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Multi-Frame Super-Resolution of High Frequency with Spatially Weighted Bilateral Total Variance Regularization

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** Short Paper*

***Abstract*:** Bayesian based Multi-Frame Super-Resolution (MF-SR) has been used as a popular and effective SR model. On the other hand, the texture region is not reconstructed sufficiently because it works on the spatial domain. In this study, the MF-SR method was extended to operate on the frequency domain to improve HF information as much as possible. For this, a spatially weighted bilateral total variation model was proposed as a regularization term for a Bayesian estimation. The experimental results showed that the proposed method can recover the texture region more realistically with reduced noise, compared to conventional methods

***Keywords*:** Multi-frame SR, HF reinforcement, Frequency domain, Spatially weighted bilateral total variance model

1. Introduction

As flat panel display technologies have been advanced, the era of Ultra High Definition (UHD) TV has just begun recently, and the necessity for resolution up-scaling is increasing. General up-scaling algorithms such as interpolation [4, 5] and, kernel regression [6], lead to blurring and jagging artifacts around the edge and texture regions. To reduce those artifacts, Super-Resolution (SR) algorithms have been popularly investigated [7-11].

Bayesian based Multi-Frame Super-Resolution (MF-SR) techniques have been investigated in the early period [1]. The problem of restoring the missing High Resolution (HR) pixels is modeled by Bayesian estimation and its optimal solution is found iteratively. Unlike the Single-Frame Super-Resolution (SF-SR) methods, this MF-SR approach is specifically robust to noise in the Low Resolution (LR) image because of its regularization term. On the other hand, the SR performance is quite sensitive to parameter configuration of the regularization term [2]. For example, heavy regularization suppresses noise better, but blurs the edge and texture regions severely. To overcome this shortcoming, [3] proposed a spatially weighted total variation model. The weight of the regularization term was determined adaptively, depending on the local signal structure of the image. This method prevents the blurring edge structure while simultaneously suppressing noise at flat region. On the other hand, the texture region is not reconstructed sufficiently yet. The most crucial problem in the existing SR methods is to recover the missing HF component realistically in particular for texture region. Therefore, this study focused on providing a better restoration of HF information for texture enhancement during the SR process.

In this paper, the MF-SR method is applied to the LR High Frequency (HF) image for restoring more HF information as much as possible. The HF component is separately reconstructed in addition to the existing SR processing on the spatial domain. On the other hand, the existing regularization term is inappropriate for the HF component SR. Therefore, a spatially weighted bilateral total variation (SWBTV) regularization term is proposed. Finally, the HR image is acquired by adding the reconstructed HF component to a spatially super-resolved HR image by the spatial MF-SR.

2. The Proposed Method

This Section, first presents the conventional MF-SR method on the spatial domain and how to reinforce the HF. The SWBTV is then proposed as a regularization term for Bayesian estimation. Fig. 1 presents the proposed overall architecture. Details of the reconstructed HR image are

