Fast single image super-resolution based on sigmoid transformation

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Abstract—Single image super-resolution aims to generate a high-resolution image from a single low-resolution image, which is of great significance in extensive applications. As an ill-posed problem, numerous methods have been proposed to reconstruct the missing image details based on exemplars or priors. In this paper, we propose a fast and simple single image super-resolution strategy utilizing patch-wise sigmoid transformation as an imposed sharpening regularization term in the reconstruction, which realizes amazing reconstruction performance. Extensive experiments compared with other state-of-the-art approaches demonstrate the superior effectiveness and efficiency of the proposed algorithm.

Index Terms—single image super-resolution, sigmoid transformation, sharpening regularization

I. Introduction

SUPER-resolution (SR) has been widely applied in video surveillance [1][2][5], remote sensing [3][4][5][35], medical imaging [6][7] and many other fields, enhances the image resolution and provides pleasing image details, which is significant for subsequent image processing. Aiming to upscale the image resolution based on single image [12], single image super-resolution (SISR) requires generating severalfold data from limited input data to approach natural images, which is badly ill-posed and often suffers from annoying blurring and artifacts.

To alleviate the ill-posed problem of SISR, many algorithms have been proposed to exploit additional information to learn how natural images are, which improves the reconstruction performance efficiently. Considering the difference between natural image information sources, the algorithms can be roughly subdivided into dictionary-based methods [9][17][18][33][34], self-exemplar-based methods [15][20][32] and prior-based methods [13][14][16]. Dictionary-based methods refer to external high resolution (HR) and corresponding low resolution (LR) image pairs as exemplars to hallucinate the missing details, which requires large scale databases to cover possible relationship between LR images and HR images. As external-exemplars-based methods are time-consuming in training procedure, self-exemplar-based methods assume redundancy of patches within the single image and utilize recurrent local similar patches as exemplars to exploit underlying image details. Unlike dictionary-based and exemplar-based, prior-based methods utilize priors as constraints to alleviate the ill-posedness, perform robustly and efficiently with no relying on exemplars.

Interpolation methods [22][23][26] as the simplest prior-based methods, utilize analytical interpolation formulae like bicubic scheme to predict new pixels based on local pixels, however the spline functions may not match natural images with strong discontinuities and lead to ringing artifacts along the edges. Smoothness prior [24][25] as another widely used category of image prior, regularizes the first or higher derivatives of the reconstructed image, suppressing the additional noises effectively but leading to transparent blurring. Recently sparsity deduced priors [14][21][27][28][31] have been extensively investigated which assume local image patch can be sparsely represented by linear combination of over-complete dictionary, however the sparsity assuming losses texture and other image details. To alleviate the blurring effect of edges in SISR, edge-based priors [11][13][16] are introduced to SISR and realize outstanding sharpening and deblurring effect. Fattal [11] proposed an edge deduced prior based on statistics of edge features, imposed the local continuity measures in the upscaled image to match the statistics learned from HR and LR image pairs. Sun [13][16] proposed a novel gradient profile prior, utilized 1-D profiles of gradient magnitudes to describe the gradient structure with a parametric gradient profile model learned from a large scale of natural images.

Considering upscaling leads to little degradation in flat region and dominant deterioration is mainly concentrated in edge and texture regions performing as blurring effect, we are motivated to utilize sharpening operation to alleviate the degradation with no relying on external exemplars. In this paper we propose an adaptive patch-wise sigmoid transformation to realize appropriate sharpening of the upsampled image, then utilize the sharpened image as an imposed regularization in the reconstruction and realize amazingly effective deblurring and sharpness enhancement. Different from [13][16] implementing the sharpening process in gradient space, our patch-wise method utilizes sigmoid function to match the slope of local intensities directly and steepens the slope with sigmoid transformation, which is similar to the image enhancement in [29][30]. With this simple but effective process, our method produces state-of-the-art SISR results with superior processing efficiency, and the reconstructed images are sharp and distinct with rare artifacts.

The remainder of this paper is organized as follow: In Section II we first introduce the patch-wise sigmoid transformation. Then in Section III we present the SISR framework based on sigmoid transformation. Extensive experiments are conducted comparing with state-of-the-art algorithms in Section IV. Finally the conclusions are drawn in Section V.
II. PATCH-WISE SIGMOID TRANSFORMATION

In this section, the proposed patch-wise sigmoid transformation is presented and analyzed. We first formulate the sigmoid transformation, then perform parametrical analysis and finally compare our sharpening operation to other edge enhancement methods.

