Fully Quantized Image Super-Resolution Networks

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Abstract

With the rising popularity of intelligent mobile devices, it is of great practical significance to develop accurate, real-time and energy-efficient image Super-Resolution (SR) inference methods. A prevailing method for improving the inference efficiency is model quantization, which allows for replacing the expensive floating-point operations with efficient fixed-point or bitwise arithmetic. To date, it is still challenging for quantized SR frameworks to deliver feasible accuracy-efficiency trade-off. Here, we propose a Fully Quantized image Super-Resolution framework (FQSR) to jointly optimize efficiency and accuracy. In particular, we target on obtaining end-to-end quantized models for all layers, especially including skip connections, which was rarely addressed in the literature. We further identify training obstacles faced by low-bit SR networks and propose two novel methods accordingly. The two difficulties are caused by 1) activation and weight distributions being vastly distinctive in different layers; 2) the inaccurate approximation of the quantization. We apply our quantization scheme on multiple mainstream super-resolution architectures, including SRResNet \cite{16}, SRGAN \cite{16} and EDSR \cite{17}. Experimental results show that our FQSR using low bits quantization can achieve on par performance compared with the full-precision counterparts on five benchmark datasets and surpass state-of-the-art quantized SR methods with significantly reduced computational cost and memory consumption.

1. Introduction

The rapid development of Deep Convolutional Neural Networks (CNNs) has led to significant breakthroughs in image super-resolution, which aims to generate high-resolution images from the low-resolution inputs. For real-world applications, the inference of SR is usually executed on edge devices, such as HD television, mobile phones and drones, which require real-time, low power consumption and fully embeddable. However, the high computational cost of CNNs prohibits the deployment of SR models to resource-constrained edge devices.

To improve computation and memory efficiency, various solutions have been proposed in the literature, including network pruning \cite{36}, low-rank decomposition \cite{31}, network quantization \cite{34, 19} and efficient architecture design \cite{11}. In this work, we aim to train a low-precision SR network, including all layers and skip connections. Although current quantization methods have achieved promising performance on the image classification task, training quantized models for more complex tasks such as super-resolution, still remains a challenge in terms of the unverifiable efficiency improvement on hardware and the severe accuracy degradation. For example, to our knowledge, existing quantized SR models typically keep the skip connections to be full-precision, making it impractical to be deployed to embedded devices. In this paper, we introduce Fully Quantized Image Super-Resolution Networks (FQSR), to yield a promising efficiency-versus-accuracy trade-off.

Typically, a common SR network consists of a feature extraction module, a nonlinear mapping module and an image reconstruction module, as shown in \cite{28}. Recently, various quantized SR methods \cite{21, 28} leverage binary quantization on the non-linear sub-module of the SR network, while paying less attention to the quantization of the feature extraction and image reconstruction. However, we observe that the feature extraction and reconstruction modules also account for significant computational cost during inference (e.g., these two sub-modules occupy 45.1\% and 38.7\% of total computational FLOPs in $\times 4$ up-scaling SRResNet and EDSR, respectively). Therefore, it is essential to pay attention to quantize all three sub-modules to obtain more compact models. Additionally, in the SR task, the feature dimensions are usually very high. These features will occupy a huge amount of memories, especially when skip connections exist in the network which require multiple copies of the tensors. Thus, with the quantization of the skip connections, the memory consumption can be saved dramatically (by approximately $8\times$ when compared to the full-precision counterparts). In this paper, we propose to quantize all layers in SR networks to reduce the burden of computation and storage starving SR tasks on resource-limited platforms.
In addition to the fully-quantized design, we further introduce specific modifications with respect to the quantization algorithm for super-resolution. In particular, we empirically observe that the data distributions of the activations and weights of different layers differ drastically for the SR task. For the distribution with a small value range, the corresponding quantization interval should be sufficiently compact in order to maintain appropriate quantization resolution. On the other hand, if the quantization interval is too compact for distribution with a large value range, it may cause severe information loss. Therefore, we propose to learn quantizers that can find the optimal quantization intervals that minimize the task loss. To achieve this, we propose to parameterize the quantization intervals to make quantizers trainable. Specifically, we first estimate the quantization intervals through moving average as the initialization and then optimize them using back-propagation with stochastic gradient descent. Moreover, we also observe that the categorical distribution of quantized values may not fit the original distribution in some layers during training. Thus, we propose a quantization-aware calibration loss to encourage the minimization of the distribution difference.

