Supplementary Materials

"Iterative Projection Reconstruction for Fast and Efficient Image Upsampling"

Yang Zhao, Ronggang Wang, Wei Jia, Wenmin Wang, and Wen Gao

1. Discussions of the weights $\boldsymbol{\omega_i}$

We have compared several kinds of weights ω_i. Some different definitions of weights are listed as follows,

- Constant weights: $\omega_i = 1 \quad (i = 1, 2, 3, \cdots N)$, where N denotes the total number of iterations.
- Average weights: $\omega_i = \frac{1}{N}$, $(i = 2, 3, \cdots N)$, $\omega_1 = 1$.
- Decreasing weights: $\omega_i = \frac{\omega_{i-1}}{\beta}$, $(i = 2, 3, \cdots N)$, $\omega_1 = 1$, where β is an artificial parameter.
- The proposed parameter-free weights ω_i defined as in Eqn. (17).

The average PSNR and SSIM values of the IPR with different kinds of weights are illustrated in the Fig. S-1 and Fig. S-2, respectively. From these figures it can be found that the proposed weights can obtain comparable or better performance than other weights. In addition, the proposed weights are non-parametric, and we don't have to select the optimal parameters. As a result, the weights ω_i are simply defined as in Eqn. (17).

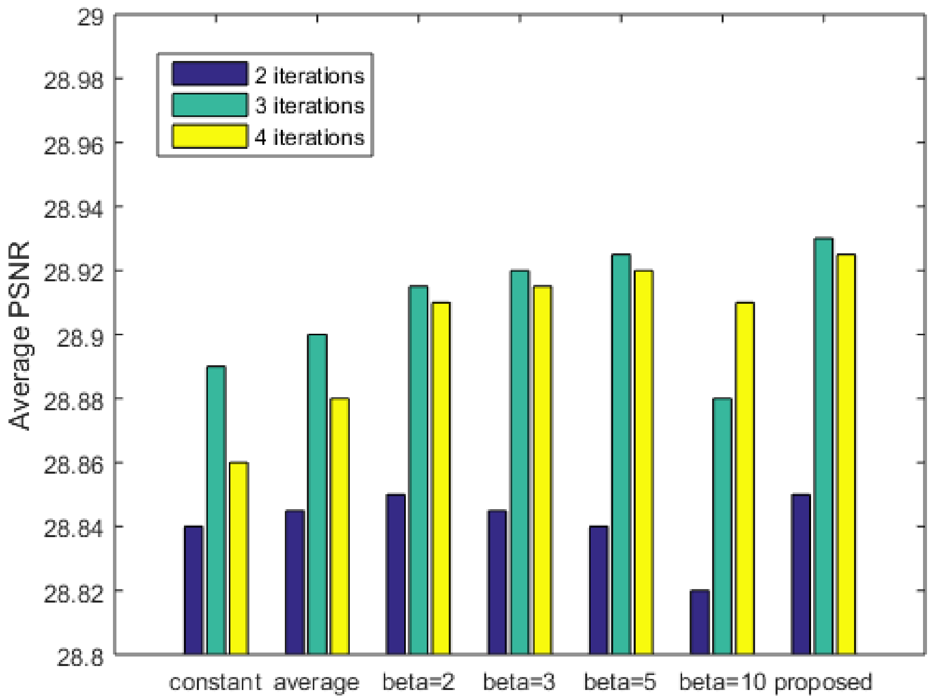

Fig. S-1. Average PSNR values of IPR (3X) results on ‘Set14’ with different weights.

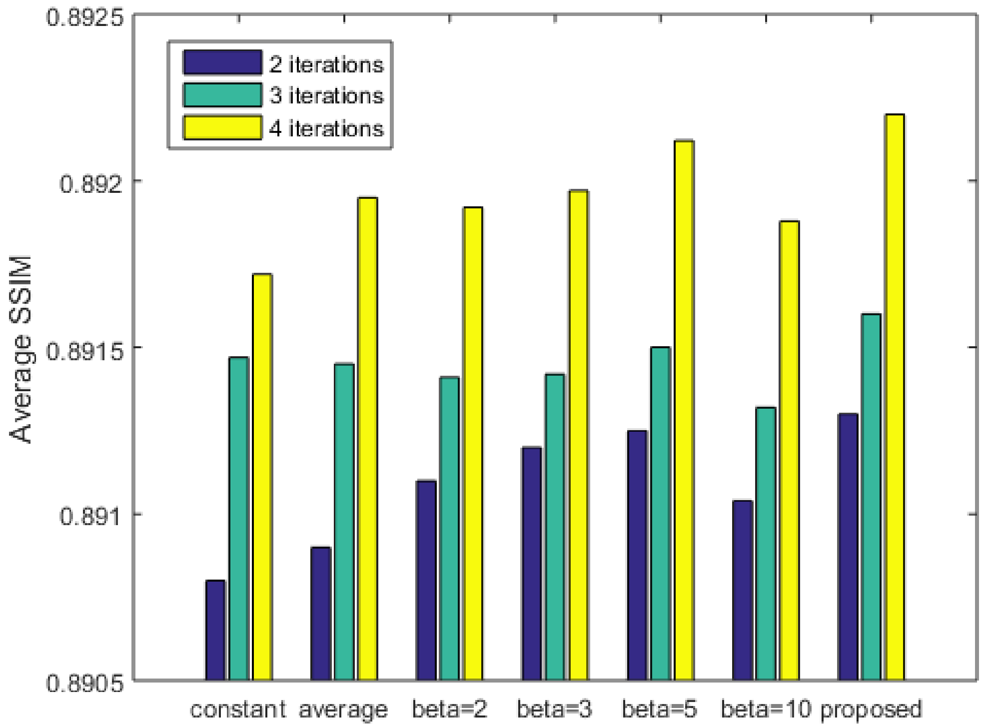

Fig. S-1. Average SSIM values of IPR (3X) results on ‘Set14’ with different weights.