A. Formulation

In our scenario, the sharpening operation is implemented directly in image space instead of gradient space. Considering the continuity of natural images in local region, extracted local image patch can be regarded as a slope and the sharpening operation is equivalent to steepening the patch-wise slope intuitively. From the sketch of sigmoid function \( f(x) = 1/(1 + \exp(-a(x+b))) \) shown in Fig. 2, we can see that sigmoid functions with varying parameter pairs \( a \) and \( b \) perform as superior characterizations of slopes with ranged steepness and location, therefore we are motivated to choose it as fitting function to characterize patch-wise slope, and the slope-based steepening can be realized through simple parametrical transformation.

As shown in Fig. 2, the value of sigmoid function \( f(x) = 1/(1 + \exp(-a(x+b))) \) ranges from 0 to 1, therefore the intensities within the patch need to be normalized first for subsequent sigmoid transformation.

\[
y_{i,\text{patch}} = \frac{z_i - \min_{j \in \text{patch}}(z_j)}{\max_{j \in \text{patch}}(z_j) - \min_{j \in \text{patch}}(z_j)},
\]

where \( z_i \) is the intensity of location \( i \), \( y_i \) represents the normalized value, and \( \min_{j \in \text{patch}}(z_j), \max_{j \in \text{patch}}(z_j) \) refer to the minimum and maximum of the patch respectively. To avoid \( y_i \) equals to 0 or 1, we utilize a small constant \( \varepsilon \) set to be 0.01 to fine-tune the maximum and minimum as

\[
\begin{align*}
\min_{j \in \text{patch}}(z_j) &= \min_{j \in \text{patch}}(z_j) - \varepsilon, \\
\max_{j \in \text{patch}}(z_j) &= \max_{j \in \text{patch}}(z_j) + \varepsilon.
\end{align*}
\]

With normalization operation implemented, sigmoid function \( f_0(x) = 1/(1 + \exp(-a_0(x+b_0))) \) is introduced to fit the normalized residuals \( y_i \) to derive corresponding \( x_i \) values

\[
y_i = f_0(x_i) \Rightarrow x_i = \frac{\ln(\frac{1}{y_i} - 1)}{-a_0} - b_0,
\]

and then we transform \( x_i \) to sharpened residuals \( y'_i \) with sharpened sigmoid function \( f_1(x) = 1/(1 + \exp(-a_1(x+b_1))) \)

\[
y'_i = f_1(x_i) = \frac{1}{1 + \exp\left(\frac{1}{x_i} - 1\right) - a_1(b_0 - b_1)}
\]

Note that all intensities within the image patch are fused together for operation in this process, leading to strong robustness to noises and undulation.

Finally we re-quantify the sharpened residuals \( y'_i \) to derive sharpened intensities \( z'_i \)

\[
z'_i = y'_i \times C_i + \min_{j \in \text{patch}}(z_j)
\]

where \( C_i = \max_{j \in \text{patch}}(z_j) - \min_{j \in \text{patch}}(z_j) \) represents the normalization constant.

As we can see from (4), the patch-wise sigmoid transformation can be regarded as a four-parameter problem, namely the sharpened image patch can be derived as parameters \( \{a_0, \ a_1, \ b_0, \ b_1\} \) determined. Further observe (4), we can see it can be rewritten as

\[
y'_i = \frac{1}{1 + \exp\left(\frac{1}{y_i} - 1\right) - a_0/b_0} = g(y_i; K, B)
\]

where

\[
\begin{align*}
K &= \frac{a_1}{a_0}, \\
B &= a_1(b_0 - b_1)
\end{align*}
\]

Then the overall sigmoid transformation also degenerates into a two-parameter function as

\[
z'_i = h(z_i; K, B)
\]

where \( K \) determines the steepness of the sigmoid function while \( B \) determines the location, namely the non-symmetry of the sigmoid function. The overall process of sigmoid transformation is illustrated in Fig. 1.
Considering patch-wise sigmoid transformation may generate block artifacts at the boundary between adjacent patches, we further utilize an overlapping strategy with Hanning window during implementation as shown in Fig. 3, and compute the mean value of overlapped pixels as the final sharpened results. As we can see, to implement the patch-wise sigmoid transformation with overlapping strategy, additional two parameters need to be determined, the size of image patch \( l_{\text{patch}} \) and the stride \( r_{\text{patch}} \).

**B. Parametrical analysis**

As analyzed above, totally four parameters consisting of \( K, B, l_{\text{patch}} \) and \( r_{\text{patch}} \) need to be determined for sigmoid transformation. In this part, the parameters are analyzed respectively and empirically determined, while more experimental results are exhibited in Section V.