Our contributions are summarized as follows.

- We introduce fully quantized neural networks for image super-resolution to thoroughly quantize the model including all layers and skip connections. To our knowledge, we are the first to perform fully end-to-end quantization for the SR task.
- We identify several difficulties faced by current low-bitwidth SR networks during training. Specifically, we first propose quantizers with learnable intervals to adapt the vastly distinct distributions of weights and activations in different network layers. To further reduce the quantization error, we also introduce a calibration loss to mimic the categorical distribution after discretization to the original continuous distribution.
- Our extensive experiments with various bit configurations demonstrate that our FQSR is able to achieve comparable performance with the full-precision counterpart, while saving considerable amount of computation and memory usage. Moreover, experiments on mainstream architectures and datasets demonstrate the superior performance of the proposed FQSR over a few competitive state-of-the-art methods.

2. Related Work

Image super-resolution. Super-resolution research has attracted increasing attention in recent years. Since the deep learning based super-resolution is first proposed by Dong et al. [5, 6], a variety of convolutional neural models have been studied. ESPCN [24] is proposed to optimize the SR model by learning sub-pixel convolutional filters. Ledig et al. [16] introduce a Generative Adversarial Networks (GANs) SR model named SRGAN, along with which the generator is described as SRResNet. Lim et al. [17] propose a model named EDSR. Residual channel attention is introduced by Zhang et al. [32] to overcome gradient vanishing problem in very deep SR networks.

Besides, much effort has been devoted to improve the efficiency of the SR models by designing light-weight structures. For example, works in [7, 24] speed up the SR without the upsampling operations. Hui et al. [14] introduce a light-weighted information multi-distillation block into the proposed super-resolution model.

Model quantization. Model quantization aims to represent the weights, activations and even gradients in low-precision, to yield highly compact DNNs. Notably, convolutions and matrix multiplications can be replaced with fixed-point or bitwise operations, which can be implemented more efficiently than the floating-point counterpart. In general, quantization methods involve binary neural networks (BNNs) and fixed-point quantization. In particular, BNNs [23, 13, 35, 19] constrain both weights and activations to only two possible values (e.g., +1 or −1), enabling the multiply-accumulations be replaced by the bitwise operations: xnor and bitcount. However, BNNs usually suffer from severe accuracy degradation. To make a trade-off between accuracy and efficiency, researchers also study fixed-point quantization with higher-bit representation. To date, most quantization studies have employed uniform quantizers and focus on fitting the quantizer to the data, based on statistics of the data distribution [33, 3], minimizing quantization error during training [4, 30] or minimizing the task loss with stochastic gradient descent [15, 8, 34].

In terms of quantization for super-resolution, Ma et al. [21] apply BNNs to compress super-resolution networks. Note that it only proposes to binarize the weights of the residual blocks within the model. Most recently, Xin et al. [28] propose a bit-accumulation mechanism for single image super resolution to boost the quantization performance. Their models are only partially quantized with the feature extraction module, image reconstruction module and skipped connections kept in full-precision. In contrast, our FQSR allows inference to be carried out using integer-only arithmetic, which delivers improved efficiency and accuracy trade-off.

3. Method

3.1. Preliminary

In this work, we propose to quantize weights of all convolutional layers and activations of all the network layers into low-precision values. According to [23, 33], for two binary vector \( a \in \{0, 1\}^N \) and \( b \in \{0, 1\}^N \) within binary neural networks (BNNs), the inner product of them can be
formulated as:
\[ a \cdot b = \text{bitcount}(a \& b), \]
where bitcount counts the number of bits in a bit vector and \& represents the bitwise “and” operation.

