skip connections. However, the residual blocks of the VSR network do not have such convolutions. Lin et al. [24] conducted runtime neural network pruning according to the input image. Furthermore, some researchers have explored unstructured pruning for the single image super-resolution (SISR) task. Wang et al. [41] explored the intrinsic sparsity of the image SR task and used sparse convolution to skip redundant computations. Similarly, Kong et al. [20] exploited a classification network to assign different regions to SR networks with different capacities, according to their restoration difficulty.

3 Methodology

Fig. 2 (a) shows the basic architecture of the VSR network based on the bidirectional recurrent unit, such as BasicVSR [2]. Given the LR frame \( I_t \), the forward propagation network in the bidirectional recurrent VSR network concatenates \( I_t \) and the previous hidden state \( H_{F,t-1} \) to extract features from \( I_t \) and aggregate the reference information from the past hidden state \( H_{F,t-1} \). Similarly, the backward propagation network extracts features from \( I_t \) and aggregates the reference information from the future hidden state \( H_{B,t+1} \). Note that both the forward and backward propagation networks consist of numerous residual blocks. Then, the features generated by these forward and backward propagation networks are fed into the upsampling network, which consists of multiple pixel-shuffle operations and convolutions, to obtain the recovered frame \( SR_t \). However, VSR networks [2, 3, 47] require massive computational and memory resources, limiting their deployment on edge devices.
To pursue more efficient VSR networks, we propose Residual Sparsity Connection Learning (RSCL), a structured pruning scheme. Specifically, network pruning has three stages, including pretraining, pruning, and finetuning. In the pretraining stage, we train a powerful VSR network. Since current VSR networks do not use BatchNorm [15], we introduce a scaling factor to tune the sparsity of each channel and filter. In the pruning stage, we select the unimportant filters according to the pruning criterion and apply sparsity-inducing regularization on corresponding scaling factors. In addition, for the residual block extensively used in VSR, we propose a Residual Sparsity Connection (RSC) scheme to increase the pruning space. Moreover, for the upsampling networks in VSR, we specially develop a pruning scheme for the pixel-shuffle operation to guarantee the accuracy of channel-space conversion after pruning. The error of the hidden state will be amplified with the propagation steps increasing in the recurrent unit after pruning. Therefore, in the finetuning stage, we further introduce Temporal Finetuning (TF) to reduce the error of temporal information propagation.

3.1 Residual Sparsity Connection Learning

Residual Sparsity Connection Learning (RSCL) is the pruning scheme that we developed for VSR, aiming to reduce the redundancy of convolution kernels and obtain more efficient models. Since structured pruning can obtain better actual acceleration than unstructured pruning [33, 38], we adopt the former. In the following, we will explain the proposed pruning scheme in detail.

(1) Scaling Factor. Structured pruning aims to remove convolution filters based on a designed importance criterion. In the classification task, previous works use BatchNorm [15] scale parameters to control the throughput of each filter. Zero scale parameters make the value of corresponding channels vanish. As a result, they contribute nothing to the subsequent convolutions and can be removed. By regularizing the scale parameter, we can assess and tune the importance of each filter. However, the BatchNorm is not useful for super-resolution tasks [23], and SOTA VSR networks do not utilize it [2, 3, 47]. Therefore, it is infeasible to apply the existing pruning schemes directly. In our pruning scheme, as shown in Fig. 1 (d) and Fig. 2 (b), we multiply the scaling factors $\gamma$ before or after convolutions. Then, we can perform regularization on scaling factors to enforce sparsity.

(2) Pruning Criterion and Regularization Form. To remove the redundant filters, we need to select unimportant scaling factors $\gamma$ to induce sparsity. In classification networks, [28] sorted the BatchNorm scaling factors globally (i.e., scaling factors of different layers are compared together). In contrast, ASSL [51] observed that the global pruning scheme could not guarantee that skip and residual connections keep the same number of filters and indices as required for the adding operation. Therefore, ASSL adopted a local pruning scheme (namely, scaling factors are only compared within the same layer, and each layer has the same pruning ratio). Given that the importance of
the convolutions in each layer differs and that our residual block pruning scheme does not have
restrictions in ASSL, we adopt the global pruning filters scheme in RSCL.