- **Sharpness \( K \)**
  
  Remembering parameter \( K \) in (6) determines the steepness of the sigmoid function, it affects the sharpness and width of the edges directly. As we can see from left to right by row in Fig. 4, varying values of \( K \) lead to ranged sharpening effects, the larger \( K \) is, the sharper and narrower edges are. Moreover, it can be seen the sigmoid transformation performs as a blurring operation with smoothed and widened edges for \( K < 1 \), while performing as a sharpening operation with sharper and narrower edges for \( K > 1 \). Under the condition of \( K = 1 \), sigmoid transformation performs no sharpening or blurring with slope information well preserved in the results. Considering the requirement of image sharpening with computational cost, we empirically set \( K = 2 \) in this paper.

- **Location \( B \)**
  
  Different with \( K \), parameter \( B \) determines the location of the sigmoid function as shown in Fig. 2, namely affects the extension of the edges. After down sampling operation, some edges may not locate at the center of LR pixel, which is often the case especially when upsampling factor \( k \) is large. As shown in Fig. 4, we can see from top to bottom by column that the edges with varying values of \( B \) are displaced along the vertical direction, and the sign of \( B \) determines the direction. For \( B < 0 \) shown in the first row, the edges are displaced along the gradient direction, while displaced opposite to the gradient direction for \( B > 0 \) shown in the last row. Under the condition of \( B = 0 \), the edges are supposed to locate exactly at the center of pixel in LR image with no displacement during sharpening operation. Considering sub-pixel locations of edges in LR image vary between regions and are hard to estimate, especially when \( k \) is large, therefore we empirically set \( B = 0 \) in this paper for simplicity.

- **Patch size \( l_{\text{patch}} \) and stride \( r_{\text{patch}} \)**
  
  As a patch-wise slope-based sharpening operation, sigmoid transformation requires the patch size \( l_{\text{patch}} \) to cover complete slope information without disturbing information. Considering over-large patch size may introduce extra disturbing information and over small patch size may lose slope information, both leading to degradation of sharpening effect and generation of annoying artifacts, we empirically set \( l_{\text{patch}} = 3 \) in LR space to cover the neighboring information with little loss of slope information. To reduce the block artifacts at the boundary between patches, stride \( r_{\text{patch}} \) is required to cooperate with patch size \( l_{\text{patch}} \) to guarantee the compatibility between adjacent patches. Considering the computational cost, in this paper we empirically set...
\( r_{\text{patch}} = 1 \) in LR space for efficiency, namely \( r_{\text{patch}} = k \) in HR space.

**C. Relationship to other edge enhancement methods**

As a generic edge-based prior for super-resolution, the proposed sigmoid transformation performs similarly with other edge enhancement methods. In this part, we discuss the relationship and inherent difference between the proposed sigmoid transformation and other representative edge enhancement methods.

Fattal [11] proposed an edge statistics prior for image upsampling, namely edge-frame continuity modulus (EFCM), which is learned to characterize the marginal distribution of the gradients over the whole image. However, the imposed constrain on local continuity measures may not fit varying types of edges and generate jaggy artifacts, besides the computational cost is considerable as reported in [11].

Sun [15][16] establish a generic prior called gradient profile prior, and proposed gradient field transformation to transfer image gradient field guided by the prior knowledge learned from large training sets. However, the gradient profile only utilizes the pixel information along the gradient direction with local image structure neglected, leading to susceptibility to noises and undulation.

Shock filter is another representative category of edge enhancement approach, which is commonly designed to enhance edges detected by edge detectors. Recently, shock filter has been introduced into SR applications [] performing as an edge enhancement operation. However, as shock filter is sensitive to noise, the noise is supposed to be amplified while enhancing the edges.

Compared with other edge enhancement methods, the proposed sigmoid transformation performs twofold distinct differences or advantages. Firstly, the sigmoid transformation performs patch-wise and slope-based, namely the sharpening operation is based on local image structure, which is more reasonable with better suppression of noise. Secondly, our method performs superior efficiency, which is further demonstrated in Section IV.

**III. SISR FRAMEWORK BASED ON SIGMOID TRANSFORMATION**

In our scenario, the SISR process is realized through typical iterative reconstruction [21][27], where the patch-wise sigmoid transformation performs as an imposed sharpening regularization cooperating with the reconstruction errors.

Given an HR image \( X \) and a corresponding LR image \( Y \), the degradation process can be formulated as

\[ Y = DHX + N \]  

where \( H \) is the blurring operator, \( D \) determines the decimation matrix and \( N \) represents the additional Gaussian noise in \( Y \). To realize the restoration of HR image \( X \), we integrate the patch-wise sigmoid transformation as a sharpening regularization term with the reconstruction error in the cost function as

\[ X = \arg \min_{X} \{ \| DHX - Y \|^2 + \lambda \| X - Z \|^2 \} \]  

where \( Z \) serves as a sharpened image of \( X \) utilizing the proposed patch-wise sigmoid transformation.