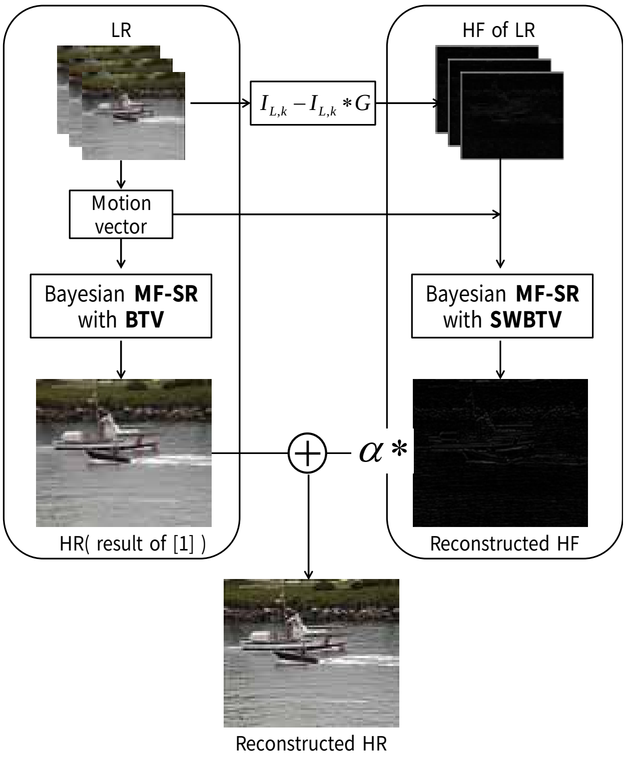

Fig. 1. Flowchart of the proposed method.

reinforced by applying MF-SR to the LR HF component. The existing regularization term, BTV is changed into SWBTV for HF SR. These two contributions become a fundamental difference from the conventional methods.

2.1 MF-SR (Multi-Frame Super-Resolution)

Suppose that an HR image I_H is warped, blurred and down-sampled to produce a sequence of LR images $I_{L,k}$. This general image degradation model is applied to the problem of MF-SR based on Bayesian approach as follows.

$$\hat{I}_H = \arg\min \left\{ \sum_{k=1}^{p} \left\| I_{L,k} - D_k B_k M_k I_H \right\|_1 - \lambda \cdot BTV\left(I_H\right) \right\} \tag{1}$$

where M_k, B_k and D_k represent the matrix for the warping, blurring, and down-sampling operation, respectively. λ is the Lagrange multiplier. The goal of MF-SR is to restore the HR image I_H from a couple of LR images $I_{L,k}$. In the right-hand of (1), the first data term guarantees fidelity between the observed and original data. The next regularization term guarantees a stable HR estimation and controls the stability of the result. Refer to [1] for more details.

2.2 High Frequency Reinforcement

As usual, the input LR images are spatially super-resolved by MF-SR, and an additional HF MF-SR is performed, as shown in Fig. 1. The HF components are extracted from LR images, and the MF-SR is applied to the LR HF images. For HF MF-SR the same motion vector is used as the spatial MF-SR because it is more accurate than one searched on the HF domain. The HF MF-SR method is equal to the spatial MF-SR except for regularization, which will be explained in detail in the next subsection.

The reconstructed HF is added to a spatially super-resolved HR with weight, α as follows.

$$\begin{aligned} HR_{recon} &= HR(bicubic, \ldots, MFSR, SFSR) \\ &\quad + \alpha \cdot HF_{recon}(MFSR) \end{aligned} \tag{2}$$

The degree of HF reinforcement is controlled by this weight which is determined experimentally. The proposed method appears similar to the unsharp masking technique, in the sense that the HR image is sharpened by adding HF. On the other hand, they make a clear distinction as follows. Because the sharpening method just emphasizes the HF signals as they are, it also tends to amplify the noise. The proposed method, however, aims to reproduce the lost HF information beyond the Nyquist frequency while suppressing the noise by the smoothing regularization term in (1).

2.3 Spatially Weighted Bilateral Total Variance Regularization

HF signals in the image are affected quite sensitively by the smoothing regularization term in (1). If its weight is so large, it blurs HF image signals as well as noise. Motivated by this observation, the SWTV [3] model determines the parameter of the regularization term, depending on local signal structure of the image, which is measured by difference curvature (C). That method prevents blurring edge structure well while suppressing noise at flat region. On the other hand, the weighting function of SWTV is derived for the image signals on spatial domain. This is inappropriate because the proposed method considers HF image signals. So, we propose the weighting function which has the same characteristic of SWTV and is suitable for HF domain as follows.

$$SWBTV = W \times BTV(I_H) \tag{3}$$

where

$$W = \frac{1}{1+\beta \cdot C^{\pi+k}}, \quad \pi = \frac{1}{1+\gamma \cdot \exp\left(C/\sigma\right)} \tag{4}$$

where C is the difference curvature [3]. β, γ, σ, k are constants, which are selected experimentally.

