Supplementary for Hierarchical Conditional Flow: A Unified Framework for Image Super-Resolution and Image Rescaling

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In this supplementary, we first give more details on flow layers used in our framework. Then, we analyze the influences of sampling temperatures and random sampling. Last, we show more visual results on general image SR, face image SR and image rescaling.

1. Flow Layer Details

1.1. Squeeze Layer

Squeeze layer \cite{3} is used to increase the number of channels by trading the spatial size. It reshapes each $2 \times 2$ neighborhood to the channel dimension. The input and output tensor sizes are $H \times W \times C$ and $\frac{H}{d} \times \frac{W}{d} \times 4C$, respectively. This layer is only used in image SR.

1.2. Haar Transform Layer

Haar transform layer \cite{9} is an alternative to the squeeze layer. We use this layer to replace the squeeze layer for image rescaling. Based on low-pass filtering, it decomposes a $H \times W \times C$ input into a $\frac{H}{2} \times \frac{W}{2} \times C$ low-pass representation and three $\frac{H}{2} \times \frac{W}{2} \times C$ residual components, which contains high-frequencies in vertical, horizontal and diagonal directions, respectively.

1.3. Actnorm Layer

Actnorm layer \cite{5} is used for channel-wise normalization. Similar to batch normalization \cite{4}, it is an affine transformation with learnable scale and translation parameters.

1.4. Invertible $1 \times 1$ Convolution Layer

Invertible $1 \times 1$ convolution layer \cite{5} is a generalization of the channel permutation operation. With learnable parameters, it can better help each dimension affect every other dimension. In image rescaling, to divide the LR image and the rest high-frequencies apart from early flow layers, we remove this layer from the flow-steps of the main flow branch, and simply exchange the first 3 channels and the rest channels as a permutation operation.

1.5. Affine Coupling Layer

Affine coupling layer \cite{3} first splits the input $h^k$ into two partitions $h^k_{1:d}$ and $h^k_{d+1:D}$ along the channel dimension. Then, the output $h^{k+1}$ are computed as follows,

$$
\begin{align*}
    h^{k+1}_{1:d} &= h^k_{1:d} \\
    h^{k+1}_{d+1:D} &= h^k_{d+1:D} \odot \exp(s(h^k_{1:d}, u)) + t(h^k_{1:d}, u)
\end{align*}
$$

where $s$ and $t$ are the scale and translation functions. $\odot$ represents the Hardmard product. Generally, scale and translation functions are implemented by a single small neural network whose input and output dimensions are $d$ and $2(D - d - 1)$, respectively. In experiments, we use three convolutional layers with ReLU activation functions for image SR, and use a RRDB block \cite{7} for image rescaling.

Generally, $h^k$ is evenly split by setting $d = \frac{D}{4}$. For image rescaling, we set $d$ to 3 or $D - 3$ alternatively to divide the low-frequencies and the high-frequencies apart from early flow layers. We also find that using translation operation is enough when we are transforming the low-frequencies (i.e., when $d = D - 3$).

1.6. Conditional Affine Coupling Layer

Conditional affine coupling layer \cite{2, 8} helps to construct conditional flows by taking the conditioning variable $u$ as an input of the affine coupling layer. It is formulated as follows,

$$
\begin{align*}
    h^{k+1}_{1:d} &= h^k_{1:d} \\
    h^{k+1}_{d+1:D} &= h^k_{d+1:D} \odot \exp(s(h^k_{1:d}, u)) + t(h^k_{1:d}, u)
\end{align*}
$$

where the concatenation of $u$ and $h^k_{1:d}$ is used as the input of scale and translation functions.

1.7. Split layer

Split layer \cite{3} is used to split the tensor into two partitions. After the squeeze operation and other transformations, the $\frac{H}{2} \times \frac{W}{2} \times 4C$ tensor is split to two $\frac{H}{2} \times \frac{W}{2} \times 2C$
2. Influence of the Sampling Temperature

As analyzed in the paper, sampling temperature has great impact on both PSNR and visual metrics. We show the SR images sampled with different temperatures in Fig. 1. As we can see, HCFLow achieves best PSNR when \( \tau = 0 \), though the images tend to be blurry. When \( \tau \) is increased, the visual quality is improved, at the cost of dropping PSNR. When \( \tau = 0.8 \), HCFlow generates the most visual-pleasing images with clear edges and photo-realistic details. When \( \tau \) is further increased to be 0.9 or 1.0, the generated images may be over-sharpened and suffer from artifacts.

3. Influence of Random Sampling

In Fig. 2, we show diverse photo-realistic SR results of HCFlow by randomly sampling from the latent space. The sampling temperature \( \tau \) is set to 0.8. As can be seen, different samples of the latent variable lead to SR images with different details such as eyes and eyebrows. Note that most of these SR images are visual-pleasing and consistent with the LR image.

4. More Visual Comparisons

We provide more visual comparisons on general image SR, face image SR and image rescaling in Fig. 3, Fig. 4 and Fig. 5 respectively, to clearly show the effectiveness of the proposed HCFlow.

References


Figure 3: More visual results of general image SR (×4) on the DIV2K [1] validation set.

Figure 4: More visual results of face image SR (×8) on the CelebA [6] testing set.
Figure 5: More visual results of image rescaling ($\times 4$) on the DIV2K [1] validation set. The first, second and third columns show the LR images generated by bicubic interpolation, IRN and HCFlow, respectively.