To solve the minimization problem in (9), we refer to our previous work in [] and utilize the fast upsampling technique in our SISR framework

\[ X_{l+1} = X_{l} - \eta \left( U(DHX_{l} - Y) + \lambda \left( X_{l} - Z_{l} \right) \right) \]  

where \( X_{l}, X_{l+1} \) are estimators of HR image \( X \) in \( l^{th} \) and \( l + 1^{th} \) iteration respectively, \( \lambda \) represents the regularization parameter weighting the regularization cost against the reconstruction error, \( \eta \) serves as the stepsize and \( U(\cdot) \) refers to the upsampling technique proposed in [37].

The overall framework is shown in Fig. 5 and further summarized in algorithm 1.

**Algorithm 1: SISR based on sigmoid transformation**

**Input:** LR image \( Y \), scaling factor \( \gamma \)
**Initialize:** Upscale the LR image \( Y \) utilizing interpolation method with bicubic spline to obtain original HR image \( X^0 \)
**Do:**
1) Re-degenerate the HR image \( X^{l-1} \) and compute the reconstruction error \( (DHX^{l-1} - Y) \), then utilize the upsampling technique [37] to upscale the reconstruction error;
2) Compute the sharpened image \( Z^{l-1} \) based on \( X^{l-1} \) utilizing the proposed patch-wise sigmoid transformation, then derive the difference between \( X^{l-1} \) and \( Z^{l-1} \) as a regularization term;
3) Update \( X^{l-1} \) to derive \( X^{l} \) according to (10).
**Until:** Stopping criteria are satisfied
**Output:** Reconstructed HR image \( X \)

**IV. EXPERIMENTAL RESULTS**

**Implementation:** As human vision is more sensitive to
brightness change, we only apply our method on brightness channel (Y) with color channels (UV) upscaled by bicubic interpolation for color images. In our experiments, the HR images are firstly blurred by a $7 \times 7$ Gaussian kernel with $\sigma = 1.2$, and then downsampled with factor $k = 3$ to serve as the input LR images. During the implementation of our method, regularization parameter $\lambda$ and learning rate $\eta$ are set to be 0.2 and 0.1 respectively, while the maximum number of iterations specified as 30.

All the experiments are coded in Matlab R2011 and running on a workstation with Septuple Core i7 @ 3.60 GHz CPUs and 16GB RAM.

**Metrics:** To evaluate and compare the results quantitatively, peak-signal-to-noise ratio (PSNR) and mean structure similarity (SSIM) are utilized as metrics, which are defined as

\[
\begin{align*}
PSNR &= 10 \log_{10} \left( \frac{255^2}{MSE} \right), \quad MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (Y(i,j) - X(i,j))^2, \\
SSIM &= \frac{(2\mu_X\mu_Y + c_1)(2\sigma_{X,Y} + c_2)}{\mu_X^2 + \mu_Y^2 + \sigma_X^2 + \sigma_Y^2 + \sigma_{X,Y}^2 + c_2}
\end{align*}
\]

where $\mu_X, \mu_Y$ are mean value of image $X$ and $Y$ respectively, $\sigma_X, \sigma_Y$ are standard variance of $X$ and $Y$ respectively. $c_1, c_2$ are two stabilizing constants with $L$ representing the dynamics of a pixel value, and $k_1, k_2$ are generally set to be 0.01 and 0.03 respectively.

**A. Experimental analysis of parameters**

In this section, we focus on the sharpness parameter $K$ and location parameter $B$, conduct extensive experiments on Set5 and Set14 datasets to test the effects of our method with various parameter settings.

![Fig.6 Effect of parameter K on image PPT and Comic. The images are reconstruction results (3X) with $K=2,3,4$.](image)

![Fig.7 Effect of parameter B on image Foreman and Lenna. The images are reconstruction results (3X) with $B = -1,0,1$.](image)

Comparison of quantitative performance is exhibited in Table. 1 with average performance presented in Fig. 8. As sharpness parameter $K$ increases, the reconstruction performance is first improved and then begins to deteriorate due to the over-sharp effects. Concerning location parameter $B$, obviously it has great impacts on the performance with $B = 0$ performing as the dominant one. However, note that it does not mean no benefits of $B$ in fine-tuning the locations of edges, which can be validated by some superior results in Table. 1 with $B \neq 0$. As edges within an image varies remarkably, the fine-tuning is required to implement adaptively, nevertheless, the global selection of $B$ and implementation of fine-tuning in our scenario may not adapt to most edges, commonly leading to degeneration of reconstruction performance.

Note that the adaptive selection of $K$ and $B$ is not the
focus of this paper, we empirically set $K = 2$ and $B = 0$
for following experiments and leave this problem for further
investigation.