More generally, for quantization with higher and arbitrary bit-widths, the quantized values can be viewed as the linear combination of binary bases. Let \( a \) be a \( M \)-bit quantized vector which can be represented as \( a = \sum_{m=0}^{M-1} a_m \cdot 2^m \), where \( a_m \in \{0, 1\}^N \). Similarly, for another \( P \)-bit vector \( b \), we have \( b = \sum_{p=0}^{P-1} b_p \cdot 2^p \), where \( b_p \in \{0, 1\}^N \). Formally, the inner product calculation between \( a \) and \( b \) is
\[ a \cdot b = \sum_{m=0}^{M-1} \sum_{p=0}^{P-1} 2^{m+p} \text{bitcount}(a_m \& b_p). \]

For a general full-precision value \( v \) (activation or weight) to be quantized, an interval parameter is introduced to control the quantization range. The quantization function can be formulated as:
\[
Q(v) = \left\lceil \frac{\text{clip}(v, v_{\text{low}}, v_{\text{up}}) - Q_{\text{min}}}{I} \times (2^M - 1) \right\rceil \times \frac{I}{2^M - 1},
\]
where \( I \) represents the quantization interval, \( 2^M \) presents the quantization levels for \( M \)-bit quantization, \( \lceil v \rceil \) rounds \( v \) to the nearest integer, and \( \text{clip}(v, v_{\text{low}}, v_{\text{up}}) = \min[\max(v, v_{\text{low}}), v_{\text{up}}] \). For unsigned data, \( Q_{\text{min}} = 0 \) and \( Q_{\text{max}} = 1 \); for signed data, \( Q_{\text{min}} = -1 \) and \( Q_{\text{max}} = 1 \). At the end of the equation, a scale factor \( (I/2^M - 1) \) is multiplied to the intermediate results after rounding operation to re-scale the value back to its original magnitude. In our paper, practically, we privatize quantizers for activations and weights in each layer.

During the training process, latent full-precision weights are kept to update the gradients during back-propagation, while being discarded during inference. The gradient is derived by using the straight-through estimator (STE) [1] to approximate the gradient through the non-differentiable rounding function as a pass-through operation, and differentiating all other operations in Eq. (3) normally.

### 3.2. Distribution-Aware Interval Adaptation

In model quantization, the values within the quantization interval \( I \) will be quantized. The quantization process would proceed smoothly if a suitable quantization interval is determined. However, once the quantization interval does not fit in the distribution of values to be quantized, it would incur large quantization error. For the super-resolution task, we empirically find that the data distributions of the features and weights of different layers are drastically different, as shown in Figure 1. Thus, different quantization intervals should be allocated for different quantizers. Toward this end, we propose to estimate the intervals automatically by parameterizing \( I \). To alleviate the optimization difficulty of the interval, we devise to find a good initial point for \( I \) of a quantizer. Specifically, we propose to use the moving average of max values within the tensor \( V_v \) (batch-wise activations or convolutional filters within a layer) to be quantized as the initial point:
\[
I = \frac{1}{l} \sum_{i=0}^{l-1} \max(V_i). \tag{4}
\]

This process is performed at the first \( l \) iterations of the model training as a warmup. Then the parameterized interval \( I \) is optimized in conjunction with other network parameters using backpropagation with stochastic gradient descent. Similar to the training process of [8], the gradient through the quantizer \( Q(\cdot) \) to the quantization interval \( I \) is approximated by STE as a pass-through function.

### 3.3. Fully Quantized Inference

According to [28], the super-resolution process can be divided into three sub-modules: input feature extraction module \( E \), nonlinear mapping module \( M \) and SR image reconstruction module \( R \). Formally, for an input low-resolution image \( lr \), the aforementioned process to generate a super-resolution image \( sr \) can be presented as:
Quantized operations of different methods. Within the table, “✓” represents whether quantization is enabled for the column; “All Layers” include convolutional layers, BN layers, ReLU layers and Element-wise addition layers; “wt” stands for weight quantization of convolutional layers; “fm” denotes the feature map quantization; “sc” denotes the quantization of skip connections.

