E2FIF: Push the Limit of Binarized Deep Imagery Super-Resolution Using End-to-End Full-Precision Information Flow

Chongxing Song, Zhiqiang Lang, Wei Wei, Senior Member, IEEE, and Lei Zhang, Member, IEEE

Abstract—Binary neural network (BNN) provides a promising solution to deploy parameter-intensive deep single image super-resolution (SISR) models onto real devices with limited storage and computational resources. To achieve comparable performance with the full-precision counterpart, most existing BNNs for SISR mainly focus on compensating for the information loss incurred by binarizing weights and activations in the network through better approximations to the binarized convolution. In this study, we revisit the difference between BNNs and their full-precision counterparts and argue that the key to good generalization performance of BNNs lies on preserving a complete full-precision information flow along with an accurate gradient flow passing through each binarized convolution layer. Inspired by this, we propose to introduce a full-precision skip connection, or a variant thereof, over each binarized convolution layer across the entire network, which can increase the forward expressive capability and the accuracy of back-propagated gradient, thus enhancing the generalization performance. More importantly, such a scheme can be applied to any existing BNN backbones for SISR without introducing any additional computation cost. To validate the efficacy of the proposed approach, we evaluate it using four different backbones for SISR on four benchmark datasets and report obviously superior performance over existing BNNs and even some 4-bit competitors.

Index Terms—Binary neural network, image super-resolution.

I. INTRODUCTION

Deep Convolutional Neural Networks (DCNNs) have achieved impressive performance in many image and video related vision tasks [1], [2], [3], [4], [5], [6], which however, always demands expensive memory consumption and computational cost. As a result, it is difficult to deploy DCNNs directly on resource-constrained devices. To alleviate this problem, a variety of model compression methods have been proposed, among which Binary Neural Networks (BNNs) are well-known for their extreme compression and acceleration performance.

Though BNNs have obtained pleasing results on image classification tasks in recent years, the research on BNNs for image super-resolution (SR) is rather limited and has thus far yielded sub-optimal performance. One of the reasons is that recent studies on SR mainly take advantage of the progress of BNNs for classification, which however, neglects the structure differences between image classification networks and SR networks.

Considering image classification network is composed of numbers of convolutional layer and a fully connected layer, BNNs for image classification mainly focus on compensating the information loss incurred by binarizing weights and activations in the network through better approximations to the binarized convolution. In contrast, the SR network is more complicated, which consists of a head module for initial feature extraction, a body module for detailed feature extraction, and a tail module for upsampling (shown as Fig. 2). Though the networks are different, the existing Binary Super-resolution Networks (BSRNs) only pay attention to the body module which accounts for most of the convolutional layers and computational budget, adopting a similar approach to that employed by BNNs for classification. As a result, the tail module is left unnoticed and to be a serious performance bottleneck of the BSRNs. Specifically, taking a typical tail module with two convolutional layers shown in Fig. 2 as an...
example, when binarizing the SR network, the first and last convolutional layers (i.e., the convolutional layer within the head module and the second convolutional layer within the tail module) are usually kept from being binarized to guarantee the final performance. Therefore, the tail module starts with a binarized convolutional layer, and the Sign function before that will binarize the full-precision feature that is output by the body module into \([-1, +1]\). This leads to a severe loss of high-frequency information of the features, which can be seen from the feature maps before and after Sign function in Fig. 2. As a result, the existing BSRNs have thus far been able to achieve only sub-optimal performance.

The above observation inspires us to rethink BSRNs and propose new guidelines to construct BSRN suitable for SR structure. Since the bottleneck of existing BSRNs are caused by Sign function within the tail module, the efforts on body module only can not help to overcome this problem, i.e., no matter how rich the deep features extracted in the body module, most of the information will be lost at the beginning of the tail module and cannot be passed to the final output. As a result, the integrity of information flow is destroyed within the existing BSRNs. To tackle with this problem, we propose the first guideline to improve the performance of BSRNs from the perspective of information flow integrity: i.e., an end-to-end full-precision information flow (E2FIF) should be able to flow through the entire BSRN. Following this guideline, we propose two tail modules applicable to BSRNs, namely a simple feature repeat shortcut tail module and a lightweight tail module, which can effectively increase the forward expressive capability.

Moreover, considering that the gradient in back-propagation is also important for BRSNs, we investigate how a gradient flow might be devised given the above-mentioned forward-propagated full-precision information flow. For this purpose, we systematically explore different combinations of forward-propagated full-precision information flow and back-propagated gradient flow within BRSNs, from which we obtain the second guideline for BSRNs: the full-precision information flow and the accurate gradient flow can be accessed by each binarized convolutional layer. Such a conclusion can also help to uncover the mechanism behind Bi-Real Net [7].

Following the two guidelines proposed above can enable us to effectively binarize any SR network architectures. From this, we build a simple but strong baseline for BSRNs, referred to as E2FIF, which outperforms the state-of-the-art methods while maintaining much lower latency (shown as Fig. 1).

In summary, the contribution of this study can be summarized as follows.

- To the best of our knowledge, we are the first one to notice that the tail module destroys the integrity of information flow within BSRNs and becomes a bottleneck; based on this observation, we accordingly propose to construct BSRNs from the perspective of information flow integrity.
- We propose the following two practical guidelines for BSRNs: 1) an end-to-end full-precision information flow (E2FIF) should be able to flow through the entire BSRN; and 2) the full-precision information flow and the accurate gradient flow can be accessed by each binarized convolutional layer. Following these two guidelines, we build a simple but strong baseline for BSRNs termed as E2FIF, which can be adopted to any SR network architectures.
- We evaluate E2FIF using four different backbones for SISR on four benchmark datasets. The results show that our approach achieves obviously superior performance over existing BNNs and even some 4-bit competitors.

II. RELATED WORKS

In this section, we first introduce the research on BNNs but closely related with this study from two perspectives. Then we present the latest research on quantized super-resolution networks.

