Sparsity-guided Network Design for Frame Interpolation
Tianyu Ding*, Member, IEEE, Luming Liang*, Zhihui Zhu, Tianyi Chen, and Ilya Zharkov

Abstract—DNN-based frame interpolation, which generates intermediate frames from two consecutive frames, is often dependent on model architectures with a large number of features, preventing their deployment on systems with limited resources, such as mobile devices. We present a compression-driven network design for frame interpolation that leverages model pruning through sparsity-inducing optimization to greatly reduce the model size while attaining higher performance. Concretely, we begin by compressing the recently proposed AdaCoF model and demonstrating that a 10× compressed AdaCoF performs similarly to its original counterpart, where different strategies for using layerwise sparsity information as a guide are comprehensively investigated under a variety of hyperparameter settings. We then enhance this compressed model by introducing a multi-resolution warping module, which improves visual consistency with multi-level details. As a result, we achieve a considerable performance gain with a quarter of the size of the original AdaCoF. In addition, our model performs favorably against other state-of-the-art approaches on a wide variety of datasets. We note that the suggested compression-driven framework is generic and can be easily transferred to other DNN-based frame interpolation algorithms. The source code is available at https://github.com/tding1/CDFI.

Index Terms—Computer vision, deep learning, frame interpolation, model pruning, sparsity optimization.

1 INTRODUCTION

Video frame interpolation is a low-level computer vision task that involves creating interim (non-existent) frames between actual frames in a sequence to greatly improve the temporal resolution. It plays an important role in many applications, including frame rate up-conversion [1], [2], slow-motion generation [3], and novel view synthesis [4], [5]. Though fundamental, the problem is challenging in that the complex motion, occlusion and feature variation in real world videos are difficult to estimate and predict in a transparent way.

Recently, a large number of researches have been conducted in this field, especially those based on deep neural networks (DNN) for their promising outcomes in motion estimation [7], [8], [9], [10], occlusion reasoning [3], [11], [12] and image synthesis [4], [5], [13], [14], [15]. In particular, due to the rapid expansion in optical flow [16], [17], many approaches either utilize an off-the-shelf flow model [11], [18], [19], [20], [21], [22] or estimate their own task-specific flow [3], [23], [24], [25], [26], [27], [28], [29], [30] as pixel-level motion interpolation guidance. However, integrating a pre-trained flow model makes the entire architecture cumbersome, and task-oriented flow alone is still insufficient in handling sophisticated occlusion and blur with only pixel-level input. Kernel-based approaches [12], [31], [32], on the other hand, synthesize intermediate frames by performing convolution operations over local patches surrounding each output pixel. Nevertheless, it is incapable of handling large motions beyond the kernel size and it typically suffers from

*Equal contribution.

T. Ding, L. Liang, T. Chen, and I. Zharkov are with Microsoft, Seattle, USA (e-mails: tianyuding@microsoft.com; lulian@microsoft.com; tianyi.chen@microsoft.com; zharkov@microsoft.com)

Z. Zhu is with the Department of Computer Science and Engineering, the Ohio State University, Columbus, USA. E-mail: zhu.3440@osu.edu

Fig. 1: A challenging example consists of large motion, severe occlusion and non-stationary finer details. Top to bottom: the overlaid two inputs, the ground-truth middle frame, the frame generated by AdaCoF [6], the frame generated by the 10× compressed AdaCoF, and the frame generated by our method. The compressed AdaCoF even outperforms the full one here.
Fig. 2: Pipeline of the framework. Stage (I): compression of the baseline; Stage (II): improvements upon the compression.

high computational cost. There are also hybrid methods as \cite{11,33} that combine the advantages of flow-based and kernel-based methods, but the networks are significantly heavier and thus limiting their applications.

We have noticed an increasing trend toward designing more intricate and heavy DNN-based models for interpolating video frames. The majority of the methods proposed in recent years \cite{8,9,10,17,45} entail training and inference on DNN models with over 20 million parameters. The hybrid MEMC-Net \cite{33}, for example, has about 70 million parameters and takes up about 280 megabytes when stored in 32-bit floating point. Large models are typically difficult to train and inefficient during inference. Furthermore, they are unlikely to be deployed on mobile devices, which severely limits their application possibilities. Meanwhile, other work \cite{23,24,25,30} concentrate on simple and light-weight video interpolation methods. However, they either perform less competitively on benchmark datasets or are restricted to a specific architecture that is difficult to adapt.

In this paper, we propose a sparsity-guided network design for video interpolation that exploits model compression \cite{37,38,39}. Concretely, we compress the recently proposed AdaCoF \cite{6} via fine-grained pruning \cite{39} based on sparsity-inducing optimization \cite{40}, and demonstrate that a 10× compressed AdaCoF is still capable of maintaining the same benchmark performance as before, indicating that the original model contains a substantial amount of redundancy. The compression provides us with two direct benefits: (i) it facilitates a thorough understanding of the model architecture, which in turn inspires an efficient design; and (ii) the resulting compact model leaves more room for further enhancements that could potentially lead to a breakthrough in performance. Observing that AdaCoF can handle large motion but is incapable of dealing with occlusion or preserving finer details, we enhance the compact model by incorporating a multi-resolution warping module that utilizes a feature pyramid representation of the input frames to aid in image synthesis. Consequently, our final model outperforms AdaCoF on three benchmark datasets by a substantial margin (>1 dB of PSNR on Middlebury \cite{16}), despite being a quarter the size of its initial version. Note that it is often challenging to implement the same enhancements on the original heavy model. Experiments show that our model also performs favorably against other state-of-the-arts.

In summary, we present a compression-driven paradigm for video interpolation, in which we reflect on over-parameterization. First, we compress AdaCoF and obtain a compact model with comparable performance, then we improve upon it (see the pipeline in Figure 2). This approach yields superior performance and can be easily transferred to other DNN-based frame interpolation algorithms.

A preliminary version of this work was published in CVPR’21 \cite{41}. Compared to the conference version, this paper makes the following additional technical contributions:

- We illustrate in detail how we utilize optimization-based fine-grained pruning on a baseline model, i.e., AdaCoF, under a variety of hyperparameter settings.
- We propose different strategies for compressing the baseline model given the layer-by-layer sparsity information obtained during the pruning process.
- We conduct extensive experiments on benchmark datasets to justify the effectiveness of making improvements upon the compact model.

We remark that one of the primary goals of the paper is to elaborate on the method of compressing neural networks by sparsity-inducing optimization using comprehensive experiments, which is omitted from \cite{41}, and how it may be leveraged to improve the performance of frame interpolation. The remaining sections are organized as follows. Section 2 reviews related works. Section 3 explains in detail the sparsity-guided compression and the subsequent improvements on AdaCoF. We conduct extensive experiments in Section 4 and conclude the paper in Section 5.

2 RELATED WORK

2.1 Video Frame Interpolation

Conventional video frame interpolation is modeled as an image sequence problem, such as the path-based \cite{42} and phase-based approach \cite{43,44}. Unfortunately, due to their inability to effectively estimate the path (flow) or represent high-frequency components, these techniques are less successful in complicated scenarios.