### Table 1

| Methods       | All Layers | wt | fm | sc |
|---------------|------------|----|----|----|
| SRResNet_Bin [21] | ✓          | ✓  | ✓  | ✓  |
| SRGAN_Bin [21]   | ✓          | ✓  | ✓  | ✓  |
| VDSR_BAM [28]    | ✓          | ✓  | ✓  | ✓  |
| SRResNet_BAM [28] | ✓          | ✓  | ✓  | ✓  |
| FQSR (Ours)      | ✓          | ✓  | ✓  | ✓  |

#### 3.4. Quantization-aware Calibration Loss

As shown in Figure 4, for the super-resolution task, we empirically observe that in some layers, the data distributions before and after quantization change drastically. It will affect the model performance significantly due to the large

Quantization for BN. During the inference phase, if the batch normalization layer is adopted in the quantized model, it can be folded into the preceding convolutional layer to get rid of the extra floating-point operations. The folding of the batch normalization operation is formally presented as:

\[
\begin{align*}
    z &= \gamma \left( \frac{(w \cdot x + b) - \mu}{\sqrt{\sigma^2 + \epsilon}} \right) + \beta, \\
    &= \frac{\gamma w}{\sqrt{\sigma^2 + \epsilon}} \cdot x + \gamma (b - \mu) + \beta, \\
    &= w_{fold} \cdot x + b_{fold},
\end{align*}
\]

where \( w, x \) and \( b \) are the weights, inputs and bias term of the preceding convolutional layer, respectively; \( \mu \) and \( \sigma \) are the mean and standard deviation of the corresponding dimension; \( z \) is the output of the batch normalization layer and \( w_{fold}, b_{fold} \) are the weights and bias after folding, respectively.

Quantization for skip connections. Residual learning is critical to fetch exceptional representations in computer vision tasks. In the residual structural networks, skip connections are the core components to build direct links between shallow layers and deeper ones. Nevertheless, in quantized models, the skip connections carrying floating-point operands will hinder the model to be applied practically on embedding systems or mobile platforms because the quantization status of each layer is inconsistent. In addition, it will inevitably increase the computation as well. Moreover, for the super-resolution task, the input images and the images after super-resolution are usually in very high-resolution (such as 2K or 4K). Therefore, the intermediate features conveyed through skip connections will occupy a huge amount of memorie consumption.

In order to address the aforementioned issues, we quantize the skip connections through quantizing the output features of all convolutional layers and the element-wise addition layers. Consequently, the memory consumption will be saved dramatically (can be saved approximately \( 8 \times \) when compared to the full-precision counterparts). Additionally, if the skip connections are quantized, the models are hardware-friendly since it is fully quantized. Formally, the element-wise addition operation of the skip connection in our quantized network can be formulated as:

\[
y = Q(x) + \text{ReLU}(Q(z)).
\]
Figure 3: The process of the quantization in a typical residual block. In the process, $Q(\cdot)$ represents the quantization function. The input $x$ is the output of the preceding layer/residual block. The outputs of the convolutional layer $z$ and the element-wise layer $y$ are quantized to ensure the quantization of skip connections.

quantization error. In order to solve this issue, an objective function termed as Quantization Calibration Loss (QCL) is adopted to calibrate the values after quantization to have an approximate distribution as before quantization. The QCL loss is able to be applied on input activations, weights and outputs of each layer.

For a real value $v$ to be quantized, here we are targeting to find optimal parameters to minimize the difference of before and after quantization through back-propagation. Formally, QCL is formulated as:

$$L_q = \| Q(v) - v \|_p,$$

(8)

where $\| \cdot \|_p$ denotes the $L_p$ norm.