A. Gradient Approximation Within BNNs

Non-differentiable Sign function results in the difficulty for training BNNs. In light of this, an alternative solution would be to obtain as more as accurate gradients by introducing various strategies, and different methods of this kind have been proposed. For example, [8], [9] proposed to approximate the gradient of the non-differentiable Sign function by a straight-through estimator (STE). Liu et al. [7] further proposed a more accurate approximation function that employed a piece quadratic function. An artificially designed progressive quantization function was used in IRNet [10] to reduce the error caused by the estimated gradient. Gong et al. [11] further proposed a differentiable soft quantization function to automatically adjust the back-propagated gradient during training. Zhuang et al. [12] proposed to construct an additional full-precision branch during training stage to provide auxiliary and accurate gradient for BNN. Chen et al. [13] proposed to generate the gradient about the full-precision weights through a learnable meta-quantizer. Besides, Helwegen et al. [14] rethought the role of latent full-precision weights during training and considered them as the provider of inertia to make the binary weights flip. Based on this, they designed the first BNN optimizer to directly control the flip of binary weight. Both of the above methods avoid the derivation of the non-differentiable Sign function. Lee et al. [15] proposed to scale the back-propagated gradient adaptively according to quantization error and the sign of the gradient about the binary
weight to obtain the gradient about the full-precision weight. In addition, Zhang et al. [16] and Xu et al. [17] proposed to solve the problem of dead weights that arises due to the tiny gradient by limiting the range of full-precision weights.

B. Representation Capacity of BNNs

Since the Sign function in BNNs directly quantifies features into \([-1, +1]\), it seriously damages the representation capacity with respect to its full-precision counterpart. To address this problem, some methods [9, 18, 19] proposed to multiply the binary value by the full-precision scaling factor to align with the full-precision counterparts in order to reduce the quantization error. Lin et al. [20] further generalized the alignment of value to the alignment of angle. Xu et al. [21] considered the coupling relationship between the scaling factor and the real-valued weights, and proposed a bilinear optimization algorithm to enable the sparse weights to be trained sufficiently. Besides, some methods opted to improve the representation capacity by fusing multiple binarized bases to approximate full-precision counterparts. For example, Lin et al. [22] directly used multiple binarized convolution layers to approximate the full-precision counterpart. Zhuang et al. [23] further pushed the limits of this idea from the perspective of group approximation. Similar methods using the same idea can be also found in [24] and [25]. In addition, the knowledge distillation method [26] that extracting useful information from full-precision teacher network has been used to improve the representation capacity of BNN. Similarly, Xu [27] proposed to fully utilize the latent full-precision weights in the process of BNN training to obtain additional supervision to improve performance. In BONN [28], the binarization-friendly bimodal Gaussian distribution is used as the prior distribution of the full-precision convolutional kernels, and the Bayesian framework is utilized for end-to-end training to reduce the quantization error. Furthermore, Liu et al. [7] proposed to connect with the real activations before a binarized convolutional layer by an identity shortcut. Bethge et al. [29] proposed to use the channel concatenation to enhance the capacity and quality of the binary feature maps. Liu et al. [30] proposed generalized Sign and PReLU functions with learnable thresholds, which enabled explicit learning of the distribution reshape and shift. Falkena et al. [31] further proposed a learnable quantizer with fine-grained threshold for binarizing activations. Both of [7] and [30] effectively improve the performance with negligible cost through unique observations of the BNNs. Similar to [7], we revisit the BNNs from the perspective of information flow; however, we opt to focus specifically on the BSRNs, the structures of which differ from those of the classification networks. The difference between this study and [7] can be seen from the discussion at the end of III-C.

C. Quantized Super-Resolution Networks

To apply quantization to super-resolution tasks, many approaches from different perspectives have been proposed. A parameterized quantization maximum scale is proposed in [32] for 8-bit and 4-bit SR networks, adaptively learning the quantization truncated parameter in the training process, which can effectively alleviate the problem of the large dynamic quantization range of the quantized SR networks. Zhong et al. [33] proposed a dynamic controller to generate the quantization upper and lower bounds to address the problem of large quantization error or wasted quantization levels caused by the asymmetric activations distribution. Based on the observations that the feature map distribution of each channel is distinctive in SR networks, Hong et al. [34] designed channel-wise distribution-aware quantized convolution to reduce the quantization error. Different from the conventional practice of keeping the first and last convolution layers as full-precision in quantized SR networks, a SR network with all convolution layers quantized is proposed in FQSR [6]. Hong et al. [35] adaptively allocated the optimal quantization bit-width for the image patch and the network layers according to the local content information of the image, so as to pursue the trade-off between accuracy and speed. Ma et al. [36] first proposed to binarize the convolution kernels in residual blocks but with full-precision activations, which is not a standard BSRN to some degree. For BSRNs, Xin et al. [37] proposed a bit-accumulation mechanism to gradually refine features through spatial attention. Jiang et al. [38] proposed a new binary training mechanism based on feature distribution for BSRNs, which enables BSRNs to be trained without BN layers. Zhang et al. [16] proposed a compact uniform prior for the full-precision weights in BSRNs and used a pixel-level curriculum learning strategy to improve the performance. Besides, the mean of the local spatial neighborhood of feature maps was used as the dynamic threshold of the binarization function to maintain more details of the feature maps and improve the SR performance in [39]. Wei et al. [40] proposed dynamic spatial-wise scaling together with channel-wise shifting and scaling mechanism to reshape the distribution of activation values in quantized super-resolution networks, thereby improving the performance. Jiang et al. [41] proposed to aggregate multiple binary convolution to approximate the multi-bit convolution to reduce the information loss. However, most of these BSRN works draw on the latest advances in BNNs for the classification task and do not analyze and study the structure characteristics of BSRNs. In contrast, we carefully considered the structure of BSRNs and found that there is an information flow bottleneck. Based on this, we designed two guidelines to improve the performance of BSRNs.

III. Method

In this section, we first revisit the BSRNs from the perspective of information flow integrity and demonstrate the problems of previous methods. We then propose two practical guidelines to construct BSRNs, which can preserve complete full-precision information flow throughout the entire network.

A. BSRNs Revisited

Different from image classification which aims to assign each image a unique class label, image super-resolution aims
to recover the high-frequency details of images, and obtain a high-resolution image from a low-resolution counterpart. As a result, the network structure of image classification is different with that from SR. Specifically, the image classification network is composed of numbers of convolutional layer for feature extraction and a fully connected layer for classifying the extracted high-level features. In contrast, a typical SR network can usually be divided into three modules: namely, the head module, the body module and the tail module, as shown in Fig. 2. The head module contains only a convolutional layer to extract initial features from the low-resolution image. The body module stacks multiple residual blocks for deep feature learning. Finally, the tail module collects the deep features and then upscales them to predict the desired high-resolution image.