Convolutional neural network (CNN) has recently proved its success in understanding temporal motion \cite{7,8,9,10,17,45} by predicting optical flow, resulting in flow-based motion interpolation methods. \cite{46} trains a deep CNN to directly synthesize the intermediate frame. \cite{23} estimates the flow by sampling the 3D spatio-temporal neighborhood of every output pixel. \cite{27,28,47} refine the estimation of intermediate flows in order to capture large and complex motions. \cite{8,24,25,26,30} utilize bi-directional flows to warp frames and additional modules to address occlusion. \cite{18,19,22} integrate an off-the-shelf flow model \cite{9} into the network, while \cite{19,22} suggest a differentiable forward mapping as opposed to the backward mapping employed by many other approaches. Instead of assuming uniform motion with linear interpolation, quadratic \cite{20,49} and cubic \cite{36} non-linear models are proposed to estimate complex motions. Similarly, \cite{49} proposes an arc trajectory based model that learns motion prior from two successive frames.
function; \cite{58} presents a deep compression pipeline consists of pruning, quantization and Huffman coding; \cite{59} suggests a regularization-based approach for soft weight-sharing. However, they may be unnecessary for our purposes of searching and constructing an architecture \textit{after the compression}. In fact, compression serves an entirely different role in our work, working as a tool for gaining a deeper understanding of the underlying architecture and allowing for additional enhancements. We therefore focus on optimization-based sparsity-inducing pruning techniques \cite{60, 61, 62, 63} that incorporate sparsity-constrained training, such as with $\ell_0$ or $\ell_1$ regularizers. Specifically, we employ a simple three-step pipeline (see Stage (I) in Figure 2) that is most similar to \cite{64, 65} and consists of: (i) training with $\ell_1$-norm sparsity constraint; (ii) reformulating a small dense network according to the sparse structures identified in each layer; and (iii) retraining the small network to verify its performance. We will see shortly (Sec. 3.2) that both its implementation and test are simple.

3 \ THE PROPOSED APPROACH

Given two consecutive frames $I_0$ and $I_1$ in a video sequence, the goal of frame interpolation is to synthesize an intermediate frame $I_t$, where $t \in (0, 1)$ is an arbitrary temporal location. A typical practice is $t = 0.5$, that is synthesizing the middle frame between $I_0$ and $I_1$. We now introduce the proposed framework with AdaCoF \cite{6} as an instance.

3.1 Motivation

To illustrate AdaCoF, we first introduce one of its major components, a spatially-adaptive separable DConv operation for synthesizing one image (denoted by $I_{out}$) from another one (denoted by $I_{in}$). In order to generate $I_{out}$ from $I_{in}$, the input image $I_{in}$ is padded so that $I_{out}$ retains the original shape of $I_{in}$. For each pixel $(i, j)$ in $I_{out}$, AdaCoF computes $I_{out}(i, j)$ by convolving a deformable patch surrounding the reference pixel $(i, j)$ in $I_{in}$:

$$F-1 \sum_{k=0}^{F-1} \sum_{l=0}^{F-1} W_{i,j}^{(k,l)} I_{in}(i + dk + \alpha_{i,j}^{(k,l)}, j + dl + \beta_{i,j}^{(k,l)}),$$  \hspace{1cm} (1)

where $F$ is the deformable kernel size, $W_{i,j}^{(k,l)}$ is the $(k,l)$-th kernel weight in synthesizing $I_{out}(i, j)$, $\Delta := (\alpha_{i,j}^{(k,l)}, \beta_{i,j}^{(k,l)})$ is the offset vector of the $(k,l)$-th sampling point associated with $I_{in}(i, j)$, and $d \in \{0, 1, 2, \ldots \}$ is the dilation parameter that helps to explore a wider area. Note that $F$ and $d$ have pre-determined values. For synthesizing each output pixel in $I_{out}$, a total of $F^2$ points are sampled in $I_{in}$. With the offset vector $\Delta$, the $F^2$ sample points are not confined to a rectangular region centered on the reference point. On the other hand, unlike the classic DConv, AdaCoF uses various kernel weights across multiple reference pixels $(i, j)$, indicated by $W_{i,j}^{(k,l)}$ in (1); hence the attribute “separable” \cite{32}.

Since the parameters $W_{i,j}^{(k,l)}, \alpha_{i,j}^{(k,l)}, \beta_{i,j}^{(k,l)}$ are computed individually for each output pixel, AdaCoF is flexible in handling large and complex motion; however, it cannot deal with severe occlusion and non-stationary finer details, as shown in Figure 3. We further visualize the difference between the interpolation and the ground-truth in Fig. 3: Visualization of the difference between the interpolation and the ground-truth image.

One major drawback of the flow-based methods is that only pixel-wise information is used for interpolation. In contrast, kernel-based approaches offer to construct the image by convolving across local patches in close proximity to each output pixel. For instance, \cite{32} estimates spatially-adaptive 2D convolution kernels and \cite{33} improves its efficiency by employing pairs of 1D kernels for all output pixels simultaneously. \cite{11, 33} integrate both optical flow and local kernels; specifically \cite{11} detects the occlusion with depth information. Nevertheless, these approaches rely solely on local kernels and are incapable of handling large motion outside the rectangular kernel region.

Inspiring by the flexible spatial sampling locations of deformable convolution (DConv) \cite{50, 51, 6}, it introduces the AdaCoF model, which synthesizes each output pixel using a spatially-adaptive separable DConv. \cite{32} generalizes it by allowing sampling in the entire spatial-temporal space. \cite{34} is similar to AdaCoF except that it approximates 2D kernels using 1D separable kernels. \cite{33} extends \cite{34} to construct the intermediate frame at an arbitrary time step. Besides, a recent work based on DConv \cite{29} uses 3D CNN at multi-scale for estimating complex motions. This paper is also based on AdaCoF; however, unlike the prior work, for the first time we investigate the over-parameterization issue existing DNN-based techniques and demonstrate that a much smaller model works comparably well through compression. Moreover, by addressing its shortcomings upon the compression, one can easily build a model (still small) that significantly outperforms the original one. This compression-driven network design is transferable to other DNN-based frame interpolation techniques.

2.2 Pruning-based Model Compression

Model compression \cite{37, 38} is especially critical to DNN models, which are known to incur large storage and computation costs. In general, model compression may be categorized into several types: pruning \cite{59}, quantization \cite{54}, knowledge distillation \cite{55} and AutoML \cite{56}. In this paper, we employ the pruning strategy due to its ease of use, which seeks to induce sparse connections. There are numerous hybrid pruning approaches that directly aiming for model deployment. For example, \cite{57} proposes a HashNets architecture to group connection weights with a low cost hash
correspond to non-zero weights. In order to solve (2), we formulate (2) promotes a sparse solution, allowing one to easily identify the connections between neurons that form the sparsity-inducing optimization results. Similarly, for a necessary information that must be encoded in that layer so that the current number of parameters is roughly \( d_i \) times fewer than it was previously. The main intuition is that the density ratio \( d_i \) reflects the least amount of necessary information that must be encoded in that layer without significantly impacting performance according to the sparsity-inducing optimization results. Similarly, for a

1. The formulation of (4) is slightly different than that proposed in (4) but is more reasonable, which is used throughout the paper.
fully connected layer with $H_{in}$ input features and $H_{out}$ output features, we can reconstruct one linear layer with shape $[\sqrt{d_l} \cdot H_{in}] \times [\sqrt{d_l} \cdot H_{out}]$. Note that we exclude the bias term in both convolutional and linear layers when counting parameters, as the density ratio is used as an inexact guide and is sufficient for the reconstruction of a compact model.

