Super-Resolution Image with Estimated High Frequency Compensated Algorithm

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Abstract—**In this paper, we propose an Estimated High Frequency Compensated (EHFC) algorithm for super resolution images. It is based on Iterative Back Projection (IBP) method combined with compensated high frequency models according to different applications. The proposed algorithm not only improves the quality of enlarged images produced by zero-order, bilinear, or bicubic interpolation methods, but also accelerates the convergence speed of IBP. In experiments with general tested images, EHFC method can increase the speed by 1 ~ 6.5 times and gets 0.4 ~ 0.7 dB PSNR gain. In text image tests, EHFC method can increase 1.5 ~ 6.5 times in speed and 1.2 ~ 8.3 dB improvement in PSNR.**

I. INTRODUCTION

Super resolution (SR) image reconstruction has been one of the important research areas in image and video applications [1]. The primary concept is to use signal processing techniques to obtain a high resolution (HR) image from observed single or multiple low-resolution (LR) images. This technique is essential and effective in many applications including video surveillance, medical imaging, satellite imaging, and video delivery and playback.

SR reconstruction techniques can be employed in the spatial or frequency domain. Simplicity in theory is a major advantage of the frequency domain approach. In addition, the frequency approach is also convenient for parallel implementation. However, this approach allows low flexibility to add priori constraints, noise models, and spatially varying degradation models. Thus, the development in practical use is limited.

On the other hand, spatial domain techniques are more flexible in incorporating priori constraints and have better performance in reconstructed images. Nevertheless, these methods also have drawbacks such as complicated theoretical work and relatively large amount of computation load. In general, spatial domain techniques can be divided into several categories as follows:

a. Non-Uniform Interpolation Methods
b. Projection onto High-Resolution Grid Methods
   IBP (Iterative Back Projection)
   POCS(Projection onto Convex Sets)
c. Probabilistic Methods
   MAP(Bayesian Maximum A Posteriori)
   ML(Maximum Likelihood)
d. Hybrid ML/MAP /POCS Methods

Among the existing SR methods, the multi-frame super-resolution reconstruction is the most well-known approach. Theoretically, it reconstructs an HR image by getting spatial difference using dependence on consecutive LR images and motion estimation. However, this method is computationally expensive such that it is not suitable for practical usages. Consequently, the proposed algorithm aims to improve the visual quality of single image with low computation complexity. It makes use of the common image interpolation methods to enlarge the image, and then process it according to Iterative Back Projection (IBP) method corporate with high frequency compensation concept. After multiple iterations, the blurring effect can be greatly reduced in enlarged images. In our previous work, we proposed a direct high frequency compensated (DHFC) algorithm [13] based on IBP. It utilizes the adequate filter to compensate the lost information in high frequency and produces better visual quality than IBP in general test images. However, it performs worse than IBP on text images because the variation of energy among the gray values on text image is large that causes the early convergence.

In section II, the related IBP algorithm is reviewed; the proposed high frequency compensated super resolution reconstruction methods are described in section III. Simulations and discussions are shown in section IV. Section V concludes this work.

II. BACK PROJECTION ALGORITHM

Irani and Peleg proposed iterative back projection SR reconstruction technique [4] based on the concepts presented in [2] and [3]. In this approach, the HR image is estimated by back projecting the difference between simulated LR images and the observed LR images. The process is repeated iteratively until some criterion is met, such as the minimization of the energy of the error, or until the maximum number of allowed iterations is reached.

IBP is an efficient method that is repeated iteratively to minimize the energy of the error. The method can be used to incorporate constraints, such as smoothness or any other additional constraint which represents a desired property of the solution.

The IBP scheme to estimate the HR image is expressed by:

$$\hat{x}_k^{(n+1)} = \hat{x}_k^{(n)} + \frac{1}{k}\sum_{k=1}^{k} T_k^{-1}(((y_k - \hat{y}_k^{(n)}) \uparrow s) * h^{BP}) \quad (1)$$

where $\hat{x}_k^{(n)}$ represents the estimated HR image of kth image after n iteration process. $\hat{y}_k^{(n)}$ denotes the simulated degenerated LR image of x after n iteration . h^{BP} is the back-projection operator. T_k^{-1} is the image geometric inverse function and $\uparrow$s is the Up-Sampling process.