Taking advantages of the recent progress on BNNs used for classification, all existing BSRNs pay attention to the body module for feature extraction, while keeping the first and the last convolutional layers within BSRNs from being binarized to guarantee the final performance. However, the tail module, which reflects the structure difference between the image classification and SR, is left unnoticed and destroys the integrity of full-precision information flow within BSRNs. Specifically, as shown in Fig. 2, although the full-precision convolution layer within the head module builds the initial information flow and multiple residual blocks within the body module subsequently enrich the information flow, the Sign function within the tail module binarizes the full-precision feature output by the body module into \( \{-1, +1\} \), this leads to a severe loss of high-frequency information of the features (see the feature maps before and after Sign function in Fig. 2 for details), which makes the tail module into the information bottleneck of BSRNs. As a result, the above observation inspires us to rethink BSRNs from how to effectively construct a body module, still from the perspective of information flow. For this purpose, from the perspective of information flow. For this purpose, we propose the End-to-End Information Flow Guideline for BSRNs.

B. End-to-End Information Flow Guideline for BSRNs

As discussed above, we can clearly see that the information flow bottleneck caused by the Sign function within the tail module limits the performance of BSRNs. As a result, one of the most important issues to consider when attempting to construct more effective BSRNs is to accommodate SR network structure, from which we propose the End-to-End Information Flow Guideline for BSRNs, i.e., an End-to-end Full-precision Information Flow (E2FIF) should be preserved throughout the entire SR network.

Following this guideline, we can remodel the existing tail module to preserve the full-precision information flow within the tail module. In this study, we construct two kinds of tail modules suitable for BSRNs accordingly. In the below, we will take the most commonly utilized Original Tail module as an example (shown as Fig. 3(a)) to clarify how we construct these two kinds of tail modules.

1) Repeat-Shortcut Tail: Since the information flow bottleneck comes from the Sign function, a straight-forward way to deal with this issue is to add a shortcut that bypasses the Sign function, similar to that in Bi-Real Net [7]. The Repeat-Shortcut tail repeats the input features in the channel dimension and connects them to the output channel-expanded features by the binarized convolutional layer, as shown in Fig. 3(b).

2) Lightweight Tail: Different with Repeat-Shortcut Tail which utilizes a shortcut to bypass the Sign function, we opt to drop the Sign function within the tail module and obtain a lightweight tail, which contains only one full-precision convolutional layer, as shown in Fig. 3(c). This enables the input full-precision features to be directly used to predict high-resolution images without a Sign function. Despite its simplicity, the lightweight tail performs even better than the Repeat-Shortcut tail. The details are provided in our experiments.

The comparison results and analysis of the three tail modules are shown in section IV-C.1.

C. Effective Binarized Convolutional Layer Guideline for BSRNs

The End-to-End information flow guideline provides an effective way to construct tail modules pertinent for preserving full-precision information flow. In what follows, we turn to investigate how to effectively construct a body module, still from the perspective of information flow. For this purpose, we take a commonly utilized structure with two blocks as an example, in which each “Binary Conv Block” (shown in Fig. 4) follows a “Sign-Conv-Bn” structure. As can be clearly seen, there are four kinds of combinations with regards to the full-precision information flow and back-propagated gradient.
flow, shown as each row in Fig. 4. The first one is the Original Block, in which a shortcut is directly implemented over two binarized convolutional layers for both the information flow of forward propagation and the gradient flow of backward propagation, as shown in Fig. 4(a) and (b). The second one is the Former Residual Block, in which we add an extra shortcut over the first binarized convolutional layer into Original Block shown as Fig. 4(c) and 4(d). It should be noticed here that the Former Residual Block allows the second binarized convolutional layer to additionally receive the full-precision information streams. The third one is the Later Residual Block, in which we add an extra shortcut over the second binarized convolutional layer into the Original Block shown as Fig. 4(e) and 4(f). The Later Residual Block allows the first binarized convolutional layer to additionally receive an accurate large gradient flow. The fourth one is the Bi-Real Block, in which each binarized convolutional layer receives both the full-precision information and the accurate gradient flow shown as Fig. 4(g) and 4(h).

While these four structures can all provide full-precision information flow, their accuracies differ, which can be seen in Table VI and section IV-C.2. To obtain better performance, the fourth one (i.e., Bi-Real block shown in Fig. 4(g) and 4(h)) are adopted in the experiment. In addition, from these results and analysis, we can conclude that the accurate gradient flow benefits the full-precision information flow, and further propose the Effective Binarized Convolutional Layer guideline for BSRNs, i.e., the full-precision information flow and the accurate gradient flow should flow through each binarized convolutional layer as much as possible. We contend that there are two main reasons for this.

Firstly, the Sign function maps the inputs of entire range to \{-1, +1\}. Therefore, only the sign of the input has an effect on the input and output of the binarized convolutional layer. We then consider a Residual Block with two binarized convolutional layers. Without the shortcut over the first binarized convolutional layer, only the sign of the input affects the second binarized convolutional layer. However, with shortcuts in place, the input is added to the output of the first binarized convolutional layer. The magnitude of the input will also affect the second convolutional layer. This makes the second convolutional layer more sensitive to the input.

Secondly, the STE is used in the backward propagation process of the Sign function to alleviate the non-differentiable problem. But the STE will also introduce the gradient error problem. However, in the case of a shortcut, a part of the accurate gradient can be passed back through the shortcut, which enables the binarized convolutional layers to be better optimized.

**Difference from Bi-Real Net [7]:** The proposed method resembles Bi-Real Net in terms of its ability to preserve full-precision information flow through shortcuts. However, they differ in the following two aspects. 1) Bi-Real Net [7] only proposed a BNN structure for classification without systematically analyzing the BNNs. In contrast, we systematically analyze the BNNs for SR from the perspective of information flow and propose two guidelines for BSRNs. More importantly, these two guidelines can be used for any SR network with complex structures. 2) Bi-Real Net [7] only mentioned that shortcuts can increase the representational capability of the BNNs. But we considered and experimented more deeply on the shortcuts in BNNs, and subsequently demonstrated that the accurate gradient flow and the full-precision information flow are equally important for an effective binarized convolutional layer.