The overall range of C in the HF domain is less than in the spatial domain. For example, the value of HF is smaller than that in the spatial domain at the same edge region. This makes the weight to be imposed high, and consequently, excessive blurring occurs when the regularization weight function for spatial MF-SR is used

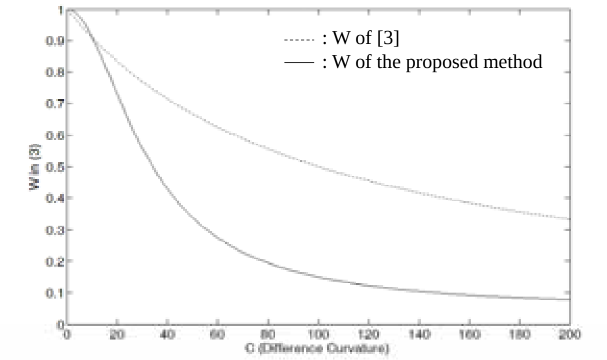

Fig. 2. Comparison of weighting functions.

for HF MF-SR. To reduce this blur artifact, HF MF-SR requires a steeper weight function. In addition to the steepness of the weighting function, another difference is that the proposed weighting function is flatter near zero, as shown in the blue line in Fig. 2. Fig. 2 illustrates the conventional and proposed weighting functions.

The C value at the noise region is confirmed experimentally to be nearby zero, so the weight of the regularization term should be large to suppress noise. Using the weighting function in (2), the regularization weight is imposed adaptively according to image region characteristics. For HF MF-SR, the conventional BTV-regularization term is replaced by the SWBTV regularization as follows.

$$\hat{I}_H = \arg\min\left\{\sum_{k=1}^{p}\left\|I_{L,k} - D_k B_k M_k I_H\right\|_1 - \lambda \cdot SWBTV\left(I_H\right)\right\} \quad (5)$$

3. Experimental Results

This study reports the performance evaluations. For the MF-SR, three successive video frames are used and the scale factor is set to 2. The selected parameters for the SWBTV were configured as follows; $\lambda = 0.8$, $\beta = 0.001$, $\sigma = 200$. These parameters were determined empirically. Fig. 3 compares the reconstructed HF for the conventional and proposed methods. The proposed method can recover HF more realistically in the overall image regions. For example, more details are recovered in the waves of the river.

Next, the reconstructed HR images are compared subjectively. Fig. 4, compares the proposed method with the three other methods. As expected easily from the HF reconstruction in Fig. 3, the proposed method (Fig. 4(d)) recovers better texture regions such as grass and wave than the conventional method [1] (Fig. 4(a)). When Figs. 4(a) and (d) are compared, the proposed method improved the sharpness by super-resolving HF. Secondly, the image reconstructed by the conventional method is sharpened by the common unsharp masking, as shown in Fig. 4(b). Although Fig. 4(b) has more image details by the sharpness improvement than Fig. 4(a), it is also affected by

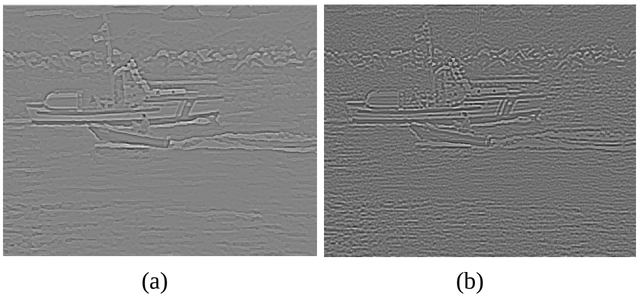

Fig. 3. Comparison of HF (a) HF of [1], (b) HF of the proposed method.