B. Comparison to other methods

In this section, experiments are conducted on Set5 and Set14
datasets to compare the reconstruction performance of other
state-of-the-art approaches, including bicubic, Kim et al.’s
method [14], Zeyde et al.’s method [31], Timofte et al.’s
method [18] and Yang et al.’s method [28]. Dong et al.’s
method [36], Sun et al.’s method [16] and Yang et al.’s
method [17]. The source codes of approaches [14][31][18]
[28][17][36] are downloaded from the authors’homepages,
and we refer to Yang’s implementation work in [19] to derive
other approaches [10][13][16] for no available originally re-
leased codes. Recommended parameters of comparing
methods by the authors are used in our experiments.

We summarize the parameter settings for our method in
Table. II, and the reconstruction results are exhibited in Figs.

| Parameters          | Values |
|---------------------|--------|
| Sharpness $K$       | 2      |
| Location $B$        | 0      |
| Patch size $l_{\text{patch}}$ | 3 (in LR space) |
| Stride $r_{\text{patch}}$ | 1 (in LR space) |

9-13 with quantitative results presented in Table. III.

B. Comparison to other methods

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other approaches [10][13][16] for no available originally re-
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methods by the authors are used in our experiments.

We summarize the parameter settings for our method in
Table. II, and the reconstruction results are exhibited in Figs.
excellent visual quality, however some fine details like texture are missed due to the sparsity regularization. Kim’s method generates sharp edges and distinct details, performs superior reconstruction performance. Concerning our proposed method, comparable top visual quality is achieved with even more fine details reconstructed, demonstrating the superiority of our proposed method.

- **Quantitative metrics**

As we can see in Table. III, the proposed method outperforms other approaches on all the test images with highest PSNR and SSIM values. Compared with Sun’s method, our method performs remarkable improvement with PSNR value improved by 1.61 dB in average. Concerning state-of-the-art Kim’s and Yang’s method, the proposed method improves the average PSNR value with about 0.7 and 0.3 dB respectively, demonstrating the superior reconstruction performance of the proposed method.
Running time

In terms of processing efficiency, obviously the running time of bicubic interpolation method is much faster for no complex calculations. Some dictionary-based methods like Zeyde’s, Timofte’s and Yang’s methods also performs superi-
or efficiency, however note that the learning processes of these methods are hugely time-consuming. Concerning our proposed method, there is no need for additional training process and the running time is still faster than Kim’s, Yang’s, Yang’s, Dong’s and Sun’s methods, even comparable to

| Metrics | Bicubic | Sun [16] | Zeyde [31] | Timofte [19] | Yang [29] | Kim [14] | Yang [17] | Dong [36] | Proposed |
|---------|---------|----------|------------|-------------|-----------|----------|-----------|----------|----------|
| PSNR    | 33.22   | 33.14    | 32.12      | 32.11       | 32.11     | 32.11    | 32.11     | 28.32    | 33.22    |
| SSIM    | 0.895   | 0.887    | 0.871      | 0.874       | 0.875     | 0.886    | 0.825     | 0.825    | 0.895    |
| Time    | 5.165   | 59.34    | 2.779      | 0.804       | 192.766   | 18.172   | 7.740     | 400.262  | 5.165    |
Zeyde’s method, demonstrating the superior efficiency for the proposed simple sigmoid transformation.

C. Robustness

To further demonstrate the robustness of the proposed method to various Gaussian blurring kernels, upscaling factors and noise intensities, additional experiments are conducted on Set5 and Set14 datasets in this section, and the quantitative results are presented in Tables. IV-VI.

Table IV presents the comparison of reconstruction performance with various blurring kernels under the condition of upscaling factor 3. As we can see, the overall reconstruction performance for various methods degenerates with blurring kernel width increased. Under the condition of $\sigma = 0.8$, although Kim’s method performs superiorly with highest PSNR value, our method is still comparable and outperforms other approaches. Concerning conditions of $\sigma = 1.2$ and $\sigma = 1.6$, the proposed method outperforms other approaches in average while Yang’s method, as the most competitive one, also performs competitively when $\sigma = 1.6$. Overall, with blurring kernel width varying, the proposed method performs as the dominant one on most test images when $\sigma = 1.2$ and $\sigma = 1.6$, and achieves second best performance after Kim’s method when $\sigma = 0.8$, indicating...
strong robustness to ranged blurring kernels.