III. THE PROPOSED RECONSTRUCTION ALGORITHM

Consider an HR image processed by a degenerated function G . An LR image is generated from the procedure written as

$$Y = (X * G) \downarrow s \quad (2)$$

Generally, the SR image reconstruction approach is an ill-posed problem. We assume the estimated HR image $\hat{X}$ is the combination of the interpolated image $\hat{x}^{(0)}$, lost-predicted high frequency image X_H , and error compensated image X_ε .

$$\hat{X} = \hat{x}^{(0)} + \hat{X}_H + \hat{X}_\varepsilon \quad (3)$$

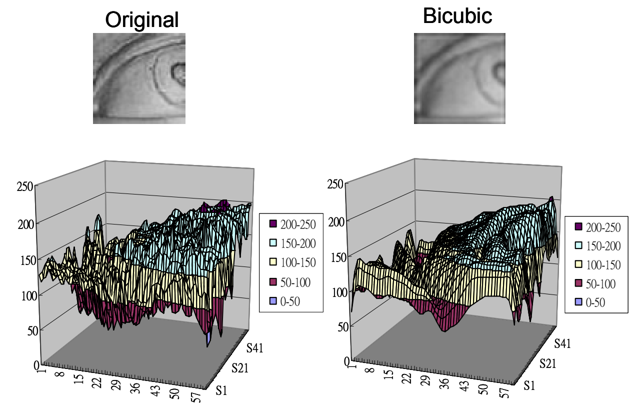
The estimated HR image after k iteration $\hat{x}^{(k+1)}$ can be expressed as

$$\hat{x}^{(k+1)} = \hat{x}^{(k)} + \hat{x}_H^{(k)} + \hat{x}_\varepsilon^{(k)} \qquad 1 \le k \le p \quad (4)$$

A. High frequency compensation

An original HR image in the natural degenerates to an LR image after being captured by a camera system will be blurred. However, it still contains pixels in gray level distribution similar to the original one as Fig. 1 illustrates.

In order to improve the blurriness of an image for better visual quality or more accurate analysis in image processing, techniques related to edge enhancement are commonly used. In the proposed algorithm, we add the edge enhancement prior model into IBP algorithm, so as to achieve better visual result and to accelerate convergence speed. Among various high pass filters, the Laplacian filter is chosen in our system. It is a spatial second order operator that has great enhancement capability on regions with large variations (including edge).



(a) (b)

Fig. 1. Interpolation effect (a) Original image and its gray level distribution (b) The gray level distribution of the reconstructed image that is reduced to half and then enlarged to the original size

However, because Laplacian filter is extremely sensitive to high frequency signal which generally includes noise. This presents a drawback that needs to be solved. Therefore, the smooth filter is usually used before applying Laplacian filter to avoid the noise interference. A LoG (Laplacian of Gaussian) filter is usually adopted as follows.

$$\mathrm{LoG(x,y)} = -\frac{1}{\pi\sigma^4}\left[1 - \frac{x^2+y^2}{2\sigma^2}\right]e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (5)$$

In IBP technique, the estimated HR image needs to be down sampled to get the estimated LR image. The down-sampling procedure results in decreased sampling frequency that generates distortions in high frequency components and the aliasing problem.

Therefore, the HR image obtained from LoG filter needs to be further filtered by a Gaussian filter to eliminate the distortions from the down sampling procedure. As a result, the mathematical equation we are looking for $\hat{x}_H$ is