**D. Theoretical Proof of the Effectiveness of Full Precision Information Flow**

The proposed full-precision connection information flow can be theoretically analyzed from the perspective of reducing gradient error in the backpropagation process. Consider a neural network with two layers of binarized convolution, with original full-precision weight matrices \(W^{(1)}\) and \(W^{(2)}\) respectively, the input and output of the first convolution layer are \(x_0\) and \(x_1\), while those of the second convolution layer are \(x_1\) and \(x_2\). The diagram of binarized convolution layers without the full-precision connections is shown as Fig. 5(a),
and the diagram of binarized convolution layers with the full-precision connections is shown as Fig. 5(b).

The binarized convolution without full-precision shortcut can be formulated as

\[
\text{sign}(W^{(1)}) \otimes \text{sign}(x_0) = x_1 \\
\text{sign}(W^{(2)}) \otimes \text{sign}(x_1) = x_2.
\]

Denoting the gradient of the loss \( L \) with respect to the output \( x_2 \) as \( \frac{\partial L}{\partial x_2} \), the gradients in the backpropagation process can be derived by applying the chain rule, as shown below.

\[
\begin{align*}
\frac{\partial L}{\partial x_1} &= \frac{\partial L}{\partial x_2} \cdot \text{sign}(W^{(2)}) \cdot \frac{\partial \text{sign}(x_1)}{\partial x_1} \\
\frac{\partial L}{\partial W^{(1)}} &= \frac{\partial L}{\partial x_2} \cdot \text{sign}(W^{(2)}) \cdot \frac{\partial \text{sign}(x_1)}{\partial x_1} \cdot \text{sign}(x_0) \\
&\quad \cdot \frac{\partial \text{sign}(W^{(1)})}{\partial W^{(1)}} \\
&= \frac{\partial L}{\partial x_2} \cdot \text{sign}(W^{(2)}) \cdot \frac{\partial \text{sign}(x_1)}{\partial x_1} \cdot \text{sign}(x_0) \\
&\quad \cdot \frac{\partial \text{sign}(W^{(1)})}{\partial W^{(1)}}.
\end{align*}
\]

In contrast, the binarized convolution process with full-precision shortcut added for each convolution layer can be formulated as

\[
\text{sign}(W^{(1)}) \otimes \text{sign}(x_0) + x_0 = x_1 \\
\text{sign}(W^{(2)}) \otimes \text{sign}(x_1) + x_1 = x_2.
\]

And the corresponding gradient calculations in the backpropagation process are as follows.

\[
\begin{align*}
\frac{\partial L}{\partial x_1} &= \frac{\partial L}{\partial x_2} \cdot (1 + \text{sign}(W^{(2)}) \cdot \frac{\partial \text{sign}(x_1)}{\partial x_1}) \\
\frac{\partial L}{\partial W^{(1)}} &= \frac{\partial L}{\partial x_2} \cdot \text{sign}(W^{(2)}) \cdot \frac{\partial \text{sign}(x_1)}{\partial x_1} \cdot \text{sign}(x_0) \\
&\quad \cdot \frac{\partial \text{sign}(W^{(1)})}{\partial W^{(1)}} + \frac{\partial L}{\partial x_2} \cdot \text{sign}(x_0) \cdot \frac{\partial \text{sign}(W^{(1)})}{\partial W^{(1)}}.
\end{align*}
\]

In the above formulas, there are errors in estimating the gradient of the sign function due to its non-differentiability property, and these errors accumulate as the gradient is backpropagated layer by layer. Formula (8) adds the term \( \frac{\partial L}{\partial x_2} \cdot \text{sign}(x_0) \cdot \frac{\partial \text{sign}(W^{(1)})}{\partial W^{(1)}} \) compared to formula (4). The term in formula (4) is multiplied twice by the differentiation of the sign function, while the new term in formula (8) is only multiplied once by the differentiation of the sign function. Since the gradient error of the additional term is smaller, it compensates for the accumulating gradient errors. Therefore, the proposed method has smaller accumulated gradient errors, and thus obtain better super-resolution performance compared with other competing methods.

IV. EXPERIMENTS

In this section, we first introduce our experiments settings, including datasets, evaluation metrics, training settings and comparison methods. Then, we compare the performance of the proposed method with other state-of-the-art comparison methods on four popular SR architectures. Next, we conduct sufficient model analysis to demonstrate the effectiveness of the proposed guidelines. Finally, we show the comparison of deployment efficiency and qualitative results.

A. Experiments Settings

1) Datasets: We train all models on DIV2K [44] datasets. DIV2K [44] contains 800 training images, 100 validation images and 100 testing images. For testing, four benchmark datasets including Set5 [45], Set14 [46], B100 [47] and Urban100 [48] are utilized.

2) Evaluation Metrics: Following standard SISR work [2], PSNR and SSIM are adopted as evaluation metrics. We compare the super-resolution image and the original high-resolution image on the luminance channel \( Y \) of the YCbCr color space. The input low-resolution images are generated by the bicubic algorithm. In addition, the total theoretical operations(\( OPs \)) is utilized to measure the complexity of the quantized models [47], which is calculated by \( OPs = FLOPs + QOPs / 64 \) \( \times (bit_w \times bit_a) \). \( FLOPs \) is the floating-point calculation complexity, and \( QOPs \) is the theoretical calculation complexity of modules with quantization operators. \( bit_w \) and \( bit_a \) represent the quantization bit numbers for weights and activation values, respectively.

3) Training Settings: All experiments are implemented and conducted using the PyTorch framework, on a server platform with 4 V100 GPUs. All models are trained for 300 epochs from scratch with binary weights and activations. The initial learning rate is set to 2e-4 and halved every 200 epochs. The mini-batch size is set to 16 and the ADAM [49] optimizer is adapted.

4) Network Architectures and Comparison Methods: To fully demonstrate the effectiveness and generality of the proposed method, we conduct comparisons with state-of-the-art methods on several most commonly utilized network architectures. Specifically, we first conduct comparisons on SRRResNet [42] and EDSR [2] architectures those previously utilized for BSRNs. The chosen comparison methods include BNN methods such as BNN [8], DoReFa Net [43], ABC Net [22], Bi-Real Net [7], BNN+ [50] and RTN [51], together with state-of-the-art BSRN methods such as BAM [37], LMBN [39], PDBC [41] and IBTM [38], multi-bit quantized SR networks such as PAMS [32], DAQ [34] and DDTB [33].