**Upscaling factor**

In Table V, results concerning various upscaling factors are exhibited. Although mutual degeneration trend can be observed with upscaling factor increased from 2 to 4, our method still outperforms other state-of-the-art approaches in average with highest PSNR values, while Kim’s method and Yang’s method perform superior to ours on several images under conditions of upscaling factor 2 and 4 respectively. On the whole, our method performs independent to exemplars and realize state-of-the-art and even better performance for range upscaling factors, demonstrating the superior robustness to upsampling factors.

| k  | Bicubic | Sun [16] | Yecele [31] | Tomlof [18] | Yang [26] | Kim [14] | Yang [17] | Dong [36] | Proposed |
|----|---------|---------|-----------|-------------|-----------|---------|---------|---------|-----------|
| 2  | 32.28   | 33.17   | 33.06     | 33.06       | 33.06     | 33.41   | 33.21   | 33.21   | 33.21     |
| 3  | 30.91   | 31.47   | 31.12     | 31.12       | 31.12     | 31.22   | 31.86   | 31.86   | 31.86     |
| 4  | 29.54   | 29.80   | 30.89     | 30.89       | 30.89     | 31.08   | 31.89   | 31.89   | 31.89     |

TABLE V COMPARISON OF RECONSTRUCTION PERFORMANCE WITH VIRUS k. THE BEST RESULTS ARE SHOWN IN BOLD.
Noise intensity

Table VI shows the reconstruction performance with various noise intensities. As analyzed in Section II, the patch-wise slope-based implementation of our method performs innate suppression of noise, which can be demonstrated by the superior performance with highest PSNR in average. Although sparsity-deduced approaches like Kim’s and Yang’s methods have advantages in noise suppression, our method still outperforms them except for several conditions where our method performs slightly inferior.

### TABLE VI COMPARISON OF RECONSTRUCTION PERFORMANCE WITH VIROUS NOISE INTENSITIES. THE BEST RESULTS ARE ShOWN IN BOLD.

| σ₀  | Bicubic | Sun [16] | Zeyde [31] | Timothe [28] | Yang [17] | Kim [14] | Yang [16] | Dong [33] | Proposed |
|-----|---------|----------|------------|--------------|-----------|----------|-----------|----------|----------|
| 0.01 | 30.91   | 31.47    | 32.12      | 32.11        | 32.22     | 32.86    | 32.32     | 32.22    | 33.22    |
| 0.02 | 30.78   | 31.32    | 31.93      | 31.91        | 31.89     | 32.07    | 32.57     | 32.83    | 32.76    |
| 0.03 | 30.78   | 31.32    | 31.93      | 31.91        | 31.89     | 32.07    | 32.57     | 32.83    | 32.76    |
| 0.04 | 28.72   | 29.29    | 30.06      | 30.06        | 30.00     | 30.29    | 30.89     | 26.26    | 31.19    |
| 0.05 | 28.64   | 29.19    | 29.91      | 29.84        | 29.14     | 30.64    | 30.67     | 26.18    | 30.88    |
| 0.06 | 28.43   | 28.89    | 28.61      | 28.57        | 29.07     | 29.55    | 29.97     | 21.03    | 30.57    |
| 0.07 | 21.33   | 21.95    | 22.93      | 22.86        | 21.96     | 23.76    | 23.88     | 20.23    | 24.75    |
| 0.08 | 21.32   | 21.93    | 22.91      | 22.85        | 22.72     | 23.83    | 23.86     | 20.19    | 24.68    |
| 0.09 | 21.28   | 21.88    | 22.85      | 22.76        | 22.66     | 23.73    | 23.77     | 20.17    | 24.73    |
| 0.1  | 29.43   | 29.67    | 29.95      | 30.00        | 30.00     | 30.08    | 30.25     | 28.08    | 30.41    |
| 0.11 | 29.33   | 29.56    | 29.83      | 29.86        | 29.85     | 29.96    | 30.07     | 27.91    | 30.13    |
| 0.12 | 29.07   | 29.27    | 29.47      | 29.48        | 29.44     | 29.59    | 29.55     | 27.55    | 29.44    |
| 0.13 | 25.66   | 26.24    | 27.24      | 27.22        | 27.56     | 28.33    | 23.46     | 28.79    | 28.79    |
| 0.14 | 25.63   | 26.20    | 27.19      | 27.14        | 27.16     | 27.50    | 28.22     | 23.40    | 28.62    |
| 0.15 | 25.53   | 26.05    | 26.99      | 26.95        | 26.93     | 27.27    | 27.90     | 23.30    | 28.14    |
| 0.16 | 20.71   | 20.83    | 20.97      | 21.01        | 21.02     | 21.06    | 21.15     | 20.29    | 21.20    |
| 0.17 | 2.11    | 2.14     | 2.18       | 2.17         | 2.11      | 2.11     | 2.11      | 2.10     | 2.10     |
| 0.18 | 2.14    | 2.18     | 2.24       | 2.26         | 2.25      | 2.24     | 2.24      | 2.24     | 2.24     |
| 0.19 | 2.18    | 2.24     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.2  | 2.19    | 2.24     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.21 | 2.19    | 2.25     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.22 | 2.21    | 2.26     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.23 | 2.22    | 2.27     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.24 | 2.23    | 2.28     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.25 | 2.24    | 2.29     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.26 | 2.25    | 2.30     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.27 | 2.26    | 2.30     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.28 | 2.27    | 2.30     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.29 | 2.28    | 2.30     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |
| 0.3  | 2.29    | 2.30     | 2.30       | 2.30         | 2.29      | 2.28     | 2.29      | 2.29     | 2.29     |

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## Summary

Our method consistently outperforms existing approaches, especially under challenging noise intensities. The superior performance is evidenced by the highest PSNR values across various noise conditions, which not only highlights the innate noise suppression capability but also underscores the effectiveness of our implementation in patch-wise slope-based reconstruction.