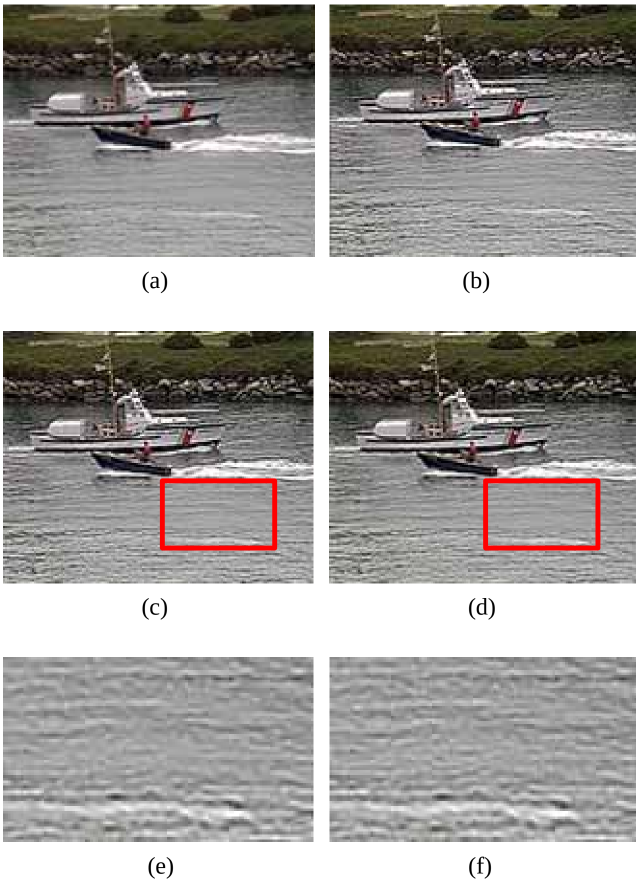

Fig. 4. Comparison of the subjective quality (a) the conventional MF-SR [1], (b) the unsharp masking of (a), (c) HF-SR with SWTV, (d) the proposed HF-SR with SWBTV, (e) enlargement of red box in (c), (f) enlargement of red box in (d).

noise, particularly at the wave and glass regions. This is because the unsharp masking method amplifies the tiny noise signals as well as the original information ones. On the other hand, the noise signals are strongly suppressed by the proposed regularization term in (5). This is a key difference between the proposed and conventional methods, and it makes the proposed method less noisy. Finally, a performance comparison between the regularization terms, SWTV and SWBTV is made. As shown in Figs. 4(c) and (d), both regularization terms achieve similar visual quality overall, but for the high detail region, as shown in Figs. 4(e) and (f), the detail