In addition to the SRRResNet and EDSR architectures, we also binarize two advanced SR architectures including RCAN [52] and RDN [53]. Since none of the previous methods have attempted to binarize these two architectures, we mainly compare the proposed method with our baseline method including Bi-Real Net [7] and the recent state-of-the-art method IBTM [38] and several multi-bit quantization
TABLE I
THE COMPARISON RESULTS OF DIFFERENT METHODS ON FOUR BENCHMARK DATASETS AT THREE SCALES (E.G., ×2, ×3, ×4) ON THE SRResNet [42] ARCHITECTURE. THE OPS ARE CALCULATED BASED ON THE INPUT IMAGE SIZE OF 48 × 48. IN THE SECOND COLUMN, THE W/A REPRESENTS THE QUANTIZATION BIT-WIDTH OF WEIGHS AND ACTIVATIONS RESPECTIVELY, AND THE MULTIPLIER FACTOR REPRESENTS THE NUMBER OF BRANCHES IN MULTI-BRANCH BINARIZATION METHOD. THE BEST RESULTS ARE BOLDFACE

| Method                  | Bitwidth(W/A) | Scale | OPs(G) | Set5 PSNR(dB) | Set5 SSIM | Set4 PSNR(dB) | Set4 SSIM | B100 PSNR(dB) | B100 SSIM | Urban100 PSNR(dB) | Urban100 SSIM |
|-------------------------|---------------|-------|--------|---------------|-----------|---------------|-----------|---------------|-----------|-------------------|---------------|
| Bicubic                 | -             | ×2    | -      | 32.66 0.930  | 32.24 0.869 | 29.36 0.843  | 26.88 0.840 |
| SRResNet-BNN [8]        | 1/1           | ×2    | 0.065  | 32.15 0.942  | 0.065 31.55 | 0.896 30.64  | 0.876 28.01 |
| SRResNet-DoReFa [43]    | 1/1           | ×2    | 0.065  | 36.09 0.978  | 32.09 0.902 | 31.55 0.892  | 28.82 0.856 |
| SRResNet-BAM [37]       | 1/1           | ×2    | 0.115  | 37.21 0.956  | 32.74 0.910 | 31.60 0.891  | 30.20 0.906 |
| SRResNet-LMBN [39]      | 1/1           | ×2    | 0.183  | 37.39 0.957  | 32.96 0.911 | 31.76 0.893  | 30.65 0.912 |
| SRResNet-E2FIF(ours)    | 1/1           | ×2    | 0.059  | 37.50 0.958  | 32.96 0.911 | 31.79 0.894  | 30.73 0.913 |
| SRResNet-PDBC [41]      | (1/1)x2       | ×2    | 0.067  | 37.42 0.957  | 32.97 0.911 | 31.75 0.893  | 30.63 0.912 |
| SRResNet-ABC [22]       | (1/1)x3       | ×2    | 0.164  | 36.34 0.952  | 32.28 0.903 | 31.16 0.884  | 29.24 0.891 |
| SRResNet-DDTB [33]      | 2/1           | ×2    | 0.208  | 37.46 0.958  | 33.02 0.913 | 31.78 0.895  | 30.57 0.913 |
| SRResNet-DDTB [33]      | 3/1           | ×2    | 0.452  | 37.67 0.959  | 33.24 0.915 | 31.95 0.897  | 31.15 0.919 |
| SRResNet-DDTB [33]      | 4/1           | ×2    | 0.797  | 37.78 0.960  | 33.32 0.916 | 32.03 0.898  | 31.40 0.921 |
| SRResNet-FullPrecision  | 32/32        | ×2    | 3.160  | 37.67 0.958  | 33.27 0.914 | 31.95 0.895  | 31.28 0.919 |

methods that have been verified in related works such as DAQ [34], PAMS [32] and DDTB [33].

B. Comparison of Quantitative Results

1) Results on SRResNet Architecture [42]: The results of all comparison BSRN methods on four benchmark datasets are shown in Table I. The proposed E2FIF obtains the best performance on all scales and datasets, except for the fact that the PSNR of our method is only 0.08 dB and 0.04 dB slightly lower than that obtained by LMBN [39] and BAM [37] on Set14 [46] at 4x scale. But it is noticeable that more full-precision computations are still used in LMBN [39] in order to obtain the local information-aware activation thresholds during inference stage. In addition, more extra computations are utilized in BAM [37] due to the bit accumulation mechanism for activations, which can be considered as extra spatial attention and thus introduces additional computation. Compared with ABC [22] and PDBC [41] which approximate the full-precision convolution through multiple binarized convolutions, the proposed E2FIF improves the PSNR of ABC over 1 dB at 2x scale super-resolution and achieves performance comparable to PDBC at 2x and 3x scale super-resolution. Besides, the proposed E2FIF even outperforms the 2-bit quantized method DDTB [33] at 2x scale super-resolution. In addition, it can be seen that the proposed E2FIF has a smaller OPs than other methods at x2, x3 and x4 scale super-resolution. All these results demonstrate the effectiveness of the proposed E2FIF.

2) Results on EDSR Architecture [2]: EDSR [2] has a similar structure as SRResNet, but with more Residual Blocks and channels. Considering that it is widely utilized for SR and BSRNs, we also conduct experiments on EDSR architecture, and compare the proposed E2FIF with more advanced methods. As can be seen from Table II, the proposed E2FIF achieves the best performance on three datasets. Though the performance of the proposed E2FIF is only slightly lower than IBTM on Set14 dataset, it has a clear advantages over IBTM as well as other methods on the other three datasets including the most difficult dataset Urban100 [48]. Compared with Bi-Real Net [7] which can be considered as the baseline of our method, the proposed E2FIF achieves more than 1 dB improvement at all settings with nearly the same amount of computations. More importantly, the proposed E2FIF also has obvious advantages compared with some multi-bit quantized super-resolution network, namely DDTB [33], PAMS [32]. For example, compared with the 4-bit
PAMS and DDTB, the proposed E2FIF improve the PSNR at 2x scale super-resolution on Urban 100 by 0.69 dB and 0.40 dB respectively. It is worth noting that the reason why the proposed E2FIF is inferior to 2-bit quantized SR method DAQ [34] may be that it uses a pre-trained full-precision model while ours does not. Besides, the experimental results show that our method has low theoretical computational complexity. Although IBTM has a smaller OPs than our proposed method at x2 and x3 scale super-resolution, our proposed method has a better image reconstruction quality than IBTM. The above-mentioned results demonstrate the superiority and importance of the proposed guidelines for BSRNs.

