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PERFORMANCE ANALYSIS OF NON LOCAL MEANS SUPER RESOLUTION OF A SINGLE IMAGE

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Abstract-Various super-resolution methods can correctly estimate the missing high frequency components of enlarged images. However, they mostly require high computational costs, which is not suitable for real-time processing. For a super-resolution with low computational costs, the proposed method is simply realized via the block matching technique with a small search area. Since it utilizes the image self similarity and sparsity, it produces visually efficient interpolated images. In the simulation, it is shown that the proposed method greatly outperforms the bicubic in a visual quality of enlarged images, objectively and perceptually.
Keywords - **Super-resolution, high frequency components, self similarity**

I. INTRODUCTION

In recent years, opportunity to handle the digital signal is rapidly increasing, there is always a high level of demand for digital signal processing technology. In particular, with high resolution of the output display device, research on digital image super-resolution for increasing the resolution of an image is conducted. Image interpolation methods such as Bicubic or Bilinear, which has been used for a long time as a general technique to enlarge the image are well known [1]. They are widely used from the high speed of the process and ease of implementation, but there is a problem image quality is degraded visually due to miss high frequency components. Therefore, the enlarged image appears blur around edges. Unlike the interpolation, super-resolution is a method of estimating the high frequency components while increasing the number of pixels. From the low resolution (LR) image, the enlarged sharp high resolution image (HR) is achieved by estimating the high frequency components. Therefore, it is possible to create a sharp image whose edges are steep by the method of super-resolution. In the super-resolution, several methods have been proposed to generate efficient enlarged images [2–7]. They utilize image priors to estimate missing high frequency components.

In [2], Maximum a posterior (MAP) estimation technique is firstly applied for the image expansion. It uses directional second-order derivatives as a regularization term, and then produces smooth images with keeping strong edges. On the other hand, super-resolution method using predefined dictionary has been proposed [4, 6, 8]. They are methods that express images by a linear combination of multiple bases, they achieve

an enlarged image and natural high resolution visually without excessive smoothing. In this way, many methods for producing an enlarged image have been proposed, but there is a problem that they require a large amount of calculation. Super-resolution can be divided into single frame super resolution as mentioned before and multi-frame super resolution mainly. LR images are obtained by shifting original HR image and down sampling. Therefore multi-frame super resolution can achieve a clear image generally by position adjustment of multiple low resolution images. Also, there is a method called BM3D [11] as a famous technique for denoising. This method searches the blocks resembling the target block in an image and takes the weighted average of these blocks. As a result, it is possible that reduces the noise efficiently and produces a clear image. This searching block in BM3D corresponds to position adjustment in multi-frame super resolution. Then we regard BM3D in single image as multi-frame super-resolution because the image includes many resembles blocks within image that is called congruity. In this paper, we propose two kind of single frame super resolution methods based on the shock filter to enhance the high frequency components and reduce the amount of calculation, NLM using self similarity of images across scales to get efficient perceptual results.

The former method is a low cost linear processing by the short length filter, and has a high sharpness of image. When we apply the shock filter to the 2D highpass filtered image, the smooth region doesn't change at all and only the edge and texture regions are emphasized. The latter method estimates high frequency components of interpolated blocks by a weighted summation of their neighbour LR blocks. The candidates of the summation are determined based on a structural similarity between local regions centring on the interpolated pixel and its neighbourhoods, similar to the NLM algorithm [9]. The prior used in the proposed method is that natural images have high structural similarities between HR and LR images. The assumption is reasonable and widely utilized in image processing, such as the fractal image coding [10]. Hence, since this proposed method reasonably estimates high frequency components of the HR image and avoids the over fitting, the proposed method perceptually improves enlarged images.

The natural image also has high structural resemblance within image. We call this congruity within image to distinguish the simlarity across scales. We utilize BM3D method which can be regarded as multi-frame super resolution to improve the quality of an enlarged image. In simulations, it is shown that the proposed methods have better results than conventional one, objectively and perceptually.

II. REVIEW

A. BICUBIC INTERPOLATION

Bicubic is image interpolation method, which is generally widely used, is a method of calculating HR by the linear combination of LR pixel values in the neighborhood. Specifically, it calculated the 4 HR pixels $x_i\,(i = 0,1,\ldots.4)$ from the 16 LR $y_i(i = 0,1,\ldots.15)$ of neighborhood. Here, each xi is calculated by

$$x_i = \sum_j y_j u(s_{0,ij}) u(s_{1,ij}) \qquad (1)$$

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$s0, ij$ *and* $s1, ij$ represent each vertical and lateral distance with x_i and y_j. We define width of LR between pixels as a one, the weight $\mathrm{u(s)}$ of the equation (1) is

$$\mathrm{u(s)} = \begin{cases} (a+2)s^3 - (a+3)s^2 + 1 & 0 < |s| \leq 1 \\ as^3 - as^2 - 4a & 1 < |s| \leq 2 \\ 0 & otherwise \end{cases} \qquad (2)$$

Here, a is a design parameter.