Let $C_{out}^l$ and $C_{in}^{l+1}$ denote the newly updated number of output channels at the $l$-th layer and the number of input channels at the $(l+1)$-th layer. One outstanding question is that one cannot simply reformulate each layer in the manner described before, such as [4] for convolutional layers, because a valid neural network architecture also requires $C_{out}^l \equiv C_{in}^{l+1}$. In other words, it is not guaranteed that $[\sqrt{d_l} \cdot C_{out}^l] \equiv [\sqrt{d_{l+1}} \cdot C_{in}^{l+1}]$. In light of the fact that the density ratio in each layer is only used as a rough guide for network design, we propose the following two strategies, which are referred as "-min" and "-max" for abbreviation:

- "-min": the minimum of $[\sqrt{d_l} \cdot C_{out}^l]$ and $[\sqrt{d_{l+1}} \cdot C_{in}^{l+1}]$ is chosen such that

$$C_{out}^l = C_{in}^{l+1} = \min \{ \sqrt{d_l} \cdot C_{out}^l, \sqrt{d_{l+1}} \cdot C_{in}^{l+1} \}$$

(5)

- "-max": the maximum of $[\sqrt{d_l} \cdot C_{out}^l]$ and $[\sqrt{d_{l+1}} \cdot C_{in}^{l+1}]$ is chosen such that

$$C_{out}^l = C_{in}^{l+1} = \max \{ \sqrt{d_l} \cdot C_{out}^l, \sqrt{d_{l+1}} \cdot C_{in}^{l+1} \}$$

(6)

We are then able to recreate a valid model architecture utilizing either of the two ways. Indeed, the above strategies are applicable to anyplace in the network accordingly where the number of input/output features or channels do not match. An example is the shortcut connections between the encoder and decoder of the U-Net, as depicted in Figure 4.

Finally, to evaluate the performance of the compressed model $M_1$, we train it from scratch (without the $\ell_1$ constraint). Due to its reduced size, the compact model typically requires substantially less time to train than that of the full model $M_0$. The entire compression pipeline is depicted in Stage (I) of Figure 2. We remark that a pre-trained $M_0$ is not essential for the purpose of compression since problem (2) is sufficient for a one-shot training/pruning, but $M_0$ allows us to ensure the compressed model performs competitively.

### 3.2.2 Compression of AdaCoF

We now apply the generic compression approach introduced in Section 3.2.1 to AdaCoF [6], utilizing the pre-trained model provided by the authors. To tackle problem (2), we employ the orthant-based stochastic method OBProx-SG [10], which is shown to be superior to other state-of-the-art methods [69, 70] in finding a sparse optimal solution to the $\ell_1$ problem. Specifically, it includes so-called Proximal Steps (P-steps) and Orthonal Steps (O-steps) during the iterative optimization process, where P-steps produce reasonable solutions but with less sparsity and O-steps are the key to encourage more sparse solutions. In the following, we investigate the performance of OBProx-SG under
Table 1: The statistics of AdaCoF and the compressed versions using “-min” and “-max” strategies.

|                  | AdaCoF (F = 5, d = 1) | lr: 10^{-2} | 10^{-1} | 10^{-2} | 10^{-3} | 10^{-4} | 10^{-5} | 10^{-6} | lr: 10^{-2} | 10^{-1} | 10^{-2} | 10^{-3} | 10^{-4} | 10^{-5} | 10^{-6} |
|------------------|-----------------------|-------------|---------|---------|---------|---------|---------|---------|-------------|---------|---------|---------|---------|---------|---------|
| PSNR            | 35.72                 | 35.22       | 35.27   | 35.15   | 34.24   | 35.56   | 35.57   | 35.47   | 34.28       |         |         |         |         |         |         |
| SSIM            | 0.96                  | 0.96        | 0.95    | 0.95    | 0.95    | 0.96    | 0.96    | 0.95    | 0.95        |         |         |         |         |         |         |
| Size (MB)       | 83.4                  | 18.2        | 9.2     | 7.8     | 4.9     | 26.7    | 14.8    | 12.8    | 7.9         |         |         |         |         |         |         |
| Time (ms)       | 61.6                  | 49.5        | 43.1    | 42.0    | 38.9    | 50.2    | 46.5    | 45.9    | 41.3        |         |         |         |         |         |         |
| FLOPS (G)       | 359.2                 | 235.6       | 183.1   | 169.8   | 142.5   | 255.4   | 205.2   | 194.0   | 163.6       |         |         |         |         |         |         |
| Params (M)      | 21.84                 | 4.64        | 2.38    | 2.02    | 1.25    | 6.83    | 3.78    | 3.27    | 2.04        |         |         |         |         |         |         |

Fig. 7: Density distributions for each layer under various hyperparameter settings.

The impact of hyperparameters. For problem (2), the regularization constant $\lambda$ plays a crucial role in controlling the sparsity level of the solution since a large $\lambda$ penalizes more on the $\ell_1$ term, resulting in a sparser solution. In addition, learning rate (lr) is also critical to the optimization result. In fact, in OBProx-SG, the sparsity of the solution is determined by the magnitude of lr · $\lambda$. In Figure 3, we plot the density of AdaCoF across the first 20 epochs when solving (2) with OBProx-SG. We observe that, for a fixed learning rate, raising $\lambda$ introduces significantly sparser solutions at each iteration. In the mean time, the several (lr, $\lambda$) pairs corresponding to a same magnitude of lr · $\lambda$ result in solutions with similar densities at each iteration. For learning rates and $\lambda$ such that lr · $\lambda = 10^{-6}$, the density declines to below 30 percent within 20 epochs however for the other settings lr · $\lambda = 10^{-7}$ the density decreases more smoothly. In order to understand how the model performs as the optimization proceeds, we display the PSNR evaluated on the Middlebury dataset [16] versus the network density, as demonstrated in Figure 5. One can detect a decline in model performance as sparsity increases. Consider the two extreme instances. When lr = 10^{-3}, $\lambda = 10^{-3}$, not only does the density decline rapidly (Figure 5), but so does the PSNR (Figure 6). In contrast, when lr = 10^{-1}, $\lambda = 10^{-6}$, even while the density decreases slowly (Figure 5), it is able to retain a reasonable level of model performance (Figure 6) at a low sparsity level. In practice, there is a trade-off between a model performance with less regression (a small $\lambda$) and a short training time. Specifically, when lr · $\lambda = 10^{-6}$, it only takes about 20 epochs to achieve a model with a density of less than 30 percent, however when lr · $\lambda = 10^{-7}$, it may take hundreds of epochs to attain a similar density level.

The impact of Proximal Steps and Orthant Steps. For the above experiments, we additionally study the effect of how P-steps and and O-steps are conducted. [40] has shown that P-steps can generate good solutions but with less sparsity, whereas O-steps are the key to encouraging sparser solutions. It suggests running O-steps before a sufficient number of P-steps. Recall that in Figure 6 we ran the experiments with lr · $\lambda = 10^{-7}$ for hundreds of epochs and with lr · $\lambda = 10^{-6}$ for tens of epochs. Figure 7 demonstrates the results when we conduct P-steps throughout each epoch for all the experiments, whereas Figure 6b shows the results when we conduct half P-steps followed by half O-steps. One can see that for $\lambda = 10^{-5}$ and 10^{-6}, the model trained with half O-steps is able to attain significantly greater sparsity while maintaining a reasonable level of performance, hence demonstrating the advantages of O-steps. Despite the slight difference between Figure 5a and Figure 5b which only depicts the first 20 epochs, a similar phenomena also happens.