Therefore the final objective function for the proposed super-resolution quantized networks is:

$$L = L_{sr} + \alpha L_q,$$

(9)

where $L_{sr}$ represents the super-resolution loss and $\alpha$ is a balancing hyperparameter.

4. Experiments

4.1. Experimental Setup

Following the existing works [17, 16, 21, 28], we train our fully quantized super-resolution networks on DIV2K [25] dataset and evaluate models on five prevalent benchmark datasets. Extensive ablation study is further conducted to validate the effectiveness of each component within the proposed method.

Datasets and evaluation metrics. We conduct the model training on DIV2k dataset, which is made up of 800 good quality high/low-resolution image pairs for model training, 100 image pairs for model validation and 100 image pairs for testing. However, the testing HR images for DIV2K is not publicly accessible, so we train models on 800 training images and validate models on 10 validation images. The best validation models are tested on Set5 [2] (5 images), Set14 [29] (14 images), BSD100 [22] (100 images), Urban100 [12] (100 images) and DIV2K (100 validation images). Two scaling settings are considered for model evaluation, containing $\times 2$ and $\times 4$.

For the super-resolution model evaluation, we take the most commonly adopted Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) [27] as our evaluation metrics. All evaluation is performed by cropping $p$ pixels for $\times p$ upscaling.

Implementation details. During training, random vertical/horizontal flips and 90-degree rotation are performed for data augmentation. The model batch size is set to 16 and Adam optimizer is adopted for model optimization. The initial learning rate is set to $1 \times 10^{-3}$ for SRResNet and SRGAN and $5 \times 10^{-5}$ for EDSR model. The models are trained for 300 epochs with cosine annealing [20] learning rate tuning strategy. The hyperparameter $l$ is set to 20 and the trade-off factor $\alpha$ is set to 0.3. The models are implemented using PyTorch with NVIDIA GTX 1080 Ti GPUs. The experimental settings are fixed to all of our trained models to keep fair comparisons.

4.2. Overall Performance

We embed the proposed fully quantized super-resolution scheme on three state-of-the-art architectures, containing SRResNet, EDSR and SRGAN, to compare the effectiveness of low-bitwidth models with full-precision models and bicubic interpolation. The results are shown in Tables 2, 3 and 4.

Evaluation on SRResNet. As shown in Table 2, we implement the FQSR on SRResNet with multiple configura-
tions. When compared to the bicubic interpolation, the 4/4/4 model (i.e., weights, activations and skip connections are all quantized to 4 bits) surpasses it by 0.864 with $\times 2$ up-scaling and 1.542 with $\times 4$ up-scaling for PSNR on Set5 dataset. By raising the skip connection precision to 8 bits, the performances are boosted by a large margin, e.g., 1.814 surpass on Set5 and 1.101 on Set14 for PSNR $\times 2$ up-scaling, respectively. It is worth noting that, on both $\times 2$ and $\times 4$ up-scaling settings, the 6/6/6 and 6/6/8 models achieve comparable results with or outperform the full-precision version of SRResNet. In addition, the 8/8/32 version fully quantized model significantly outperforms the full-precision counterpart by 0.121 and 0.336 on the PSNR metric with Set5 dataset for $\times 2$ and $\times 4$ up-scaling, respectively. The last rows of both $\times 2$ and $\times 4$ up-scaling settings are the lite version 6/6/8 configuration of the proposed FQSR model named as FQSR_Lite, within which the nonlinear mapping $M$ module only consists of 10 residual blocks rather than 16. Thus, we intend to save more computational cost while not losing much performance. On both $\times 2$ and $\times 4$ up-scaling settings, the FQSR_Lite surpasses or receives comparable results with the 6/6/6 configuration but with a less computational cost.

**Evaluation on EDSR.** In the evaluation on EDSR, as shown in Table 3, the 4/4/4 model is able to outperform bicubic interpolation by 0.847 for $\times 2$ and 0.753 for $\times 4$ on Set5. On both $\times 2$ and $\times 4$ up-scaling settings, the 6/6/6 and 6/6/8 models achieve comparable results with the full-precision version of EDSR. The 8/8/8 and 8/8/32 models outperform the full-precision baseline model on most of the metrics. On $\times 2$, 0.131 PSNR improvement on Set14 and 0.216 PSNR improvement on Urban100 are obtained by the 8/8/32 model compared to the full-precision model.