B. NLM

NLM is a technique that has been proposed for the purpose of denoising of an image $\hat{v}_i (i \in I)$, and is a technique to estimate the linear combination of the noise pixels in the neighborhood of the denoising pixels $vj\ (j \in Ri)$. Here, $I\ , Ri$ represent each set of coordinates of the entire image, and set of coordinates near the pixel of i. The estimated pixel is formulated as

$$\overline{vi} = \sum_{j \in R_i} w_{i,j} v_j \qquad (3)$$

and the weight $w_{i,j}$ applied to each pixel neighborhood is defined in

$$w_{i,j} = \frac{1}{Z_i} \exp\left(-\frac{||V_{N_i} - V_{N_j}||_2^2}{\sigma^2}\right) \qquad (4)$$

$$Z_i = \sum_j \exp\left(-\frac{||V_{N_i} - V_{N_j}||_2^2}{\sigma^2}\right) \qquad (5)$$

By the definition, the weight $w_{i,j}$ satisfy $0 \leq w_{i,j} \leq 1$, $\sum_j w_{i,j} = 1$. Here, each $exp(\cdot)$ and $|| \cdot ||_2$ represent the norm and the exponential function, σ represents design parameter, $N_i \in Z_N$ represent the set of neighboring pixel coordinates centred at i as in R_i , and each V_{N_i} represents a vector of all pixels within the Ni. Ri and Ni are synonymous but different ranges, R represents the pixel, N represents the neighbourhood including the pixel, and we have defined to distinguish each for different purposes. In this paper, we call R and N search range and range blocks, respectively.

C. BM3D

Similarly to NLM, BM3D also perform image denoising based on the similarity of the neighboring blocks and the target using a block matching [11]. BM3D can remove the noise in block units rather than in pixel units, which is different from the NLM. BM3D find some blocks by block matching which are similar to the target block and then stack them together in a 3D array that is called grouping. The 3D transform is applied to the grouped 3D array and the transformed coefficients are denoised by hard-thresholding. The denoised coefficients are inverse 3D transformed and return to their original positions. Next we compute the first estimate by weighted averaging all of the obtained block-wise estimates that are overlapping.

This procedure using Wiener filtering instead of thresholding is applied in the second step to improve the quality.

IV. NLM SUPER RESOLUTION

In this section, the NLM image super resolution algorithm which enlarges image with factor 2. The LR and HR pixels are defined as x_i and y_i respectively.

Initially, HR pixels are interpolated via bicubic interpolation. 3×3 Interpolated HR pixel centred on i which is called as neighbour window and search window is defined according to that neighbour window of LR pixels as 5×5. The weight is calculated according to these two windows.

$$w_{i,j} = \frac{1}{Z_i} \exp\left(-\frac{\|v_{N_i} - v_{N_j}\|_2^2}{\sigma^2}\right) \qquad (6)$$

$$Z_i = \sum_j \exp\left(-\frac{\|v_{N_i} - v_{N_j}\|_2^2}{\sigma^2}\right) \qquad (7)$$

Finally, the weight is multiplied with the centred pixel and replaces that value of centre pixel. Here $v_j$is cetred pixel value and $\overline{vi}$ is the new replaced HR pixel value.

$$\overline{v}_i = \sum_{j \in R_i} w_{i,j} v_j \qquad (8)$$

IV. RESULT COMPARISION

In this chapter, we compare visually and quantitatively image enlargement by Bicubic as conventional and the proposed method. We compared double enlarged images in this experiment. We used test images which is the standard image during this experiment.

(a) (b) (c)

Fig. 1 Image of Lena shows result comparison: (a) LR image (b) Bicubic interpolated image (c) NLM SR image.

For all images, we have created a reduced image down sampled to the size of the half in both vertical and horizontal directions. We considered the reduced image as the input image, and calculated the enlarged image of the same size as the original image by using the proposed enlargement methods. We used PSNR [dB] that shows below as quantitative evaluation index of an original image and an enlarged image.