Layer-wise density distribution analysis. We further investigate the density distribution for each layer under various hyperparameter settings in Figure 7. The results pertain to models trained with an equal number of P-steps and O-steps (see Figure 6b). We are not plotting the results for lr = 10^{-5}, $\lambda = 10^{-3}$ due to its inferior performance relative to other settings, as shown in Figure 6. First, we note that, for all the configurations, the three 512 × 512 × 3 × 3 convolutional layers (labeled as “DeConv5”) in the center of the U-Net are among the most redundant. Specifically, the entire middle part of the U-Net, beginning roughly with “Conv5” and ending with “UpSample4”, achieves a density ratio of less than 10%, indicating that more than 90% of the kernel is mostly useless. This observation confirms our early hypothesis that the original architecture contains significant redundancy. Another observation is that, the settings with lr · $\lambda = 10^{-7}$ almost have consistently lower density levels in each layer than those with lr · $\lambda = 10^{-6}$. Moreover, smaller $\lambda$ (with longer training time) is always advantageous for inducing sparser connections in each layer. Finally, we note that the results of setting lr = 10^{-6}, $\lambda = 10^{-4}$ and lr = 10^{-3}, $\lambda = 10^{-4}$ coincide, which is also evident via Figure 6 that the red and purple curves are nearly identical.

Performance of the reconstructed compact model. We now reformulate different compact networks based on the computed density ratio in each layer corresponding to various (lr, $\lambda$) settings during optimization (Figure 7). We train the models from scratch using the entire training set (51312...
video triplets) of Vimeo-90K. In this case, the training is around 5× faster than it was earlier. Then, we compare the before-and-after models in Table 1 for different (Ir, λ) settings with “−min”/“−max” strategies, where PSNR and SSIM are evaluated on the Middlebury dataset, and time and FLOPs are determined for synthesizing a 3 × 1280 × 720 frame on RTX 6000 Ti GPU. Notice that the “−max” strategy yields better performance than the “−min” strategy at the expense of a bigger model size and higher computational cost. Interestingly, for the setting $\text{Ir} = 10^{-1}, \lambda = 10^{-5}$, even though the PSNR falls below 34.2 during the $\ell_1$ optimization (Figure 6b), after reformulation and training the PSNR of the compressed model rises to 35.27 (35.57) with the “−min” ("−max") strategy, which is comparable to the original uncompres sed AdaCoF but with a much smaller size (∼ 10× for “-min”). Note that although the setting $\text{Ir} = 10^{-1}, \lambda = 10^{-6}$ achieves a higher sparsity during the initial $\ell_1$ optimization, the reconstructed networks do not perform well due to their limited model capacities.

### 3.3 Second Stage: Improve upon the Compression

In the second stage, we improve upon the compression by addressing its flaws. The point is that the compression allows for additional improvements due to its compactness, which is often impossible when operating directly on the original huge model, e.g., the lengthy training and validation period appears overwhelming in the first place.

Observing that AdaCoF is incapable of handling severe occlusion and preserving finer features, we design three particular components on top of the compressed AdaCoF: a feature pyramid, an image synthesis network, and a path selection mechanism. Note that improvements are case-by-case, as each baseline model has its own weakness.

**Feature pyramid.** AdaCoF computes the final interpolation frame by blending the two warped frames through a single sigmoid mask $V_1$ (see Figure 4), which is a generalization of using a binary mask to determine the occlusion weights of the two warped frames for each output pixel. We argue that the loss of contextual details in the input frames is unavoidable with only raw pixel information, as it lacks feature space guidance. Instead, we extract from the encoder portion of the U-Net a feature pyramid representation [19] of the input frames. In particular, it includes five feature levels corresponding to the encoder, and for each level, we employ a 1-by-1 convolution to filter the encoder at multi-scale with 4, 8, 12, 16, 20 output features (in descending order by the feature scale). The retrieved multi-scale features are then warped by AdaCoF operation [1], which captures motion in the feature space.

**Image synthesis network.** To better utilize the extracted multi-scale features, we synthesize the image using a GridNet [71] architecture with three rows and six columns, which is also used in [18, 19] for its superiority in combining multi-scale information. Specifically, we feed the synthesis network with both the forward- and backward-warped multi-scale feature maps in order to generate a single RGB image that emphasizes contextual features.

**Path selection.** In order to take advantage of both AdaCoF (handling complex motion) and our own components (handling contextual details), we use a path selection mechanism to generate the final interpolation result. As shown in Figure 4, one path leads to the output of the original AdaCoF (designated $I_{0.5}^{(1)}$), which is generated by blending two warped input frames with the occlusion mask $V_1$. Another path leads to the output of the synthesis network (designated $I_{0.5}^{(2)}$), which is generated by combining the warped multi-scale feature maps. In the end, we learn another occlusion module $V_2$ to synthesize the final result from $I_{0.5}^{(1)}$ and $I_{0.5}^{(2)}$, and we expect that $I_{0.5}^{(2)}$ to compensate for the lack of contextual information in $I_{0.5}^{(1)}$.

### 3.4 Training

With the architecture described above, we train it using AdaMax [22] with $\beta_1 = 0.9, \beta_2 = 0.999$, an initial learning

| Compressed arch. w/ (Ir, λ) | Which strategy? | Other params. | Vimeo-90K [24] | Middlebury [16] | UCF101-DVF [23] | Parameters (million) |
|-----------------------------|-----------------|---------------|---------------|-----------------|------------------|---------------------|
| Original AdaCoF [6]         |                 | (F, d)        | PSNR          | SSIM            | LPIPS            |                    |
| (10^{-2}, 10^{-4})         | “−min”          | (5, 1)        | 34.35         | 0.956           | 0.019            | 35.72              | 0.959              | 0.019              | 35.16              | 0.950              | 0.019              | 21.84              |
| (10^{-1}, 10^{-5})         | “−min”          | (5, 1)        | 34.71         | 0.960           | 0.011            | 36.56              | 0.963              | 0.008              | 35.16              | 0.949              | 0.015              | 7.05               |
| (10^{-2}, 10^{-6})         | “−min”          | (5, 1)        | 35.02         | 0.962           | 0.011            | 36.34              | 0.962              | 0.008              | 35.14              | 0.949              | 0.015              | 4.41               |
| (10^{-3}, 10^{-6})         | “−min”          | (5, 1)        | 34.86         | 0.961           | 0.011            | 36.31              | 0.962              | 0.008              | 34.14              | 0.949              | 0.015              | 3.63               |
| (10^{-2}, 10^{-4})         | “−max”          | (5, 1)        | 34.97         | 0.962           | 0.010            | 36.43              | 0.963              | 0.008              | 35.14              | 0.949              | 0.015              | 9.25               |
| (10^{-1}, 10^{-5})         | “−max”          | (5, 1)        | 34.98         | 0.962           | 0.010            | 36.23              | 0.962              | 0.008              | 35.14              | 0.949              | 0.015              | 6.18               |
| (10^{-2}, 10^{-6})         | “−max”          | (5, 1)        | 34.81         | 0.961           | 0.011            | 36.62              | 0.964              | 0.008              | 35.14              | 0.949              | 0.015              | 5.66               |
| (10^{-3}, 10^{-6})         | “−max”          | (5, 1)        | 34.93         | 0.962           | 0.010            | 36.66              | 0.964              | 0.008              | 35.14              | 0.949              | 0.015              | 4.42               |
| Original AdaCoF+ [6]       |                 | (11, 2)       | 34.56         | 0.959           | 0.018            | 36.09              | 0.962              | 0.017              | 35.16              | 0.950              | 0.015              | 22.93              |
rate of 0.001 that halves every 20 epochs, a mini-batch size of 8, and a maximum of 100 training epochs.