3) Results on RCAN Architecture [52]: RCAN trains a very deep network through hierarchical residual structures and channel attention mechanisms, and thereby achieves pleasing SR performance. We binarize a RCAN network with 10 residual groups (each group includes 5 two-layer residual blocks), and retain the full-precision channel attention which can be combined with BN layers. Following the proposed guidelines, we improve three parts in RCAN [52], including the Shortcut in Residual Group, the Discard of the binarized End of Body module and the Lightweight Tail module. The detailed network structure and variants are shown in Fig. 6. The effects of these three parts are given in Table III, from which we can see that the three parts obtained from the proposed guidelines can effectively improve the performance of the model. In particular, the proposed Lightweight Tail brings the largest performance improvement and significantly outperforms the state-of-the-art IBTM [38]. In addition, the proposed E2FIF has smaller OPs and better reconstruction performance than RCAN-BiReal and its variants. Compared with IBTM that has smaller OPs, the proposed E2FIF has better reconstruction performance. For example, compared with IBTM, the proposed method improves the PSNR by 2.36dB at x4 scale super-resolution on Urban100 dataset. These results demonstrate the compatibility of the proposed guidelines with the attention mechanism.

4) Results on RDN Architecture [53]: RDN is a strong SR network based on a residual dense structure. In addition to its dense connections, RDN also proposes the local and global feature fusion strategy to fuse the shallow and deep features, which has been utilized by many recent SR networks. In this study, we improve the three modules of RDN (including the Shortcut in Local Feature Fusion, the Shortcut in Global Feature Fusion and the Lightweight Tail module) by adding shortcuts and its variants. The detailed network structure and variants are shown in Fig. 7 and the experimental results are shown in Table IV. Similar to RCAN, three proposed modules bring about an obvious improvement, with the Lightweight Tail bringing the largest improvement. Moreover, the proposed E2FIF outperforms the state-of-the-art 1-bit quantized IBTM [38], 2-bit quantized DDTB [33], and 4-bit quantized PAMS [32]. Similarly, our method achieves the best trade-off in terms of OPs and reconstruction performance compared with other methods. These results demonstrate the applicability and robustness of the proposed method when it comes to coping with complex structures.

C. Model Analysis

1) Ablation Study of Different Tail Module: To verify the effectiveness of the proposed Repeat-Shortcut and Lightweight Tails, we compare them with the Original Tail module on SRResNet [42] architecture, as shown in Table V. It can be seen that the performance of the network is effectively improved by simply adding a repeat shortcut to the Original Tail. Furthermore, the proposed Lightweight Tail directly removes the first binarized convolutional layer, which further reduces the information flow loss and improves the performance, while also reducing the computation cost. These results effectively demonstrate the applicability of the proposed Lightweight Tail and the importance of the E2FIF guideline for BSRNs. Therefore, our final solution adopts the lightweight tail for quantizing various network structure in all experiments.

2) Analysis of Different Block: The results of binarized SRResNet [42] with different blocks on Urban100 [48] at ×4
TABLE II

| Method            | Bitwidth(W/A) | Scale | OPs(G) | Set5 PSNR(\text{dB}) \downarrow | SSIM↑ | Set14 PSNR(\text{dB}) \downarrow | SSIM↑ | B100 PSNR(\text{dB}) \downarrow | SSIM↑ | Urban100 PSNR(\text{dB}) \downarrow | SSIM↑ |
|-------------------|---------------|-------|--------|-------------------------------|-------|-------------------------------|-------|-------------------------------|-------|-------------------------------|-------|
| Bi-cubic          | /-            | x2    | -      | 33.66 0.950                   | 30.24 0.869 | 39.56 0.843                   | 26.88 0.840 |                               |       |                               |       |
| EDSR-BNN [8]      | 1/1           | x2    | 1.568 34.47 0.938 | 31.06 0.891 | 30.27 0.872 | 27.72 0.864 |                               |       |                               |       |
| EDSR-BiReal [7]   | 1/1           | x2    | 1.568 37.13 0.956 | 32.73 0.909 | 31.54 0.891 | 29.94 0.903 |                               |       |                               |       |
| EDSR-BNN+ [50]    | 1/1           | x2    | 1.568 37.49 0.958 | 33.00 0.912 | 31.76 0.893 | 30.49 0.911 |                               |       |                               |       |
| EDSR-RTN [51]     | 1/1           | x2    | 1.568 37.66 0.956 | 33.13 0.914 | 31.85 0.895 | 30.82 0.915 |                               |       |                               |       |
| EDSR-BTM [38]     | 1/1           | x2    | 1.568 37.68 0.956 | 33.20 0.914 | 31.87 0.895 | 30.98 0.916 |                               |       |                               |       |
| EDSR-IBTM [38]    | 1/1           | x2    | 1.191 37.80 0.960 | 33.38 0.916 | 32.04 0.898 | 31.49 0.922 |                               |       |                               |       |
| EDSR-LMBN [39]    | 1/1           | x2    | 2.512 37.93 0.924 | 33.25 0.915 | 32.13 0.899 | 31.79 0.924 |                               |       |                               |       |
| EDSR-E2FFI (ours) | 1/1           | x2    | 1.462 37.95 0.960 | 33.37 0.915 | 32.13 0.899 | 31.79 0.924 |                               |       |                               |       |
| EDSR-PDBC [41]    | (1/1)x2       | x2    | 1.575 37.75 0.960 | 33.30 0.915 | 31.98 0.897 | 31.45 0.920 |                               |       |                               |       |
| EDSR-DDTB [33]    | 2/2           | x2    | 5.925 37.25 0.958 | 32.87 0.911 | 31.67 0.893 | 30.34 0.910 |                               |       |                               |       |
| EDSR-DDTB [33]    | 3/3           | x2    | 6.975 37.51 0.958 | 33.17 0.914 | 31.89 0.896 | 31.01 0.919 |                               |       |                               |       |
| EDSR-DDTB [33]    | 4/4           | x2    | 28.870 37.72 0.959 | 33.35 0.916 | 32.01 0.898 | 31.39 0.922 |                               |       |                               |       |
| EDSR-PAMS [32]    | 4/4           | x2    | 28.870 37.67 0.959 | 33.30 0.915 | 31.94 0.897 | 31.10 0.919 |                               |       |                               |       |
| EDSR-FullPrecision | 32/32         | x2    | 38.974 38.48 0.960 | 33.92 0.915 | 32.98 0.903 | 32.49 0.920 |                               |       |                               |       |