TABLE I:- COMPARISION OF ENLARGED IMAGES IN PSNR

	Bicubic[dB]	Lancoz[dB]	NLM[dB]
Lena	31.94	31.97	34.09
Barbara	24.44	24.66	25.32
Pepper	32.53	32.79	33.45
Cameraman	32.61	32.72	33.12

V. CONCLUSION

In this paper, we have proposed the super-resolution method that is applying the shock filter to the high frequency components, and NLM method using self similarity. The proposed method realized the natural HR image by applying the shock filter to the high frequency component because it sharpened effectively only edge region and reduced the unnatural emphasis of texture region. Also, it was possible to obtain the clear HR image by taking advantage of the similarity of the image across scales. In the experiment, the proposed method indicates better PSNR as compared with the conventional method, and realizes the better quality of the enlarged image on the visual.

REFERENCES

[01] Rafael C. Gonzalez and Richard E. Woods, “Digital Image Processing “, Prentice Hall,2002

[02] Richard R. Schultz and Robert L. Stevenson, “A Bayesian approach to image expansion for improved definition“, IEEE Trans. Image Process, vol.3, no.3, pp233-242, May 1994.

[03] Taichi Yoshida, Tomoya Murakami, and Masaaki Ikehara “Image Super-Resolution Method based on Non-Local Means and Self Similarity” EEE Dept., Keio Univ., Yokohama, Kanagawa 223-8522

[04] William T. Freeman and Thouis R. Jones and Egon C. Pasztor, “Example-based super-resolution“, IEEE Comput. Graph.Appl., vol.22, no.2,pp.56–65,2002.

[05] Xiangjun Zhang and Xiaolin Wu, “Image Interpolation by Adaptive 2- D Autoregressive Modeling and Soft-Decision Estimation“, IEEE Trans. Image Process., vol.17, no.6, pp.887–896, Jun 2008.

[06] Jianchao Yang and John Wright and Thomas S. Huang and Yi Ma, “Image Super-Resolution Via Sparse Representation“, IEEE Trans Image Process., vol.19, no.11, pp.2861–2873, Nov 2010.

[07] Kwok-Wai Hung and Wan-Chi Siu, “Robust Soft-Decision Interpolation Using Weighted Least Squares“, IEEE Trans. Image Process., vol.21, no.3, pp.2861–2873, Mar 2012.

[08] Weisheng Dong and Lei Zhang and Guangming Shi and Xiaolin 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, July 2011.

[09] Antoni Buades and Bartomeu Coll and Jean-Michel Morel, “ A nonlocal algorithm for image denoising“, Proc. IEEE Computer Soc. Conf. Comput. Vision Pattern Recognition, vol.2, pp.60–65, Jun 2005

[10] Arnaud E. Jacquin, “Image coding based on a fractal theory of iterated contractive image transformations“, IEEE Trans. Image Process., vol.1, no.1, pp.18–30,Jan 1992.

[11] Kostadin Dabov, Alessandro Foi , Vladimir Katkovnik and Karen Egiazarian, “Image Denoising by Sparse 3-D Transform-Domain Collaborative Filtering“, IEEE Trans. Image Process., vol.16, no.8, pp.2080– 2095, Aug 2007.

[12] Y.Sakuta, Y.Kawamoto, M.Watanabe, T.Goto, S.Hirano and M.Sakurai, “A study of super-resolution magnification utilizing TV regularization and shock filter“, IEICE Trans. Inf.Syst., vol.J96-D, no.3, pp.686–694, Mar 2013.

[13] L.Alvarz and L.Mazorra, “Signal and image restoration using shock filters and anisotropic diffusion“, SIAM J.Numer. Anal., vol.31, no.2, pp.590– 605, Apr 1994.

[14] P.Kornprobst,R.Deriche,and G.Aubert, “Image coupling, restoration and enhancement via PDE’s“, Proc.IEEE Int.Conf.Image Process.,vol.2,pp.458-461,1997.

[15] G.Gilboa, N.Sochen, and Y.Y.Zeevi, “Image enhancement and denoising by complex diffusion processes“,IEEE Trans. Pattern Anal.Mach.Intell., vol.26, no.8,pp.1020–1036,Aug 2004.

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InputImage=imread(‘Input.jpg’);
ReconstructedImage=imread(‘recon.jpg’);
n=size(InputImage);
 M=n(1);
 N=n(2);
 MSE = sum(sum((InputImage-ReconstructedImage).^2))/(M*N);
PSNR = 10*log10(256*256/MSE);
 fprintf(‘\nMSE: %7.2f ‘, MSE);
 fprintf(‘\nPSNR: %9.7f dB’, PSNR);
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