$$\hat{x}_H = (\hat{x} * H_{LoG}) * W \quad (6)$$

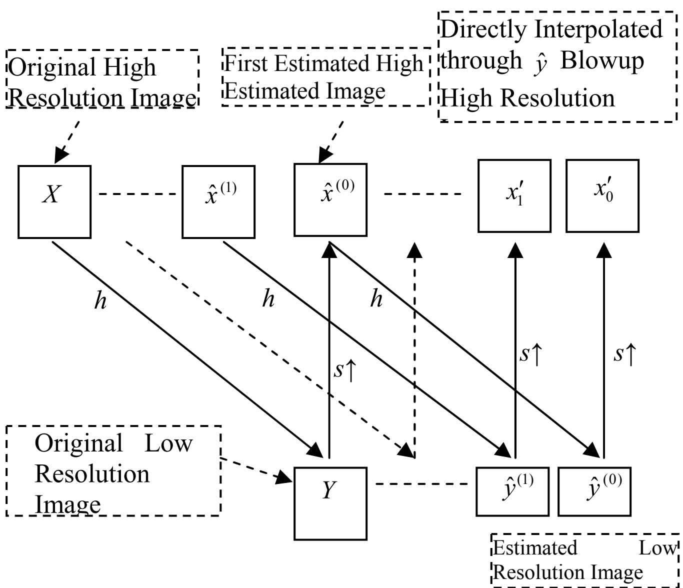
where $\hat{x}$ is the estimated HR image, H_{LoG} is LoG filter, and W is Gaussian low pass filter.

To achieve a more accurate high frequency reconstruction, and to comply with the IBP iterative reconstruction theory, the compensated high frequency energy amplitude should be limited in a reasonable range. The subjective visual quality will be degraded by large high frequency energy although the image could be clearer, just like the case of edge enhancement. Aside from that, it will also cause the iteration process to converge too early, and thus fails to achieve a better visual quality. Therefore, the sum value W of the 2D Gaussian low pass filter we use is between 0.01 ~ 0.1 to compensate for high frequency components progressively.

B. Estimated High Frequency Compensated (EHFC) Model

The EHFC model is developed to compensate the frequency data lost in the iteration processes including Down-Sampling, Up-sampling and degeneration of the LR images. It overcomes the early convergence problem in our previous works [13] by estimating the lost information in high frequency.

As shown in Fig. 2, we consider the first interpolated image $\hat{x}^{(0)}$ enlarged from Y as the central point which the same as proposed in the IBP approach. In the iteration process, each of the estimated HR image $\hat{x}$ will be more similar to the original HR image X. Because $\hat{x}$ is degenerated to form an estimated LR image $\hat{y}$ and $\hat{y}$ is then used to interpolate to get HR image x', it could be predicted that x' will have more serious blurring effect than $\hat{x}^{(0)}$. To overcome this problem, we calculate the lost high frequency data ($\hat{x}^{(0)} - x'$) to compensate the error in estimated image x' in our EFHC model. The iteration processes can reduce both the blurring effect and the error in high frequency.



h: Degradation Process & Down-Sampling
s↑: Up-Sampling

Fig.2. EHFC Algorithm Iteration Diagram

The equation of high frequency compensation is

$$\hat{x}_H^{(k)} = \hat{x}_H^{(0)} - \left\{ ((\hat{y}^{(k)}) \uparrow s) * H_{LoG} \right\} * W \tag{7}$$

where $\hat{x}_H^{(0)}$ is the high frequency data of the image $\hat{x}^{(0)}$ that is obtained from the first interpolation. The equation for $\hat{x}_H^{(0)}$ can be expressed as

$$\hat{x}_H^{(0)} = (\hat{x}^{(0)} * H_{LoG}) * W \tag{8}$$

for $\hat{y}^{(k)}$, the equation is

$$\hat{y}^{(k)} = (\hat{x}^{(k)} * G) \downarrow s \tag{9}$$

and the error correction is expressed as

$$\hat{x}_\varepsilon^k = (\hat{y}^{(k)} - y) \uparrow s \tag{10}$$

the iteration process is formulated as

$$\hat{x}^{(k+1)} = \hat{x}^{(k)} + \hat{x}_H^{(k)} + \hat{x}_\varepsilon^{(k)} \tag{11}$$

or

$$\hat{x}^{(k+1)} = \hat{x}^{(k)} + \left\{ \hat{x}_H^{(0)} - \left\{ ((\hat{y}^{(k)}) \uparrow s) * H_{LoG} \right\} * W \right\} + \left\{ (\hat{y}^{(k)} - y) \uparrow s \right\} \tag{12}$$

The flow chart of EHFC is shown as Fig. 3.