**Objective function.** Given the interpolated frame \( I_{\text{out}} \) of our network and its ground truth \( I_{\text{gt}} \), we first employ the Charbonnier penalty [23] as a surrogate for the \( \ell_1 \) loss:

\[
\mathcal{L}_{\text{Charbon}} = \rho(I_{\text{out}} - I_{\text{gt}})
\]

where \( \rho(x) = (\|x\|^2 + \epsilon^2)^{1/2} \) and \( \epsilon \) is set to 0.001. Next, we follow [6] and use a perceptual loss with feature \( \phi \) extracted from conv4_3 of the pre-trained VGG16 [73]:

\[
\mathcal{L}_{\text{vgg}} = \| \phi(I_{\text{out}}) - \phi(I_{\text{gt}}) \|_2.
\]

Then, inspired by the implementation of AdaCoF, we apply a total variation loss on the offset vectors to guarantee spatial continuity and smoothness:

\[
\mathcal{L}_{\text{tv}} = \tau(\alpha_1) + \tau(\alpha_2) + \tau(\beta_1) + \tau(\beta_2)
\]

where \( \tau(I) = \sum_{i,j} \rho(I_{i+1,j} - I_{i,j}) + \rho(I_{i,j+1} - I_{i,j}) \), and \( \alpha_1, \alpha_2, \beta_1, \beta_2 \) are the offsets modules computed within our network. Lastly, we formulate our final loss function as

\[
\mathcal{L} = \mathcal{L}_{\text{Charbon}} + \lambda_{\text{vgg}} \mathcal{L}_{\text{vgg}} + \lambda_{\text{tv}} \mathcal{L}_{\text{tv}}
\]

where we set \( \lambda_{\text{vgg}} = 0.005, \lambda_{\text{tv}} = 0.01 \) in the experiments.

**Training dataset.** We use the Vimeo-90K dataset [24] for training, which contains 51312/3782 video triplets of size \( 256 \times 448 \) for training/validation. We further augment the data by randomly flipping them horizontally and vertically as well as perturbing the temporal order.

**Evaluation.** In addition to the Vimeo-90K validation set, we evaluate the model on the well-known Middlebury dataset [16] and UCF101-DVF [23]. The metrics we use are PSNR, SSIM [77] and LPIPS [78]. Note that higher PSNR and SSIM values indicate better performance, whereas lower LPIPS values suggest better results.

---

### TABLE 3: Ablation experiments on the architecture design of our approach.

|                  | Vimeo-90K [24] | Middlebury [16] | UCF101-DVF [23] | Parameters (million) |
|------------------|---------------|----------------|----------------|----------------------|
|                  | PSNR | SSIM | LPIPS | PSNR | SSIM | LPIPS | PSNR | SSIM | LPIPS |                 |
| AdaCoF (\( F = 5, d = 1 \)) | 34.35 | 0.956 | 0.019 | 35.72 | 0.959 | 0.019 | 35.16 | 0.950 | 0.019 |                 |
| Compressed AdaCoF (\( F = 5, d = 1 \)) | 34.08 | 0.954 | 0.020 | 35.27 | 0.952 | 0.019 | 35.10 | 0.950 | 0.019 | 21.84 |
| AdaCoF+ (\( F = 11, d = 2 \)) | 34.56 | 0.959 | 0.018 | 36.09 | 0.962 | 0.017 | 35.16 | 0.950 | 0.019 | 22.93 |
| Compressed AdaCoF+ (\( F = 11, d = 2 \)) | 34.33 | 0.957 | 0.019 | 35.63 | 0.959 | 0.018 | 35.12 | 0.950 | 0.019 | 2.38 |
| Ours: FP (\( F = 5, d = 1 \)) | 34.59 | 0.962 | 0.011 | 36.12 | 0.960 | 0.008 | 35.05 | 0.949 | 0.015 | 4.66 |
| Ours: FP + 1x1 Conv (\( F = 5, d = 1 \)) | 34.79 | 0.963 | 0.011 | 36.50 | 0.964 | 0.008 | 35.10 | 0.949 | 0.015 | 4.51 |
| Ours: FP + 1x1 Conv (\( F = 11, d = 2 \)) | 34.99 | 0.963 | 0.011 | 36.88 | 0.966 | 0.007 | 35.17 | 0.950 | 0.015 | 5.64 |
| Ours: FP + 1x1 Conv + PS (\( F = 11, d = 2 \)) | **35.14** | **0.963** | **0.010** | **37.25** | **0.967** | **0.007** | **35.20** | **0.950** | **0.015** | **5.78** |

---

**Fig. 8:** Examples of adding the path selection (PS) mechanism in our design.

**Performance of the proposed full model.** Given the sparsity-guided compression (Section 3.2), the improvements (Section 3.3), and the training/evaluation protocol (Section 3.4), we compare the full models with all the combinations of compressed baselines, “-min”/”-max” strategies, and \( F, d \) (parameters in (1)) choices. The comprehensive quantitative results are summarized in Table 2. First, we observe that the proposed sparsity-guided full models perform much better than their AdaCoF counterparts, even with a significantly smaller model size. Second, while having a little larger model, the “plus” versions with \( F = 11, d = 2 \) are much superior to those with \( F = 5, d = 1 \). Also, despite the fact that the “-max” strategy usually delivers higher performance than the “-min” one, as we observed in Table 1, the improvement is not that significant in comparison to the increase in model size. Particularly, we find that the model with a compressed baseline of setting \( lr = 10^{-1}, \lambda = 10^{-5} \), “-min” strategy, and \( F = 11, d = 2 \) achieves the overall best quantitative results with only a quarter of the size (5.78M) of the AdaCoF+ (22.93M) while obtaining > 1.1 dB of PSNR on Middlebury. In the rest of the paper, we refer to this version as “ours” for convenience.

4 **More Experiments**

#### 4.1 Ablation Study

We analyze three components in our proposed method: model compression, feature pyramid, and path selection.

**Model compression.** As described in Section 3.2, we compress the baseline model to eliminate a substantial mount of redundancy, which also facilitates training and inference. In Table 3, we compare the performance of AdaCoF and its compressed counterpart. It shows that a 10x compressed model does not sacrifice much when evaluated...
on the three benchmark datasets, indicating the redundancy in AdaCoF and the necessity of the compression stage.