Previous regularization-based pruning methods [21] have demonstrated the effectiveness of the
$L_1$-norm pruning criterion. Therefore, we choose the $L_1$-norm as our pruning criterion. Specifically,
for the $k$-th convolution filter $\mathbf{W}_i[k,…] \in \mathbb{R}^{C_{in} \times K_h \times K_w}$ in the $i$-th layer, we calculate the sum of its
absolute kernel weights with $s_{i,k} = \sum |\mathbf{W}_{i}[k,…]|$. In particular, for our RSC in Fig. 1 (d), we require
to additionally prune the input channels for the first convolution, and calculate its $L_1$-norm score with
$s_{i,k} = \sum |\mathbf{W}_{i}[k,…]|$, where $\mathbf{W}_{i}[k,…] \in \mathbb{R}^{C_{out} \times K_h \times K_w}$. Moreover, for the convolution before
the pixel-shuffle operation, we take four consecutive filters as a pruning unit and calculate the score
with $s \left[4(k + 1)\right] = \sum |\mathbf{W}_{i}[4k : 4(k + 1),…]|$. Then, given the pruning ratio $p$ and the number $N$ of filters
or channels participating in the sorting, we sort all $L_1$-norm scores $s$ together and choose the $N \times p$
filters with the smallest $L_1$-norm values as unimportant filters or channels, denoted as set $S$.

After identifying the unimportant filters and channels set $S$, we apply sparsity-inducing regularization
(SIR) to the corresponding scaling factors, denoted as set $S_{sf}$. Note that we do not enforce sparsity-
inducing regularization to the important filters and channels since they will remain in the network.
Motivated by [39, 40, 51], we use $L_2$ regularization on the scaling factors to enforce sparsity:

$$\mathcal{L}_{SIR} = \alpha_{\gamma} \sum_{\gamma \in S_{sf}} \gamma^2,$$

where $\gamma$ is the scalar selected from $\gamma \in \mathbb{R}^{C}$ corresponding to unimportant filters or channels; $\alpha_{\gamma}$
is a scalar. We increment $\alpha_{\gamma}$ by a presetting constant $\Delta$ every $T_1$ iterations. When $\alpha_{\gamma}$ reaches the
pre-defined upper limit $\tau$, we keep $\alpha_{\gamma}$ constant and continue training $T_2$ iterations.

(3) Pruning Scheme for Residual Blocks. Residual blocks are infamously difficult to prune because
the addition operations in residual blocks require the pruned filter indices between the skip and
residual connections to be the same. As shown in Fig. 1 (b), previous pruning schemes simply
skipped the pruning of the last convolution in residual blocks, which restricted the pruning space
and limited the pruned network performance. Moreover, as shown in Fig. 1 (c), ASSL [51] pruned
the last convolution in the residual block with aligned structural sparsity learning. However, ASSL
demanded all the pruned filter indices of the last convolution in the residual blocks to be the same,
which still limited the pruning space and performance. To break the restriction of pruned indices in
the last convolution, as shown in Fig. 1 (d), we propose the RSC to prune residual blocks. As we
can see, our RSC preserves all channels of input $\mathbf{F}_{i}$ and output $\mathbf{F}'_{i+1}$ in the residual blocks. For the
first convolution, we select the important channels (the indices not in $S$) to participate in the first
convolution, which can be expressed as Eq. 2. After the last convolution, we obtained $\mathbf{F}_{i+1}$ and add
$\mathbf{F}'_{i+1}$ to $\mathbf{F}'_{i}$ on the corresponding channel indices to obtain $\mathbf{F}'_{i+1}$, which can be expressed as Eq. 3.

$$\mathbf{F}_{i} = \mathbf{F}'_{i} \otimes (\gamma_{j-1}\mathbf{W}_{i}\gamma_{j}),$$

$$\mathbf{F}'_{i+1} = \mathbf{F}_{i} \otimes (\mathbf{W}_{i+1}\gamma_{j+1}) + \mathbf{F}'_{i},$$

where $\otimes$ indicates convolution. $\mathbf{F}'_{i}, \mathbf{F}'_{i+1} \in \mathbb{R}^{C \times H \times W}$ are the input and output feature maps of the
residual block, respectively. $\mathbf{F}_{i}, \mathbf{F}_{i+1} \in \mathbb{R}^{C_{in} \times H \times W}$ are intermediate feature maps. $\mathbf{W}_{i}, \mathbf{W}_{i+1} \in \mathbb{R}^{C_{out} \times C_{in} \times K_h \times K_w}$ are weights of convolution kernels. $\gamma_{j-1} \in \mathbb{R}^{C_{in}}$ and $\gamma_{j}, \gamma_{j+1} \in \mathbb{R}^{C_{out}}$ are
scaling factors to apply sparsity-inducing regularization. It is noteworthy that, compared with ASSL,
our residual block pruning has the same number of parameters and the same computation cost.