**Evaluation on SRGAN.** The evaluation on SRGAN is shown in Table 4. Similar to the evaluation on SRResNet, the performance of 4/4/4 models achieves better performance than bicubic interpolation on most of the metrics and datasets. Surprisingly, on $\times 2$ setting, the 6/6/8 outperforms the full-precision model on multiple metrics, i.e., 0.075 PSNR improvement on Set5 and 0.189 PSNR boost on Set14 compared with the full-precision model. Moreover, the 8/8/32 model outperforms the full-precision model on most of the metrics.

### 4.3. Comparison with Existing SR Quantization Models

The comparison of the proposed FQSR model with Ma et al. [21] and Xin et al. [28] on SRResNet is shown in Table 2, since they all provide results on SRResNet structure. Worth noting that, in [21], the models are trained 500 epochs for SRResNet and in [28] the learning rate is decreased by half every 200 epoch, while we only train the FQSR model 300 epochs for comparison. With much less training epochs, the proposed FQSR models are able to achieve better performance with less computation cost and memory consumption. Following [18, 26, 9], OPs is the sum of low-bit operations and floating-point operations, i.e., for $M$-bit networks, $\text{OPs} = \text{BOPs} / 64 \cdot M + \text{FLOPs}$. Only the multiplication operations are calculated for OPs. In terms of the memory consumption, because of the existence of long and short skip connections within the networks, we consider the peak memory consumption of each model at the inference stage. Maximally, feature maps of three convolutional layers are considered for SRResNet_Bin and our proposed FQSR networks (one for long skip connection feature storing, one for short connection and another for the main trunk); the features of only one convolutional layer is considered for SRResNet_w/o $M$, since it just consists of three convolutional layers without skip connections. However, in terms of the SRResNet_BAM model, because the activation quantization of each layer takes outputs of several preceding layers into consideration (these activations should be stored for re-using), features of 33 convolutional layers within $M$ are computed. We consider 1020x678 resolution DIV2K dataset images as inputs and $\times 2$ up-scaling as the configuration. The OPs are in the unit G ($=1 \times 10^9$) OPs and Memory consumption is in the unit M ($=1 \times 10^9$) Bytes.

In the table, SRResNet_Bin is the binary SR network from paper [21]. Because only the weights of each layer are quantized, floating-point operations are still required each layer, the OPs and memory consumption will not be reduced. SRResNet_BAM is the bit accumulation model proposed by [28]. It binarizes both the activation and weights of each convolutional layer, so it reduces the OPs and memory consumption in some extent. However, it does not take the quantization of convolutional layers before and after up-sampling into consideration, which introduces huge OPs consumption. This is because in SR models, the convolutional channels should be raised before upsampling and the size of features is increased to their multiples after upsampling operations. SRResNet_w/o $M$ is the model only consists of one convolutional layer within $R$ and two convolutional layers within $\hat{R}$. The results show without $M$, the simple full-precision super-resolution model could achieve promising performance, such that the existence of full-precision sub-net will shrink the significance of model quantization dramatically.

In this case, from the table, we can perceive that with approximately 1/2 of the OPs and 1/50 memory consumption only (6/6/6 model) on $\times 2$ up-scaling, the FQSR model is able to achieve better results on multiple metrics and datasets compared to SRResNet_BAM models. If we increase the bit number, the gaps will be bigger. Finally, our proposed lite version 6/6/8 model is able to receive better results compared to SRResNet_BAM with fewer OPs.
4.4. Ablation Study