**Feature pyramid.** In order to better capture the contextual details, we incorporate the feature pyramid (FP) module, followed by warping operations and an image synthesis network, into the compressed AdaCoF. We isolate its effect by training a network that simply outputs the synthesized image without a path selection mechanism. It turns out that using merely the FP module (see “Ours - FP”, Table 3) improves PSNR, SSIM and LPIPS significantly on the Vimeo-90K and Middlebury datasets. Note that it substantially improves LPIPS across all the three benchmark datasets. Moreover, filtering the multi-scale feature maps with 1-by-1 convolutions leads to better PSNR and SSIM as well as a slightly smaller model size.

**Path selection.** Although by adding only the FP module (and 1-by-1 convolutions) we can achieve promising quantitative results as shown in Table 3, it does not take advantage of the capability of AdaCoF to handle complex motion, which can be incorporated into our design with the proposed path selection (PS) mechanism. The left example in Figure 8 shows that when there are simply fluctuations in fine detail in the input frames, adding PS or not does not significantly affect our interpolation performance because the FP module can synthesize details (also note the output of AdaCoF is blurry due to the loss of information). On the other hand, with only the FP module, it is difficult for the model to correctly capture the motion of the right ball in the right example, which involves the large motion of two balls. In contrast, our final model, which has a PS mechanism, is able to handle large motion very well (even sharper on the edges of the balls compared to AdaCoF). Importantly, our approach preserves the finger shape (see bottom-left corner), whereas AdaCoF completely misses this detail. In conclusion, our full model with FP and PS is capable of handling both fine details and big motion, and produces considerable quantitative improvements.

### 4.2 Quantitative Evaluation

We compare our sparsity-guided approach (the compressed AdaCoF with setting $\text{lr} = 10^{-1}, \lambda = 10^{-5}$, “-min” strategy, and $F = 11, d = 2$) to various state-of-the-art DNN methods in Table 4. Since SepConv [32], CtxSyn [18] and SoftSplat [19] are not open source, we directly copy their numerical results as well as DAIN’s [11] from [19]. For the rest of the methods, we evaluate their pre-trained models on the three datasets. First note that our approach performs favorably against other methods in terms of SSIM and LPIPS. For PSNR, the proposed method surpasses most competitors with the exception of SoftSplat [19]. Moreover, our model is considerably smaller than those of our competitors. We note that there have been some lightweight frame interpolation models in the past, such as DVF [25], ToFlow [24] and CyclicGen [80], but they are unable to compete with SepConv [32] or CtxSyn [18], as reported in [19]. In addition, the preliminary work [41] triggers many recent researches in developing efficient models, such as DRVI [74] and $L^2$BEC [30], but their results are not comparable to ours. Lastly, we observe that AdaCoF [6] is only average among the other approaches, but our final model, which is built on AdaCoF, has arguably the best overall performance while maintaining compactness, demonstrating the superiority of the proposed sparsity-guided design framework.

### 4.3 Qualitative Evaluation

We present the visual comparisons on the DAVIS dataset [79] in Figure 9. The first and third example contain complex motion and occlusion, while the second example involves many non-stationary finer details. Note that AdaCoF+ [6] generates relatively hazy interpolation frames for each of these cases (see the motorbike, house and swing stool). In contrast, thanks to our newly incorporated FP module and PS mechanism, the outcomes predicted by our method based on it are more precise and realistic. Additionally, we compare with BMBC [26], CAI [35] and EDSC [53]. EDSC utilizes deformable separable convolution but estimates an additional mask to aid in image synthesis. However, they are less appealing than our method on the provided examples. One can see that their interpolations typically contain apparent artifacts and are incapable of preserving clear features. Note that BMBC [26] occasionally produces sharp results but not as consistently as we do. We

**TABLE 4: Quantitative comparisons with state-of-the-art methods.** The results of methods marked with $^\dagger$ are cloned from [19].

| Training dataset | Vimeo-90K | Middlebury | UCF101-DVF | Parameters (million) |
|------------------|----------|------------|------------|---------------------|
| PSNR | SSIM | LPIPS | PSNR | SSIM | LPIPS | PSNR | SSIM | LPIPS |
| 1-SepConv + $L^2$ | proprietary | 33.80 | 0.956 | 0.027 | 35.73 | 0.959 | 0.017 | 34.79 | 0.947 | 0.029 | 21.6 |
| 1-SepConv + $L^2$ | proprietary | 33.45 | 0.951 | 0.019 | 35.03 | 0.954 | 0.013 | 34.69 | 0.945 | 0.024 | 21.6 |
| 1-CtxSyn - $L^2$ | proprietary | 34.39 | 0.961 | 0.024 | 36.93 | 0.964 | 0.016 | 34.62 | 0.949 | 0.031 | – |
| 1-CtxSyn - $L^2$ | proprietary | 33.76 | 0.955 | 0.017 | 35.95 | 0.959 | 0.013 | 34.01 | 0.941 | 0.024 | – |
| 1-SoftSplat + $L^2$ | proprietary | 36.10 | 0.970 | 0.021 | 38.42 | 0.971 | 0.016 | 35.39 | 0.952 | 0.033 | – |
| 1-SoftSplat + $L^2$ | proprietary | 35.48 | 0.964 | 0.013 | 37.55 | 0.965 | 0.008 | 35.10 | 0.948 | 0.022 | – |
| 1-DAIN | proprietary | 34.70 | 0.964 | 0.022 | 36.70 | 0.965 | 0.017 | 35.00 | 0.950 | 0.028 | 24.0 |
| AdaCoF | proprietary | 34.35 | 0.956 | 0.019 | 35.72 | 0.959 | 0.019 | 35.16 | 0.950 | 0.019 | 21.8 |
| AdaCoF+ | proprietary | 34.56 | 0.959 | 0.018 | 36.09 | 0.962 | 0.017 | 35.16 | 0.950 | 0.019 | 22.9 |
| EDSC - $L^2$ | proprietary | 34.86 | 0.962 | 0.016 | 36.76 | 0.966 | 0.014 | 35.17 | 0.950 | 0.019 | 8.9 |
| EDSC - $L^2$ | proprietary | 34.57 | 0.958 | 0.010 | 36.48 | 0.963 | 0.007 | 35.04 | 0.948 | 0.015 | 8.9 |
| BMBC | proprietary | 35.06 | 0.964 | 0.015 | 36.79 | 0.965 | 0.015 | 35.16 | 0.950 | 0.019 | 11.0 |
| CAIN | proprietary | 34.65 | 0.959 | 0.020 | 35.11 | 0.951 | 0.019 | 34.98 | 0.950 | 0.021 | 42.8 |
| DRVI | proprietary | 35.14 | 0.965 | 0.013 | 36.74 | 0.964 | 0.011 | 35.13 | 0.950 | 0.018 | 1.3 |
| RRIN | proprietary | 35.21 | 0.964 | 0.015 | 35.47 | 0.958 | 0.014 | 34.93 | 0.949 | 0.019 | 19.19 |
| $L^2$BEC | proprietary | 34.55 | 0.959 | 0.018 | 35.84 | 0.961 | 0.017 | 35.18 | 0.950 | 0.019 | 7.1 |
| Ours | proprietary | 35.14 | 0.963 | 0.010 | 37.25 | 0.967 | 0.007 | 35.20 | 0.950 | 0.015 | 5.8 |
Fig. 9: Visual comparisons on the DAVIS 2016 dataset [79]. Our sparsity-guided method not only outperforms the baseline model AdaCoF but also surpasses many other methods in handling large motion, occlusion and fine details.

conjecture that the bilateral cost volume in BMBC improves the estimations of intermediate motion, which can also be incorporated into our design. Note that our model is the smallest among them, which once again demonstrates the benefit of the sparsity-guided network design.