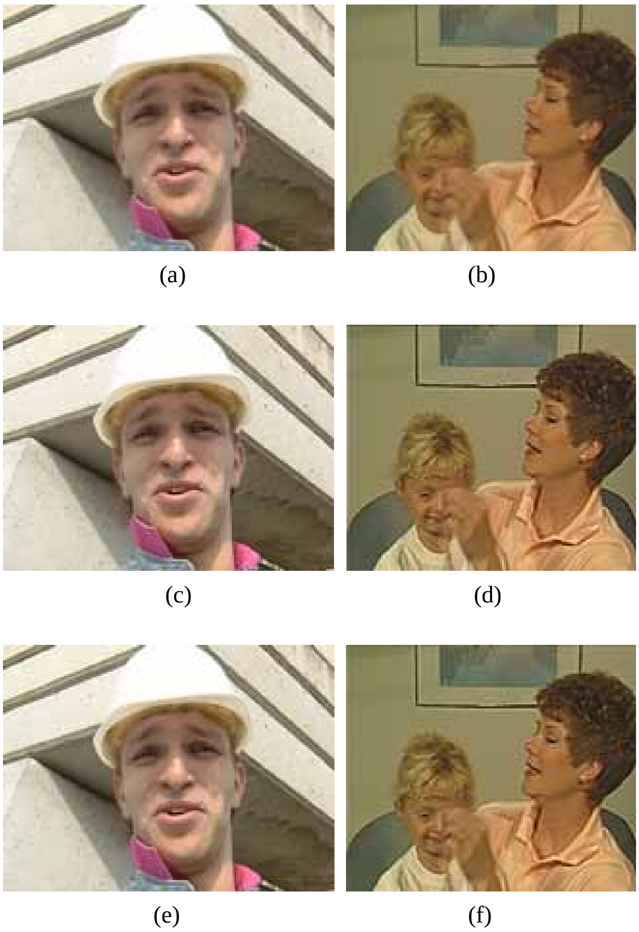

Fig. 5. Comparison of the subjective quality (a) and (b) are the conventional MF-SR [1], (c) and (d) are the unsharp masking of (a) and (b), (e) and (f) are the proposed HF-SR.

reconstruction capability of the SWTV is still lower than SWBTV. These results confirm that SWBTV is more appropriate for HF-SR than SWTV. Fig. 5 also shows performance comparisons for other test images, and performances similar to Fig. 4 can be observed.

4. Conclusion

Reconstructing the HF details in Bayesian based MF-SR is quite challenging because of its smoothing regularization. This paper proposes to super-resolve the HF component separately, and the SWBTV regularization is proposed for HF MF-SR. The experimental results confirmed that the proposed method is more effective in reconstructing the HF detail textures while still reducing noise.

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References

[1] S. Farsiu, M. Robinson, M. Elad, and P. Milanfar, “Fast and Robust Multi-Frame Super-Resolution,” *IEEE Trans. Image process.*, vol. 13, no.10, pp. 1327-1344, Oct. 2004. Article (CrossRef Link)

[2] A. Panagiotopoulou, V. Anastassopoulos, “Super-Resolution Image Reconstruction Techniques: trade-offs between the data-fidelity and regularization terms,” *Inform. Fusion, 2008*, vol.13, pp. 185–195, July. 2012. Article (CrossRef Link)

[3] Q. Yuan, L. Zhang, H. Shen, “Multi-Frame Super-Resolution Employing a Spatially Weighted Total Variation Model,” *IEEE Trans. Circuits and Systems for Video Technology*, vol. 22, no.3, pp. 379–392, Mar. 2012. Article (CrossRef Link)

[4] X. Li and M. Orchad. “New Edge-Directed Interpolation,” *IEEE Trans. Image Process.*, vol. 10, pp. 1521-1527, Oct. 2001. Article (CrossRef Link)

[5] J.W. Hwang, H.S. Lee, “Adaptive Image Interpolation Based on Local Gradient Features,” *IEEE Signal Processing Letters*, vol. 11, pp. 359-362, Mar.2004. Article (CrossRef Link)

[6] Takeda, H., Farsiu, S., and Milanfar, P., "Kernel Regression for Image Processing and Reconstruction", *IEEE Trans. Image Process*., pp. 349-366, Feb. 2007. Article (CrossRef Link)

[7] W.T. Freedman, T.R Jones, and E.C. Pasztor “Example-Based Super-Resolution,” *IEEE Computer Graphics and Applications*, vol. 22, pp. 56-65, Mar. 2002. Article (CrossRef Link)

[8] S. Chen, H. Gong, and C. Li, “Super Resolution from a Single Image Based on Self-Similarity,” *IEEE Int. Conf. on Computational and Information Sciences*, pp. 91-94, Oct. 2011. Article (CrossRef Link)

[9] D. Glasner, S. Bagon, and M.Irani, “Super-Resolution from a Single Image,” *12th IEEE Int. Conf. on Computer Vision*, pp. 349 – 356, Sept. 2009. Article (CrossRef Link)

[10] G. Freeman, and R. Fattal, “Image and Video Upscaling from Local Self-Examples,” *ACM Trans. on Graphics*, vol. 30, Article No. 12, April. 2011. Article (CrossRef Link)

[11] C.Y Yand, J.B Huang, and M.H Yang, “Exploiting Self-Similarities for Single Frame Super-Resolution,” *Proc. of Asian Conf. on Computer Vision*, pp. 497-510, Nov, 2010. Article (CrossRef Link)