scale is shown as Table VI. As can be seen, the addition of the former and later shortcut into the Original Tail improved the performance, which demonstrates the importance of the full-precision information flow and the accurate gradient flow. More importantly, the performance of Bi-Real Net whose each convolutional layer receives both full-precision information flow and accurate gradient flow is further improved, which demonstrates the compatibility of the effective binarized
3) Analysis of Cutoff at Different Position: The effect of cutoffs at different position of the binarized SRRResNet [42] is shown as Table VII. As can be seen, more close to the beginning and end of the network, the performance will be hurt more by cutoff. In addition, the cutoff of the tail has the largest impact on the performance. This is consistent with our conjectures that the truncated information flow will be gradually restored by the following layers and the gradient error will accumulate due to the chain rule. However, a cutoff at the beginning will cause the initial information flow to be damaged of the forward propagation process, while a cutoff at the end will cause the information flow to be too late to be restored, as well as the gradient flow to be disrupted in the initial stages of backpropagation.

4) Sensitivity Analysis of Models With Different Widths to Binarization: EDSR [2] can be regarded as the deeper and wider SRRResNet [42] with more residual blocks and channels. As can be seen from Table I and Table II, the proposed E2FIF has more obvious performance advantages compared with other quantized SR networks on EDSR architecture, even outperforming most of the multi-bit quantization competitors. The analysis from the perspective of reducing the quantization error is helpful to demystify this problem. Consider a binary convolutional layer with filters $W$ of size $3 \times 3 \times 3$ and a output feature map $A$ of size $C \times H_{out} \times W_{out}$, where $C$ (assuming $C$ is even) is the number of input and output channels, $3 \times 3$ is the kernel size and $H_{out}$ and $W_{out}$ is the height and width of the output feature map respectively. The output of the convolution operation between a binarized activation map and a binarized kernel would be any odd integer in the range of $[-9, 9]$ and the value of each element in $A$ would be any even integer between $[-9 \times C, 9 \times C]$. Following the definition of the representation capacity of a variable $x$ in Bi-Real Net [7], that is, the number of all cases in $x$ that can be configured, we can analyze the effect of the model width on the representation capacity BSRNs. It is easy to know that the larger $C$ is, the larger the representation capacity of $A$ is, and the smaller the overall quantization error is, so the performance of corresponding BSRN is better and easier to surpass the ones of some multi-bit quantized SR networks.

### Table IV

The results of binarized SRRResNet with different tail modules at x4 super-resolution. The best results are bolded.

| Method       | Bitwidth(W/A) | SLFF | SGGF | LWT | OPS(G) | Set5 PSNR(dB)† | SSIM† | Set14 PSNR(dB)† | SSIM† | B100 PSNR(dB)† | SSIM† | Urban100 PSNR(dB)† | SSIM† |
|--------------|---------------|------|------|-----|--------|----------------|-------|----------------|-------|----------------|-------|-------------------|-------|
| IBTM [38]    | 1/1           | -    | -    | -   | 0.334  | 28.29         | 0.797 | 25.87          | 0.700 | 23.81          | 0.671 | 23.21             | 0.600 |
| Bi-Real [7]  | 1/1           | x    | x    | x   | 0.468  | 28.97         | 0.822 | 26.29          | 0.719 | 26.14          | 0.684 | 23.64             | 0.684 |
| Variant1     | 1/1           | ✓    | x    | ✓   | 0.468  | 29.20         | 0.826 | 26.47          | 0.722 | 26.26          | 0.687 | 23.72             | 0.688 |
| Variant2     | 1/1           | ✓    | ✓    | ✓   | 0.468  | 29.38         | 0.825 | 26.62          | 0.723 | 26.38          | 0.686 | 23.85             | 0.689 |
| E2FIF(outs)  | 1/1           | ✓    | ✓    | ✓   | 0.442  | 31.55         | 0.884 | 28.09          | 0.769 | 27.30          | 0.726 | 25.28             | 0.758 |
| DAQ [34]     | 2/2           | -    | -    | -   | 1.721  | 31.61         | -     | 28.21          | -     | 27.31          | -     | 25.52             | -     |
| PAMS [32]    | 4/4           | -    | -    | -   | 4.465  | 30.44         | 0.862 | 27.54          | 0.753 | 26.87          | 0.710 | 24.52             | 0.726 |
| DDBT [33]    | 2/2           | -    | -    | -   | 1.721  | 30.57         | 0.867 | 27.56          | 0.757 | 26.91          | 0.714 | 24.50             | 0.728 |
| DDBT [33]    | 3/3           | -    | -    | -   | 2.040  | 31.49         | 0.883 | 28.17          | 0.772 | 27.30          | 0.728 | 25.35             | 0.764 |
| DDBT [33]    | 4/4           | -    | -    | -   | 4.465  | 31.97         | 0.891 | 28.49          | 0.780 | 27.49          | 0.735 | 25.90             | 0.783 |
| Full Precision | 32/32       | -    | -    | -   | 26.800 | 32.14         | 0.893 | 28.44          | 0.778 | 27.52          | 0.733 | 26.12             | 0.786 |

### Table V

The results of binarized SRRResNet with different tail modules at x4 super-resolution. The best results are bolded.