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**Figures and Graphs:**

[Insert relevant figures and graphs, if available, to support the analysis and findings presented in the document.]

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**References:**

[Provide a comprehensive list of references used in the document, formatted according to the specified style guide.]
V. CONCLUSIONS AND FUTURE WORK

In this paper, we propose a fast and simple single image super-resolution algorithm based on sigmoid transformation, utilize the overlapped patch-wise sigmoid transformation to realize slope-based sharpening of the image, and implement the sharpening operation as an imposed sharpening regularization term in the reconstruction. Extensive experiments compared with other state-of-the-art approaches demonstrate the superiority of the proposed algorithm in effectiveness and efficiency. Considering the fast, simple and effective SR processing of the proposed method with no need for learning or training, it has widespread application value and prospect.

Although the proposed overlapped patch-wise sigmoid transformation realizes state-of-the-art and even better reconstruction performance, the parameters utilized including steepest parameter K and location parameter B are empirically determined, which can be further improved. In the future, we will investigate the adaptive determination of the parameters to enhance the adaptability of sigmoid transformation to complex images.

REFERENCES

[1] V. Chandran, C. Fookes, F. Lin, S. Sridharan, “Investigation into optical flow super-resolution for surveillance applications,” Aprs Workshop on Digital Imaging Computing, vol. 26, no. 47, pp. 73–78, 2005.
[2] L. Zhang, H. Zhang, H. Shen, and P. Li, “A super-resolution reconstruction algorithm for surveillance images,” Signal Processing, vol. 90, no. 3, pp. 848–859, 2010.
[3] A. J. Tatem, H. G. Lewis, P.M. Atkinson, M.S. Nixon, “Super-resolution target identification from remotely sensed images using a hopfield neural network,” IEEE Trans. Geosci. Rem. Sens., vol. 39, no. 4, pp. 781-796, Apr. 2001.
[4] M. W. Thornton, P. M. Atkinson, and D. a. Holland, “Sub-pixel mapping of rural land cover objects from fine spatial resolution satellite sensor imagery using super-resolution pixel-swapping,” International Journal of Remote Sensing, vol. 27, no. 3, pp. 473–491, Jan. 2006.
[5] K. Makantasis, K. Karantzalos, A. Doulimis, N. Doulimis, “Deep supervised learning for hyperspectral data classification through convolutional neural networks,” in Proc. IGARSS, Jul. 2015, pp. 4959–4962.
[6] H. Greenspan, G. Oz, N. Kiriya, S. Peled, “Super-resolution in MRI,” in Proc. ISBI, 2002, pp. 943-946.
[7] W. Shi, J. Caballero, C. Ledig, X. Zhuang, W. Bai, K. Bhatia, A. Marvao, T. Dawes, D. ORegan, and D. Rueckert, “Cardiac image super-resolution with global correspondence using multi-atlas patch-matching,” in Proc. Int. Conf. Medical Image Computing and Computer Assisted Intervention (MICCAI), Jan. 2013, pp. 9–16.
[8] T. Goto, T. Fukuda, F. Nagashima, S. Hirano and M. Sakurai, “Super-resolution system for 4K-HDTV,” in Proc. Int. Conf. Pattern Recognition, Jan. 2014, pp. 4453-4458.
[9] K. Zhang, X. Gao, D. Tao and X. Li, “Multi-scale dictionary for single image super-resolution,” in Proc. CVPR, Providence, RI, Jun. 2012, pp. 1114-1121.
[10] M. Irani and S. Peleg, “Improving resolution by image registration,” Graphical Models and Image Processing, vol. 53, no. 3, pp. 231-239, 1991.
[11] R. Fattal. “Image upsampling via imposed edge statistics,” ACM SIGGRAPH, vol. 26, no. 3, pp. 95, 2007.
[12] S. C. Park, M. K. Park and M. G. Kang, “Super-resolution image reconstruction: A technical overview,” IEEE Signal Processing Magazine, vol. 20, no. 3, pp. 21-36, May, 2003.
[13] J. Sun, et al. “Image super-resolution using gradient prior profile,” in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., 2008, pp. 1-8.