2. Extended experiments for depth-image upsampling

Recently, depth-image upsampling has drawn many attentions [50]-[52]. We thus implemented some extended experiments for the depth-image upsampling scenario.

Firstly, we directly apply the proposed IPR for depth-image upsampling. Test images of “Art”, “Books”, and “Moebius” are used as in [51]. Since the depth-images are with low-quality and low-resolution, we utilized the BM3D filter to reduce the noise and then apply the IPR method to obtain the HR depth-image. Table S-1 listed the upsampled results with different methods. Ferstl’s method [51] slightly outperforms the proposed BM3D+IPR method. It should be noted that the proposed BM3D+IPR method does not need extra HR RGB images. These experimental results demonstrate that in some scenarios, e.g., only LR depth-images can be captured, the proposed method can be an effective way to directly upsample the depth-image with small magnification factors.

Table S-1. Depth-image upsampling results with different methods

Methods	**Art**				**Book**				**Moebius**			
	2X		4X		2X		4X		2X		4X	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bicubic	33.62	0.9376	32.47	0.8680	29.16	0.8660	28.36	0.8344	28.77	0.8660	25.20	0.8376
Bilinear	33.93	0.9502	33.14	0.9008	28.83	0.8904	28.47	0.8723	28.41	0.8909	25.37	0.8761
NN	31.81	0.9502	30.64	0.8795	27.81	0.8904	27.48	0.8483	27.59	0.8909	23.27	0.8513
Ferstl’s[51]	**35.41**	**0.9882**	**32.77**	**0.9728**	**29.70**	**0.9538**	**28.92**	**0.8871**	**29.59**	**0.9632**	**26.73**	**0.9175**
BM3D+IPR	35.36	0.9811	32.57	0.9684	29.59	0.9472	28.67	0.8823	29.52	0.9603	26.46	0.9125

Secondly, we implement related experiment for another scenario. Some works [50], [51] utilize HR RGB image to refine the upsampled depth-image. But if the RGB image is also with low-resolution, will the super-resolution methods be helpful to these works? To answer this question, we firstly upsampled the LR RGB image to a HR RGB image by means of proposed IPR, and then we applied Ferstl’s method [51] to upsamle the depth-images with the reconstructed HR RGB images. Table S-2 listed the results of same Ferstl's method [51] by means of the RGB images upsampled with different methods. We can find that although using the RGB images upsampled with IPR method are slightly worse than using original HR RGB image. It still performs much better than that using the simply interpolated RGB images.

Table S-2. Depth-image upsampling results (2X magnification) with different RGB images

Methods	**RGB image**	**MSE**
Bicubic	Full size	4.16
Bilinear	Full size	3.59
NN	Full size	5.01
Ferstl's [51]	Full size	**2.18**
Ferstl's [51]	2X magnification with bicubic	2.39
Ferstl's [51]	2X magnification with ANR	2.31
Ferstl's [51]	2X magnification with IPR	2.28
Ferstl's [51]	4X magnification with bicubic	2.67
Ferstl's [51]	4X magnification with ANR	2.57
Ferstl's [51]	4X magnification with IPR	2.50

3. Future work

This work is focused on refining the HF components during the upsampling process. However, it is still very difficult to recover the HF details from a LR input, especially when the magnification factor is large. As illustrated in Fig. 3 and Fig. 10, texture area is totally blurred after the 4X upsampling. Hence, we plan to propose a co-upsampling method to further refine the magnified texture in our future work.

In some scenario, similar HR image of a LR image can be obtained. For example, the key frames in Video-Codec are with HR while the other frames are with LR; people may need to magnify some photos and his another HR photo can be obtained; etc. In these scenarios, we can use another similar HR image to assist the image upsampling. However, the dictionary based single-image super-resolution method may be not very suitable for this condition. Hence, we planned to apply the local-self-exemplar framework to solve this co-upsampling problem. The main principle is simply described as follows,

- Given a LR image $\boldsymbol{Y}$ and similar HR image $\boldsymbol{X_H}$;
- Generate the $\boldsymbol{X_L}$ by downsampling $\boldsymbol{X_H}$;
- For each patch $\boldsymbol{y}$ in $\boldsymbol{Y}$, find its similar patch $\boldsymbol{x_l}$ in $\boldsymbol{X_L}$;
- Calculating the HF residual $\boldsymbol{R}$ between interpolated $\boldsymbol{x_l}$ and its corresponding HR patch $\boldsymbol{x_h}$;
- Adding the residual $\boldsymbol{R}$ to the interpolated $\boldsymbol{y}$ to estimate its final HR patch.
- After HR patch of each input patch has been computed, the final HR reconstructed image $\boldsymbol{X}$ then can be obtained.