5 CONCLUSION

We presented a sparsity-guided network design for frame interpolation that employs model compression as a guide for selecting an efficient architecture, which we then improved. As an instance, we showed that a considerably smaller AdaCoF model performs comparably to the original one, and with simple modifications it is able to significantly outperform the baseline and is also superior to other state-of-the-art methods. We emphasize that the optimization-based compression over a baseline model is independent of the baseline’s specific architecture. Therefore, we believe that our framework is generic to be extended to various models and provides a new perspective on the design of effective frame interpolation algorithms. In future work, it will be beneficial to establish a strong connection between the compression and design stages which iteratively improves the underlying architecture.

REFERENCES

[1] W. Bao, X. Zhang, L. Chen, L. Ding, and Z. Gao, “High-order model and dynamic filtering for frame rate up-conversion,” IEEE Transactions on Image Processing, vol. 27, no. 8, pp. 3813–3826, 2018.

[2] Z. Geng, L. Liang, T. Ding, and I. Zharkov, “Rstt: Real-time spatial temporal transformer for space-time video super-resolution,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 17 441–17 451.

[3] H. Jiang, D. Sun, V.Jampani, M.-H. Yang, E. Learned-Miller, and J. Kautz, “Super slomo: High quality estimation of multiple intermediate frames for video interpolation,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 9000–9008.

[4] J. Flynn, I. Neulander, J. Philbin, and N. Snavely, “Deepstereo: Learning to predict new views from the world’s imagery,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 5515–5524.

[5] T. Zhou, S. Tulsiani, W. Sun, J. Malik, and A. A. Efros, “View synthesis by appearance flow,” in European conference on computer vision. Springer, 2016, pp. 286–301.

[6] H. Lee, T. Kim, T.-y. Chung, D. Pak, Y. Ban, and S. Lee, “Adacof: Adaptive collaboration of flows for video frame interpolation,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 5316–5325.

[7] A. Dosovitskiy, P. Fischer, E. Ilg, P. Hausser, C. Hazirbas, V. Golkov, P. Van Der Smagt, D. Cremers, and T. Brox, “Flownet: Learning optical flow with convolutional networks,” in Proceedings of the IEEE international conference on computer vision, 2015, pp. 2758–2766.

[8] E. Ilg, N. Mayer, T. Saikia, M. Keuper, A. Dosovitskiy, and T. Brox, “Flownet 2.0: Evolution of optical flow estimation with deep networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 2462–2470.

[9] D. Sun, X. Yang, M.-Y. Liu, and J. Kautz, “Pwc-net: Cnns for optical flow using pyramid, warping, and cost volume,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 8934–8943.

[10] P. Weinzaepfel, J. Revaud, Z. Harchaoui, and C. Schmid, “Deepflow: Large displacement optical flow with deep matching,” in Proceedings of the IEEE international conference on computer vision, 2013, pp. 1385–1392.

[11] W. Bao, W.-S. Lai, C. Ma, X. Zhang, Z. Gao, and M.-H. Yang, “Depth-aware video frame interpolation,” in Proceedings of the
M. Werlberger, T. Pock, M. Unger, and H. Bischof, “Optical flow estimation with bilateral cost volume for video interpolation,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 2398–2407.

A. Dosovitskiy, J. Tobias Springenberg, and T. Brox, “Learning to generate chairs with convolutional neural networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 1538–1546.

N. K. Kalantari, T.-C. Wang, and R. Ramamoorthi, “Learning-based view synthesis for light field cameras,” ACM Transactions on Graphics (TOG), vol. 35, no. 6, pp. 1–10, 2016.

T. D. Kulkarni, W. F. Whitney, P. Kohli, and J. Tenenbaum, “Deep convolutional inverse graphics network,” in Advances in neural information processing systems, 2015, pp. 2539–2547.

S. Baker, D. Scharstein, J. Lewis, S. Roth, M. J. Black, and R. Szeliski, “A database and evaluation methodology for optical flow,” International journal of computer vision, vol. 92, no. 1, pp. 1–31, 2011.

M. Werlberger, T. Pock, M. Unger, and H. Bischof, “Optical flow guided tv-l1 video interpolation and restoration,” in International Workshop on Energy Minimization Methods in Computer Vision and Pattern Recognition. Springer, 2011, pp. 273–286.

S. Niklaus and F. Liu, “Context-aware synthesis for video frame interpolation,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 1701–1710.

———, “Softmax splatting for video frame interpolation,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 5437–5446.

X. Xu, L. Siyao, W. Sun, Q. Yin, and M.-H. Yang, “Quadratic video interpolation,” in Advances in Neural Information Processing Systems, 2019, pp. 1647–1656.

P. Hu, S. Niklaus, S. Sclaroff, and K. Saenko, “Many-to-many splatting for efficient video frame interpolation,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 3535–3562.

S. Niklaus, P. Hu, and J. Chen, “Splatting-based synthesis for video frame interpolation,” arXiv preprint arXiv:2011.10075, 2022.

Z. Liu, R. A. Yeh, X. Tang, Y. Liu, and A. Agarwala, “Video frame synthesis using deep voxel flow,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 4463–4471.

T. Xue, B. Chen, J. Wu, D. Wei, and W. T. Freeman, “Video enhancement with task-oriented flow,” International Journal of Computer Vision, vol. 127, no. 8, pp. 1106–1125, 2019.

L. Yuan, Y. Chen, H. Liu, T. Kong, and J. Shi, “Zoom-in-to-check: Boosting video interpolation via instance-level discrimination,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 12183–12191.

J. Park, K. Ko, C. Lee, and C.-S. Kim, “Bmbc: Bilateral motion estimation with bilateral cost volume for video interpolation,” arXiv preprint arXiv:2007.12622, 2020.

Z. Huang, T. Zhang, W. Heng, B. Shi, and S. Zhou, “Rife: Real-time intermediate flow estimation for video frame interpolation,” arXiv preprint arXiv:2011.06294, 2020.

D. Danier, F. Zhang, and D. Bull, “St-mfnet: A spatio-temporal multi-flow network for frame interpolation,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 3521–3531.

———, “Enhancing deformable convolution based video frame interpolation with coarse-to-fine 3d cnn,” arXiv preprint arXiv:2207.07731, 2022.

D. Zhang, P. Huang, X. Ding, F. Li, W. Zhu, Y. Song, and G. Yang, “L-1bec: Local lightweight bidirectional encoding and channel attention cascade for video frame interpolation,” ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM).

S. Niklaus, L. Mai, and F. Liu, “Video frame interpolation via adaptive convolution,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 670–679.

———, “Video frame interpolation via adaptive separable convolution,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 261–270.

W. Bao, W.-S. Lai, X. Zhang, Z. Gao, and M.-H. Yang, “Memc-net: Motion estimation and motion compensation driven neural network for video interpolation and enhancement,” IEEE transactions on pattern analysis and machine intelligence, 2019.
[57] W. Chen, J. Wilson, S. Tyree, K. Weinberger, and Y. Chen, “Compressing neural networks with the hashing trick,” in International conference on machine learning, 2015, pp. 2285–2294.