Effect of different components. In this section, we examine the effect of each component in our FQSR model. The experimental results are reported in Table 5. We empirically find that the proposed distribution-aware trainable quantization interval in Sec. 3.2 and the calibration loss in Sec. 3.4 are critical for the model to gain promising performance in the super-resolution process. With the trainable quantizers only, the PSNR performance of the baseline model is raised only, the PSNR performance of the baseline model is raised

| Methods                | Scale | wt | fm | sc | OPs          | Memo | Set5       | Set14      | B100       | Urban100   | DIV2K      |
|-----------------------|-------|----|----|----|--------------|------|------------|------------|------------|------------|------------|
| SRResNet [16]         | ×2    | 32 | 32 | 32 | 997.018      | 531.117 | 37.760     | 0.958      | 33.270     | 0.914      | 31.950     |
| Bicubic               | ×2    | 32 | 32 | 32 | -            | -     | -          | -          | -          | -          | -          |
| SRResNet_Bin [21]     | ×2    | p1 | 32 | 32 | 997.018      | 531.117 | 35.660     | 0.946      | 31.560     | 0.897      | -          |
| SRResNet_BAM [28]     | ×2    | p1 | p1 | 32 | 168.894      | 5842.287 | 37.210     | 0.956      | 32.740     | 0.910      | 31.600     |
| SRResNet_w/o M        | ×2    | 32 | 32 | 32 | 155.749      | 177.039 | 36.863     | 0.954      | 32.536     | 0.907      | 31.379     |

Table 2: The comparison between existing methods and our FQSR on SRResNet [16]. The OPs in the unit G Flops and Memory consumption is in the unit M Bytes. Similar as Table 1, “wt” represents weight quantization of convolutional layers; “fm” is the feature map quantization of layers; “sc” denotes the quantization of skip connections; “p1” represents the corresponding models are partially binarized.

| Methods                | Scale | wt | fm | sc | OPs          | Memo | Set5       | Set14      | B100       | Urban100   | DIV2K      |
|-----------------------|-------|----|----|----|--------------|------|------------|------------|------------|------------|------------|
| EDSR [17]             | ×2    | 32 | 32 | 32 | 37.885       | 0.958 | 33.425     | 0.915      | 32.106     | 0.897      | 31.777     |
| Bicubic               | ×2    | 32 | 32 | 32 | 37.885       | 0.958 | 33.425     | 0.915      | 32.106     | 0.897      | 31.777     |

Table 3: The comparison of our FQSR with full-precision networks on EDSR [17] and Bicubic interpolation.
Table 4: The comparison of Fully Quantized Super-resolution networks with full-precision networks on SRGAN [16] and Bicubic interpolation.