| Tail                  | Set5 PSNR(dB)† | SSIM† | Set14 PSNR(dB)† | SSIM† | B100 PSNR(dB)† | SSIM† | Urban100 PSNR(dB)† | SSIM† |
|-----------------------|----------------|-------|----------------|-------|----------------|-------|-------------------|-------|
| Original Tail         | 29.08          | 0.809 | 26.40          | 0.711 | 26.22          | 0.675 | 23.67             | 0.673 |
| Repeat-Shortcut Tail  | 30.74          | 0.868 | 27.57          | 0.757 | 26.98          | 0.716 | 24.62             | 0.733 |
| Lightweight Tail      | 31.33          | 0.880 | 27.93          | 0.766 | 27.20          | 0.723 | 25.08             | 0.750 |
| Full Precision        | 31.76          | 0.888 | 28.25          | 0.773 | 27.38          | 0.727 | 25.54             | 0.767 |

### Table VI

The results of binarized SRRResNet with different blocks on Urban100 [48] at x4 super-resolution. The best results are bolded.

| Metrics    | Original | Former | Later | Bi-Real |
|------------|----------|--------|-------|---------|
| PSNR(dB)†  | 24.86    | 24.92  | 24.95 | 25.08   |
| SSIM†      | 0.741    | 0.744  | 0.745 | 0.750   |

### Table VII

The results of binarized SRRResNet with cutoff at different position on Urban100 [48] at x4 super-resolution. The best results are bolded.

| Metrics    | 0 | 8 | 16 | 24 | 30 | 31 | Tail |
|------------|---|---|----|----|----|----|------|
| PSNR(dB)†  | 24.91| 25.00 | 25.03 | 24.99 | 24.80 | 24.66 | 23.67 |
| SSIM†      | 0.743 | 0.747 | 0.748 | 0.745 | 0.740 | 0.735 | 0.673 |
5) Analysis of High-Frequency Information Improvement of the Features: We present the visualization results of different methods on the Set14 dataset at x4 scale super-resolution on four structures (i.e. SRResNet, EDSR, RCAN and RDN) in Fig. 8, which are obtained from the input feature map of the first convolutional layer in the tail module. It can be seen from Fig. 8 that our proposed method can better preserve high-frequency information in images and reduce information loss compared to the original comparative method (i.e. Bi-Real). This is mainly because the comparison methods do not optimize the first binary convolutional layer in the tail module, resulting in an input feature map with discrete numerical after passing through the sign function. However, our designed lightweight tail directly removes the first binary convolution layer, so that the input feature map is full-precision and avoids discrete binarization, thus having more numerical diversity and preserving the high-frequency information.

D. Comparison of Deployment Efficiency

As shown in Fig. 1, we compare the inference latency and performance of the proposed E2FIF along with other methods (i.e. Original, Bi-Real, IBTM, LMBN, PDBC) on Oppo realme GT Master Edition mobile phone equipped with a Qualcomm Snapdragon 870 SoC through Bolt, an efficient binary network inference framework. The proposed method achieved the highest and second highest PSNR with half latency due to the lightweight tail module when testing on Urban100 at x4 scale on SRResNet and EDSR architecture, respectively. On the SRResNet [42] network structure, although the reconstruction performance of our proposed 1bit method is in the second place, the inference latency is only 0.2 times that of PDBC [41] which is a two-branch binarized super-resolution method demanding a longer inference time. This is mainly because the designed lightweight tail in our solution discards the convolution operator performed on high-resolution feature

maps compared to the original tail, which reduces the computation and enhances the speed remarkably.

**E. Comparison of Reconstruction Perceptual Metrics**

We compare two image perceptual evaluation metrics (FID [54] and NIQE [55]) with various quantization mechanisms (i.e. BNN, BiReal, DDTB and PAMS) on EDSR structure at x2 scale super-resolution, and on RCAN structure at x4 scale super-resolution on four datasets and the results are shown in Table VIII and IX. The experimental results show that our method still has better perception metrics compared to other binarized super-resolution methods in most
cases. Among them, FID is a full reference image quality assessment measure, which is obtained via calculating the feature similarities between the ground-truth images and the reconstructed ones. Specifically, FID first extracts feature representations of ground-truth and reconstructed image sets in the latent space, and then calculates their Frchet distance. Since FID is a full reference image quality assessment measure, its value is strongly related with the disparity...
between the ground-truth image and the reconstructed one. Lower FID score indicates better reconstruction result, viz., when more information is recovered, the reconstructed image will get a lower FID score. Our proposed E2FIF, with its full-precision information flow, is capable of preserving more high-frequency information in the tail module compared to other methods (the detail can be seen from Fig. 2 together with the relative analysis in section I as well as the visual results and analysis in subsection IV-C.5). As a result, the reconstructed images exhibit a smaller gap with real images, which is reflected in a better FID score.

In contrast, NIQE is a no-reference image quality assessment measure, which first separately models the reconstructed images and nature scene images using multi-variate Gaussian distributions, and then computes their distribution distance. Lower NIQE score usually indicates better visual quality. In our experiments, we can find that the proposed method gets the best NIQE scores in most cases, which benefits from the preservation of high-frequency information.

F. Comparison of Qualitative Results

We visualize the reconstruction results on SRResNet [42] and EDSR [2] architecture in Fig. 9 and Fig. 10 for comparison. As can be seen, the reconstruction results of Repeat-Shortcut Tail and Lightweight Tail much better than that from the Original Tail, and even has no obvious difference with the visual results from its Full-precision counterpart. Compared to the multi-bit quantized super-resolution methods such as DDTB and PAMS, our proposed method can achieve similar or even better visual results. In addition, we also visualize the reconstruction results at \( \times 4 \) super-resolution on RCAN [52] and RDN [53] architecture of different variants. As can be seen from Fig. 11 and Fig. 12, the edge of the super-resolution images reconstructed by the proposed E2FIF is more sharper, and more closer to the result from its full-precision counterpart.\(^1\)

V. CONCLUSION

In this work, we systematically analyzed the BSRNs from an information flow perspective and proposed two guidelines for the BSRNs. Firstly, preserving the integrity of the end-to-end full-precision information flow is necessary for the BSRNs. Secondly, the accurate gradient flow and the full-precision information flow are equally important for an effective binarized convolutional layer. The proposed E2FIF, which is developed based on these guidelines, achieves state-of-the-art performance with adding little computational cost. More importantly, we can effectively binarize any complex SR network with the proposed guidelines.

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