(4) Pruning Scheme for Pixel-Shuffle. The upsampling network of the VSR network uses
convolution to increase channels of feature maps and adopts the pixel-shuffle [34] operation to convert
the channels to space realizing upsampling. As shown in Fig. 2 (b), given the input feature map $\mathbf{F}_{i} \in \mathbb{R}^{C \times H \times W}$, we expand its channels $4 \times$ by a convolution with weight $\mathbf{W}_{i}$ to obtain
$\mathbf{F}'_{i+1} \in \mathbb{R}^{4C \times H \times W}$. Then, the pixel-shuffle operation takes four channels as a group to convert $\mathbf{F}'_{i+1}$ to
$\mathbf{F}'_{i+1} \in \mathbb{R}^{C \times 2H \times 2W}$ realize $2 \times$ upsampling. Thus, if we adopt the pruning scheme without any re-
striction, the pruned feature maps will be spatially reordered after passing the pixel-shuffle operation.
To address the problem, we specially design a pruning scheme for the pixel-shuffle operation. Given
the input feature map, we take four filters as a pruning unit to evaluate the importance, as described
in the pruning criterion, and impose the scaling factor $\gamma_{j}$ on filters to enforce sparsity:

$$\mathbf{W}'_{i} = \mathbf{W}_{i}[4k : 4(k + 1),…] \gamma_{j}[k], k \in [0, C_{in}),$$
where \( W_i \in \mathbb{R}^{C_{in} \times C_{in} \times K_h \times K_w} \) is the weights of convolution kernel. \( \gamma_j \) is the scaling factor.

(5) **Loss Functions for Finetuning.** As shown in Fig. 2 (a), the pruned VSR network generates a minor error in hidden state \( H_F \) and \( H_B \), which will be amplified as the hidden state propagates along with the recurrent unit. Thus, we introduce Temporal Finetuning (TF), formulated as:

\[
L_{tf} = \| H_{F,T} - H'_{F,T} \| + \| H_{B,0} - H'_{B,0} \| ,
\]

where \( T \) is the number of input frames, and \( H_{F,T} \) and \( H'_{F,T} \) are the final hidden states after \( T \) frames forward propagation of pruned and original VSR networks, respectively. Similarly, \( H_{B,0} \) and \( H'_{B,0} \) are the final hidden states after backward propagation of the pruned and original VSR networks.

In addition, we use the Charbonnier loss \([2, 42]\) as reconstruction loss to finetune the spatial representation ability of the VSR network, which can be formulated as:

\[
L_{rec} = \sqrt{\| SR_t - HR_t \|^2 + \varepsilon^2},
\]

where \( \varepsilon \) is set to \( 10^{-6} \). \( SR_t \) and \( HR_t \) are super-resolved results and corresponding high-resolution groundtruth, respectively. The overall loss function for pruned network finetuning is designed as:

\[
L_{all} = L_{rec} + \lambda_{tf} L_{tf},
\]

where \( \lambda_{tf} \) is set to \( 10^{-2} \) to balance the reconstruction loss and temporal finetuning loss.

### 3.2 Arm VSR Models with RSCL

Our RSCL can be used for state-of-the-art VSR networks. Here, we choose practical BasicVSR \([2]\) as our VSR pruning backbone. In addition, we further propose to use unidirectional BasicVSR (BasicVSR-uni), obtained by removing the backward propagation network, for online inference. Since the SpyNet in BasicVSR is used for flow estimation, we do not apply our pruning scheme to it. In the pruning stage, we first add the scaling factor to the convolution and residual blocks as described in Sec. 3.1. Then we use the pruning criterion to select unimportant filters globally and apply sparsity-inducing regularization to the corresponding scaling factor. Afterward, we remove the unimportant convolution filters and finetune the pruned VSR network with \( T_3 \) iterations.