| Methods | Scale | wt | fm | sc | Set5 | Set14 | B100 | Urban100 | DIV2K |
|---------|-------|----|----|----|------|-------|------|----------|-------|
|         |       | PSNR | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR | SSIM |
| SRGAN [16] | ×2 | 32 | 32 | 32 | 37.446 | 0.958 | 35.033 | 0.917 | 31.971 | 0.896 | 31.300 | 0.920 | 33.885 | 0.942 |
| Bicubic | ×2 | 32 | 32 | 32 | 33.660 | 0.930 | 30.240 | 0.869 | 29.560 | 0.843 | 26.880 | 0.840 | 31.010 | 0.939 |
| FQSR (Ours) | ×2 | 4 | 4 | 4 | 34.522 | 0.927 | 31.405 | 0.879 | 30.531 | 0.861 | 31.971 | 0.896 | 31.300 | 0.920 |
|         | ×2 | 4 | 4 | 8 | 36.935 | 0.950 | 32.644 | 0.906 | 31.565 | 0.888 | 30.737 | 0.908 | 32.921 | 0.933 |
|         | ×2 | 4 | 8 | 32 | 36.731 | 0.952 | 32.640 | 0.906 | 31.550 | 0.889 | 30.327 | 0.907 | 32.859 | 0.934 |
|         | ×2 | 6 | 6 | 6 | 37.288 | 0.955 | 33.071 | 0.910 | 31.859 | 0.892 | 31.145 | 0.917 | 34.162 | 0.942 |
|         | ×2 | 6 | 6 | 8 | 37.521 | 0.957 | 33.222 | 0.913 | 31.955 | 0.894 | 31.343 | 0.919 | 34.162 | 0.942 |
|         | ×2 | 8 | 8 | 32 | 36.765 | 0.958 | 33.254 | 0.914 | 31.980 | 0.895 | 31.378 | 0.919 | 34.060 | 0.941 |
|         | ×2 | 8 | 8 | 64 | 37.665 | 0.956 | 33.254 | 0.914 | 31.980 | 0.895 | 31.378 | 0.919 | 34.060 | 0.941 |
| SRGAN [16] | ×4 | 32 | 32 | 32 | 31.934 | 0.890 | 28.451 | 0.776 | 27.470 | 0.728 | 25.824 | 0.775 | 28.712 | 0.832 |
| Bicubic | ×4 | 32 | 32 | 32 | 28.420 | 0.810 | 26.000 | 0.703 | 25.960 | 0.668 | 23.140 | 0.658 | 26.660 | 0.852 |
| FQSR (Ours) | ×4 | 4 | 4 | 4 | 29.657 | 0.844 | 27.027 | 0.732 | 26.666 | 0.689 | 24.277 | 0.712 | 26.388 | 0.789 |
|         | ×4 | 4 | 4 | 8 | 30.963 | 0.872 | 27.854 | 0.759 | 27.078 | 0.713 | 24.932 | 0.742 | 27.833 | 0.814 |
|         | ×4 | 4 | 8 | 32 | 31.253 | 0.897 | 27.997 | 0.766 | 27.164 | 0.718 | 25.105 | 0.752 | 27.967 | 0.820 |
|         | ×4 | 6 | 6 | 6 | 31.731 | 0.886 | 28.319 | 0.773 | 27.385 | 0.726 | 25.639 | 0.771 | 28.277 | 0.828 |
|         | ×4 | 6 | 6 | 8 | 31.874 | 0.889 | 28.398 | 0.775 | 27.443 | 0.726 | 25.732 | 0.772 | 28.625 | 0.830 |
|         | ×4 | 8 | 8 | 8 | 32.050 | 0.891 | 28.482 | 0.778 | 27.499 | 0.729 | 25.864 | 0.777 | 28.793 | 0.833 |

Table 5: Ablation study on each component. The experiments are conducted on the 4/4/32 and ×2 up-scaling setting.

| Models | DAIA | QCL | Set5 | Set14 | B100 | Urban100 | DIV2K |
|--------|------|-----|------|-------|------|----------|-------|
|        |      | PSNR | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR | SSIM |
| 1      |      | 35.536 | 0.944 | 31.775 | 0.898 | 30.972 | 0.883 | 28.893 | 0.888 | 31.792 | 0.926 |
| 2 ✓    |      | 36.372 | 0.945 | 32.395 | 0.901 | 31.397 | 0.884 | 30.164 | 0.902 | 32.455 | 0.927 |
| 3 ✓ ✓  |      | 36.854 | 0.953 | 32.71 | 0.908 | 31.583 | 0.89 | 30.43 | 0.909 | 32.985 | 0.935 |

5. Conclusion

In this paper, we have proposed a fully quantized super-resolution framework, including all network layers and skip connections, as a practical solution to achieve a good trade-off between the accuracy and efficiency. We have also identified multiple difficulties faced by current low-bitwidth SR networks during training, which are 1) activation and weight distributions being vastly distinctive in different layers; 2) the inaccurate approximation of the quantization. To tackle these challenges, we have first proposed a distribution-aware interval adaptation strategy to automatically decide the quantization intervals during training. We have further proposed a quantization calibration loss to explicitly minimize the quantization error. We have evaluated our method on multiple state-of-the-art deep super-resolution models on five benchmark datasets. The extensive experimental results have shown that our proposed FSQR is able to achieve the state-of-the-art results while saving considerable computational cost and memory usage compared to the full-precision counterparts and competing methods.

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