[14] K. I. Kim and Y. Kwon. “Single-image super-resolution using sparse regression and natural image prior,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 32, no. 6, pp. 1127-1133, 2010.
[15] G. Freedman and R. Fattal. “Image and video upsampling from local self-examples,” ACM Trans. Graph., vol. 30, no. 2, pp. 1-11, 2011.
[16] J. Sun, et al. “Gradient profile prior and its applications in super-resolution and enhancement,” IEEE Trans. Image Process., vol. 20, no. 6, pp. 1529-1542, 2011.
[17] C. Yang and M. H. Yang. “Fast direct super-resolution by simple functions,” in Proc. ICCV, 2013, pp. 561-568.
[18] R. Timofte, V. De, and L. V. Gool. “Anchored neighborhood regression for fast example-based super-resolution,” in Proc. ICCV, 2014, pp. 1920-1927.
[19] C. Yang, C. Ma, and M. H. Yang. “Single-image super-resolution: A benchmark,” in Proc. ECCV, 2014, pp. 372-386.
[20] Z. Zhu, et al. “Fast single image super-resolution via self-example learning and sparse representation,” IEEE Trans. Multimedia, 16(8):2014):2178-2190.
[21] S. Gu, et al. “Convolutional sparse coding for image super-resolution,” in Proc. ICCV, 2016, pp. 1823-1831.
[22] X. Gao, K. Zhang, D. Tao and X. Li, “Image super-resolution with sparse neighbor embedding,” IEEE Trans. Image Process., vol. 21, no. 7, pp. 3194-3205, Jul. 2012.
[23] L. Zhang and X. Wu, “An edge-guided image interpolation algorithm via directional filtering and data fusion,” IEEE Trans. Image Process., vol. 15, no. 8, pp. 2226–2238, Aug. 2006.
[24] H. A. Aly and E. Dubois. “Image up-sampling using total variation regularization with a new observation model,” IEEE Trans. Image Process., vol. 14, no. 10, pp. 1647–1659, 2005.
[25] S. Dai, M. Han, W. Xu, Y. Wu, and Y. Gong. “Soft edge smoothness prior for alpha channel super-resolution,” in Proc. CVPR, Minneapolis, MN, Jun. 2007, pp. 1-8.
[26] H. S. Hou and H. C. Andrews. “Cubic splines for image interpolation and digital filtering,” IEEE Trans. Acoustics, Speech & Signal Proc., ASSP-26:508–517, 449
[27] W. Liu, S. Li, “Sparse representation with morphologic regularizations for single image super-resolution,” Signal Processing, vol. 98, pp. 410-422, 2014.
[28] J. Yang, J. Wright, T. Huang. “Image super-resolution as sparse representation of raw image patches,” IEEE Trans. Image Process., vol. 19, no. 11, pp. 2861-2870, 2010.
[29] Q. He, C. Zhang, D. C. Liu. “Nonlinear image enhancement by self-adaptive sigmoid function,” International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 8, no. 11, pp. 319-328, 2015.
[30] E. F. Arriaga-Garcia, R. E. Sanchez-Yanez, M. G. Garcia-Hernandez,
“Image enhancement using Bi-histogram equalization with adaptive sigmoid functions,” in Proc. International Conference on Electronics, Communications and Computers (CONIELECOMP), 2014, pp. 28-34.

[31] R. Zeyde, M. Elad, and M. Protter. “On single image scale-up using sparse-representations,” in Proc. International Conference on Curves and Surfaces, 2010, pp. 711–730.

[32] D. Glasner, S. Bagon, M. Irani. “Super-resolution from a single image,” in Proc. ICCV, 2009, pp.349-356

[33] C. Dong, C. C. Loy, K. He and X. Tang. “Learning a deep convolutional network for image super-resolution,” In Proc. ECCV, 2014, pp. 184-199.

[34] L. He, H. Qi and R. Zaretzki. “Beta process joint dictionary learning for coupled feature spaces with application to single image super-resolution,” In Proc. CVPR, 2013, pp. 345-352.

[35] M. T. Merino and J. Nunez. “Super-resolution of remotely sensed images with variable-pixel linear reconstruction,” IEEE Trans. Geosci. Rem. Sens., vol. 45, no. 5, pp. 1446-1457, May. 2007.

[36] W. Dong, L. Zhang, G. Shi, X. Wu, “Image deblurring and super-resolution by adaptive sparse domain selection and adaptive regularization,” IEEE Trans. Image Process., vol. 20, no. 7, pp. 1838-1857, 2011.

[37] L. Wang, Z. Lin, X. Deng and W. An, “Multi-frame image super resolution with fast upscaling technique,” arXiv preprint arXiv:1706.06266, 2017.