### 4 Experiments

#### 4.1 Experimental Settings

We adopt two widely used datasets for training: REDS \([31]\) and Vimeo-90K \([46]\). For REDS, following BasicVSR \([2]\), we use REDS4 containing 4 clips as our test set. Additionally, we adopt REDSval4 as our validation set, which contains 4 clips selected from the REDS validation set. The remaining clips of REDS are used for training. In addition, we utilize Vid4 \([25]\) and Vimeo90K-T \([46]\) as test sets along with Vimeo-90K. We train and test models with \( 4 \times \) bicubic downsampling.

We pretrain the unidirectional BasicVSR (BasicVSR-uni) as done for BasicVSR. In sparsity-inducing regularization, the iterations \( T_1 \) and \( T_2 \) are set to 5 and 3,375 separately. The scalars \( \Delta \) and \( \tau \) are set to \( 10^{-4} \) and 0.1, respectively. Note that we fix the parameters of the flow estimator in sparsity-inducing regularization. In the pruned VSR network finetuning, we set \( T_3 \) to 300,000. We adopt the Adam optimizer \([19]\) and Cosine Annealing scheme \([29]\). The initial learning rate of the flow estimator is \( 2.5 \times 10^{-5} \). The learning rate for all other modules is \( 2 \times 10^{-4} \). The batch size is 8, and the patch size of input LR frames is \( 64 \times 64 \). Our models are trained with 4 Tesla V100 GPUs.

#### 4.2 Quantitative and Qualitative Comparisons

Since BasicVSR violates causality and cannot be evaluated online, we construct the unidirectional BasicVSR (BasicVSR-uni) by removing the backward propagation network for online inference. We compare the proposed RSCL with three other pruning schemes at pruning ratio \( p = 0.5 \): training from scratch, \( L_1 \)-norm pruning \([21]\) (which simply removes filters with the smallest \( L_1 \)-norms and is
Table 1: Quantitative comparison (average PSNR/SSIM). All results are calculated on the Y-channel except REDS4 [31] (RGB-channel). “bi” and “uni” represent unidirectional and bidirectional, respectively. The FLOPs and runtime are computed based on an LR size of $180 \times 320$.

| Methods          | Params (M) | FLOPs (G) | Runtime (ms) | REDS4 | Vimeo-90K-T | Vid4 |
|------------------|------------|-----------|--------------|-------|-------------|------|
| Bicubic          | -          | -         | -            | -     | -           | -    |
| TOFlow [46]      | 1.4        | 274.9     | 1610         | 26.14/0.7292 | 31.32/0.8684 | 23.78/0.6347 |
| RBPN [13]        | 12.2       | 8516      | 1507         | 30.09/0.8590 | 37.07/0.9435 | 27.12/0.8180 |
| EDVR-M [42]      | 3.3        | 304.2     | 118          | 30.53/0.8699 | 37.09/0.9446 | 27.10/0.8186 |
| PFNL [48]        | 3.0        | 940.0     | 295          | 29.63/0.8502 | 36.14/0.9363 | 26.73/0.8029 |
| BasicVSR [2]     | 6.3        | 358.1     | 63           | 31.42/0.8909 | 37.18/0.9450 | 27.24/0.8251 |
| Scratch-bi      | 2.7        | 105.1     | 31           | 30.61/0.8756 | 36.62/0.9401 | 26.91/0.8109 |
| $L_1$-norm-bi [21] | 2.7        | 105.1     | 31           | 30.68/0.8765 | 36.67/0.9405 | 26.98/0.8139 |
| ASSL-bi [51]     | 2.7        | 105.1     | 31           | 30.72/0.8783 | 36.71/0.9410 | 27.03/0.8163 |
| RSCL-bi (Ours)   | 2.7        | 105.1     | 31           | 30.99/0.8831 | 36.83/0.9421 | 27.16/0.8213 |
| BasicVSR-uni     | 4.0        | 227.9     | 42           | 30.70/0.8722 | 37.05/0.9438 | 27.29/0.8248 |
| Scratch-uni      | 2.1        | 72.2      | 22           | 29.96/0.8566 | 36.42/0.9379 | 26.85/0.8078 |
| $L_1$-norm-uni [21] | 2.1        | 72.2      | 22           | 30.01/0.8587 | 36.46/0.9383 | 26.90/0.8097 |
| ASSL-uni [51]    | 2.1        | 72.2      | 22           | 30.03/0.8596 | 36.49/0.9388 | 26.93/0.8121 |
| RSCL-uni (Ours)  | 2.1        | 72.2      | 22           | 30.27/0.8637 | 36.61/0.9398 | 27.05/0.8163 |