[58] S. Han, H. Mao, and W. J. Dally, “Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding,” arXiv preprint arXiv:1510.00149, 2015.

[59] K. Ullrich, E. Meeds, and M. Welling, “Soft weight-sharing for neural network compression,” arXiv preprint arXiv:1702.04008, 2017.

[60] V. Lebedev and V. Lempitsky, “Fast convnets using group-wise brain damage,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2554–2564.

[61] H. Li, A. Kadav, I. Durdanovic, H. Samet, and H. P. Graf, “Pruning filters for efficient convnets,” arXiv preprint arXiv:1608.08710, 2016.

[62] W. Wen, C. Wu, Y. Wang, Y. Chen, and H. Li, “Learning structured sparsity in deep neural networks,” in Advances in neural information processing systems, 2016, pp. 2074–2082.

[63] H. Zhou, J. M. Alvarez, and F. Porikli, “Less is more: Towards compact cnns,” in European Conference on Computer Vision. Springer, 2016, pp. 662–677.

[64] T. Chen, B. Ji, Y. Shi, B. Fang, S. Yi, T. Ding, and X. Tu, “Neural network compression via sparse optimization,” arXiv preprint arXiv:2011.04868, 2020.

[65] S. Han, J. Pool, J. Tran, and W. Dally, “Learning both weights and connections for efficient neural network,” in Advances in neural information processing systems, 2015, pp. 1135–1143.

[66] T. Chen, “A fast reduced-space algorithmic framework for sparse optimization,” Ph.D. dissertation, Johns Hopkins University, 2018.

[67] T. Chen, G. Wang, T. Ding, B. Ji, S. Yi, and Z. Zha, “Half-space pruning: Stochastic gradient method for group-sparsity regularized problem,” arXiv preprint arXiv:2009.12078, 2020.

[68] T. Chen, B. Ji, T. Ding, B. Fang, G. Wang, Z. Zhu, L. Liang, Y. Shi, S. Yi, and X. Tu, “Only train once: A one-shot neural network training and pruning framework,” Advances in Neural Information Processing Systems, vol. 34, 2021.

[69] L. Xiao, “Dual averaging method for regularized stochastic learning and online optimization,” Advances in Neural Information Processing Systems, vol. 22, 2009.

[70] L. Xiao and T. Zhang, “A proximal stochastic gradient method with progressive variance reduction,” SIAM Journal on Optimization, vol. 24, no. 4, pp. 2057–2075, 2014.

[71] D. Fourure, R. Emonet, E. Fromont, D. Muselet, A. Tremeau, and C. Wolf, “Residual conv-deconv grid network for semantic segmentation,” arXiv preprint arXiv:1707.07958, 2017.

[72] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[73] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” arXiv preprint arXiv:1409.1556, 2014.

[74] X. Wu, Z. Zhou, and A. Basu, “Drvi: Dual refinement for video interpolation,” IEEE Access, vol. 9, pp. 113,566–113,576, 2021.

[75] H. Li, Y. Yuan, and Q. Wang, “Video frame interpolation via residue refinement,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 2613–2617.

[76] K. Soomro, A. R. Zamir, and M. Shah, “Ucf101: A dataset of 101 human actions classes from videos in the wild,” arXiv preprint arXiv:1212.0402, 2012.

[77] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, “Image quality assessment: from error visibility to structural similarity,” IEEE transactions on image processing, vol. 13, no. 4, pp. 600–612, 2004.

[78] R. Zhang, P. Isola, A. A. Efros, E. Shechtman, and O. Wang, “The unreasonable effectiveness of deep features as a perceptual metric,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 586–595.

[79] F. Perazzi, J. Pont-Tuset, B. McWilliams, L. Van Gool, M. Gross, and A. Sorkine-Hornung, “A benchmark dataset and evaluation methodology for video object segmentation,” in Computer Vision and Pattern Recognition, 2016.

[80] Y.-L. Liu, Y.-T. Liao, Y.-Y. Lin, and Y.-Y. Chuang, “Deep video frame interpolation using cyclic frame generation,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 33, 2019, pp. 8794–8802.

[81] A. Stergiou and R. Poppe, “Adaapool: Exponential adaptive pooling for information-retaining downsampling,” arXiv preprint arXiv:2111.00772, 2021.

[82] S. Lee, H. Lee, C. Shin, H. Son, and S. Lee, “Beyond natural motion: Exploring discontinuity for video frame interpolation,” arXiv preprint arXiv:2202.07291, 2022.

[83] M. Choi, S. Lee, H. Kim, and K. M. Lee, “Motion-aware dynamic architecture for efficient frame interpolation,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 13,839–13,848.

[84] M. Liu, C. Xu, C. Yao, C. Lin, and Y. Zhao, “Jmr: Joint non-linear motion regression for video frame interpolation,” arXiv preprint arXiv:2206.04231, 2022.

[85] T. Yang, P. Ren, X. Xie, X. Hu, and L. Zhang, “Beyond a video frame interpolator: A space coupled learning approach to continuous image transition,” arXiv preprint arXiv:2203.09771, 2022.

Tianyu Ding is currently a Senior Researcher at Microsoft, Redmond, USA. He received his PhD degree in Applied Mathematics and Statistics from Johns Hopkins University (JHU). Before that, he received two Master’s degrees in Computer Science and Financial Mathematics from JHU. He received his Bachelor’s degree in Mathematics from Sun Yat-sen University. His research interests are in computer vision, deep learning and numerical optimization.

Luming Liang BS05'; MEng08'; PhD14' is currently a Principal Research Manager at Applied Sciences Group, Microsoft, Redmond, USA. He got his Ph.D. in 2014 from the Colorado School of Mines, majored in Computer Science, with a minor in Geophysics. His research interests are in computer vision, computer graphics, deep learning and signal processing.

Zhihui Zhu is currently an Assistant Professor with the Department of Computer Science and Engineering at the Ohio State University. He was an Assistant Professor in the Department of Electrical and Computer Engineering at the University of Denver from 2020-2022 and a Post-Doctoral Fellow with the Mathematical Institute for Data Science, Johns Hopkins University, from 2018 to 2019. He received his Ph.D. degree in electrical engineering in 2017 from the Colorado School of Mines, where his research was awarded a Graduate Research Award. His research interests cover modeling and algorithmic aspects of data science and machine learning. He is or has been an Action Editor of the Transactions on Machine Learning Research and an Area Chair for NeurIPS.

Tianyi Chen is a Senior Researcher in Microsoft, Redmond, USA. He received his Ph.D. degree in Applied Mathematics and Statistics and Master degree in Computer Science from Johns Hopkins University, and Bachelor degree in Mathematics from Dalian University of Technology. His research interests fall in numerical optimization and its applications in deep learning ranging from computer vision to natural language processing.

Ilya Zharkov is currently a Principal Research Manager at at Applied Sciences Group Micro- soft, Redmond, USA. Before joining Microsoft in 2017, he worked on automated map generation from aerial imagery, optical character recognition (OCR), and handwriting text recognition. Ilya graduated with an M.S. in physics from the Moscow State University in 2005. His current research interests include people and object detection, segmentation, tracking, and 3D reconstruction.