The most prevailing filter pruning method now), and ASSL [51]. We apply these pruning schemes on BasicVSR, thus obtaining Scratch-bi, $L_1$-norm-bi, ASSL-bi, and RSCL-bi separately. In addition, we also use these pruning schemes on BasicVSR-uni, obtaining Scratch-uni, $L_1$-norm-uni, ASSL-uni, and RSCL-uni. For fair comparisons with other pruning schemes, we double the training iterations of Scratch-bi and Scratch-uni. Furthermore, we compare our pruned BasicVSR and BasicVSR-uni with other lightweight VSR networks, including TOFlow [46], RBPN [13], EDVR-M [42] and PFNL [48]. Following [2], for fair comparisons, the parameters and FLOPs of BasicVSR and BasicVSR-uni include those for the optical flow network, SPyNet [32].

The quantitative performance measures (PSNR and SSIM), the number of parameters, runtime, and FLOPs comparisons of the different methods are shown in Tab. 1. (1) Compared with competitive lightweight VSR networks, our RSCL-bi obtains 0.46 dB gain on REDS4 over EDVR-M. Note that, different from careful network designs like EDVR-M, we prune the BasicVSR, a simple backbone with 60 residual blocks, obtaining superior performance while only consuming about 1/3 of the FLOPs of EDVR-M. (2) Our RSCL-bi surpasses the Scratch-bi by 0.38 dB, and RSCL-uni surpasses the Scratch-uni by 0.31 dB. This demonstrates the effectiveness of applying RSCL for offline and online VSR network pruning. (3) Comparing the existing pruning schemes in classification and SISR tasks, such as the $L_1$-norm and ASSL, our RSCL achieves superior performance on BasicVSR and BasicVSR-uni. These comparisons show that RSCL can make better use of the internal sparsity of the network and increases the efficiency of the learned network parameters.

The qualitative results are shown in Fig. 3. Our RSCL-bi achieves the best visual quality containing more realistic details, as these come closer to their groundtruth counterparts. More examples are provided in the appendix. These visual comparisons are consistent with the quantitative results, demonstrating the superiority of our method. RSCL can learn to remove the redundant filters to compress a large network to a much smaller one while maintaining most representation ability.

4.3 Ablation Study

The Validation of Components in RSCL. We conduct an ablation study to demonstrate the effectiveness of the proposed RSCL method by progressively adding components. The results are shown in Tab. 2. RSCL$_1$ uses the aligned pruning [51] scheme for residual blocks. Comparing RSCL$_1$ and RSCL$_3$, we can see that our Residual Sparsity Connection (RSC) is superior to the advanced residual block pruning scheme. Additionally, RSCL$_2$ and RSCL$_3$ keep the same model size, but RSCL$_3$ surpasses RSCL$_2$ by 0.11 dB. It is because introducing a pruning scheme for the pixel-shuffle operation can increase the available pruning space. Comparing RSCL$_2$ and RSCL$_3$, we can see that adopting Temporal Finetuning can further bring a 0.1 dB improvement, reducing the error amplification of hidden states as propagating along with the recurrent unit after pruning.
Figure 3: Qualitative comparison between different VSR and pruning methods on REDS4 [31] testing set (the first example), Vid4 [25] (the second example), and Vimeo90K-T [46] (the third example).

Table 2: Validation of the components in our RSCL. PSNR (dB) results evaluated on REDS4 [31] (4×). The backbone is BasicVSR [2], and the pruning ratio is set to 0.5.

| Methods               | RSCL₁ | RSCL₂ | RSCL₃ | RSCL₄ (Ours) |
|-----------------------|-------|-------|-------|--------------|
| Aligned Pruning [51]  | ✓     | ✓     | ✓     | ✓            |
| Residual Sparsity Connection | ✓     | ✓     | ✓     | ✓            |
| Pixel-Shuffle Pruning | ✓     | ✓     | ✓     | ✓            |
| Temporal Finetuning   | ✓     | ✓     | ✓     | ✓            |
| PSNR (dB)             | 30.82 | 30.78 | 30.89 | 30.99        |

Comparison with Pruning Methods with Various Pruning Ratios. To further demonstrate RSCL’s effectiveness, we compare it with widely used pruning schemes, including training the same size model from scratch, $L_1$-norm [21], ASSL [51] at pruning ratios 0.1, 0.3, 0.5, 0.7 and 0.9. The results are shown in Tab. 3. (1) Our RSCL achieves the best performance compared with other pruning schemes at different pruning ratios. Note that RSCL even surpasses the training from scratch in the same model size by 0.55 dB at the 0.9 pruning ratio. This demonstrates the superiority of our pruning schemes for VSR. Moreover, this shows that RSCL is more effective than simply applying the existing pruning schemes of image classification or SISR to VSR (outperforming the $L_1$-norm and ASSL). (2) With the pruning ratio increasing, the performance advantage brought by our RSCL becomes more evident compared with training from scratch, $L_1$-norm and ASSL.
Table 4: PSNR (dB) comparison on REDS4 (4×) for our pruning scheme (RSCL) with different pruning criteria and pruning ratios. The unpruned model is BasicVSR [2] baseline.

| Pruning Ratios | Min + Global (Ours) | Max + Global | Min + Local | Max + Local | Rand  |
|----------------|---------------------|--------------|-------------|-------------|-------|
| 0.3            | 31.26               | 30.57        | 31.20       | 30.95       | 31.08 |
| 0.5            | 30.99               | 28.88        | 30.78       | 30.33       | 30.63 |
| 0.7            | 30.38               | 25.86        | 30.17       | 29.48       | 30.06 |

Figure 4: (a) and (b) show the pruning ratios of residual blocks in forward and backward propagation networks, respectively. (c) shows the pruning ratios of convolution layers in the upsampling network.

**Comparison with Different Pruning Criteria.** We explore the influence of different pruning criteria on the pruned VSR model at different pruning ratios. Specifically, we select and remove the unimportant filters globally (namely, comparing all filters from all layers together) with minimum $L_1$-norm scores, which is expressed as “Min + Global”. In addition, we select and remove the unimportant filters locally (namely, filters are compared with each other in the same layer, and each layer has the same pruning ratio) with maximum $L_1$-norm scores, which is expressed as “Max + Local”. Similarly, we determine “Max + Global” and “Min + local”. Furthermore, we randomly remove the unimportant filters as “Rand”. Then, we compare all pruning criteria at 0.3, 0.5, and 0.7 pruning ratios. The results are shown in Tab. 4. (1) The “Min + Global” pruning criterion achieves the best performance at different pruning ratios. It implies that the filters with minimum $L_1$-norm scores are relatively unimportant, and selecting unimportant filters globally is superior to pruning locally. (2) As the pruning ratio increases, compared with “Min + Global”, the performance drop of “Max + Global” gets larger because of the removal of more important filters. This demonstrates that filters with large $L_1$-norm scores are more important than those with small ones for the VSR network.

**The Pruning Ratios of Different Layers in the VSR Network.** We take BasicVSR pruned by RSCL at 0.5 pruning ratio as an example and visualize its pruning ratios in different layers. The results are shown in Fig. 4. (1) In the forward and backward propagation networks, the pruning ratios of the first convolution input channels (corresponding to the $\gamma_j-1$ in Fig. 1 (d)) are lower than the pruning ratios of second convolution output filters (corresponding to the $\gamma_{j+1}$ in Fig. 1 (d)), implying that BasicVSR tends to aggregate information from the numerous input channels into several important output channels. (2) The average pruning ratio of the upsampling network is 0.2 (less than 0.5), suggesting that the upsampling network plays a quite important role in VSR.

### 5 Conclusion

In this work, we propose Residual Sparsity Connection Learning (RSCL), a structured pruning scheme, for efficient VSR in resource-limited situations. Specifically, for the difficulty of pruning residual blocks, we propose the Residual Sparsity Connection (RSC). Compared with previous pruning schemes for residual blocks, RSC does not have restrictions and increases the pruning space for better performance. In addition, for the pixel-shuffle operation in the upsampling network, we specially design a pruning scheme by grouping filters to guarantee the accuracy of channel-space conversion after pruning. Furthermore, to reduce the hidden state error amplification with temporal propagation, we propose Temporal Finetuning. We apply RSCL on the BasicVSR, and RSCL achieves superior performance to that of recent state-of-the-art methods, quantitatively and qualitatively.
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