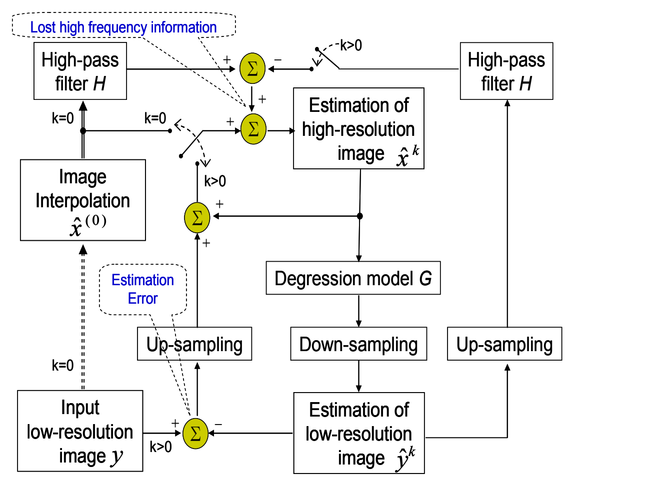


Fig. 3. EHFC Iteration Flowchart

The convergence condition of the proposed EHFC is when the minimum SAD that is the absolute value of the difference between the estimated LR image $\hat{y}^{(k)}$ and original LR image y is reached. This condition can also be expressed as (13).

$$\varepsilon^{(k)} = \sum_{(x,y)\in R^2} |\hat{y}^{(k)}(x,y) - y(x,y)| \tag{13}$$

$$if \begin{cases} \varepsilon^{(k)} > \varepsilon^{(k-1)} \\ \varepsilon^{(k)} \le \varepsilon^{(k-1)} \end{cases}$$

IV. EXPERIMENT RESULTS

To evaluate the SR systems effectively, this work assumes that the original HR images exist and the image quality degradation is resulted from Gaussian blurring, and such Gaussian blurring function is known. In simulations, the HR images is blurred with a 5 x 5 Gaussian blurring function of σ = 1.0 to degrade its image quality, and then to be down-sampled to produce LR image for experiments. The degeneration process is shown in Fig. 4.

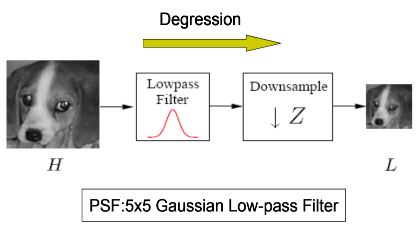
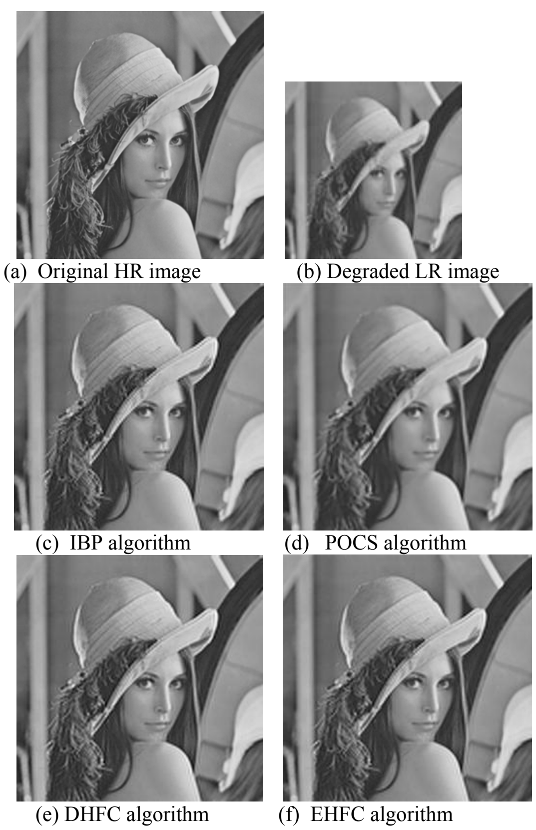


Fig. 4. Image degeneration procedure

To present the performance of the algorithm, several images of different types are tested and their results are compared with the other methods including bilinear interpolation (BI), bicubic interpolation (BC), POCS, and IBP. The image quality is determined based on PSNR evaluation.

A. *Image Quality Comparison*

From Fig. 5, 6, 7, 8, and Table I, we can find that the proposed EHFC algorithm can improve the PSNR value considerably in most cases.

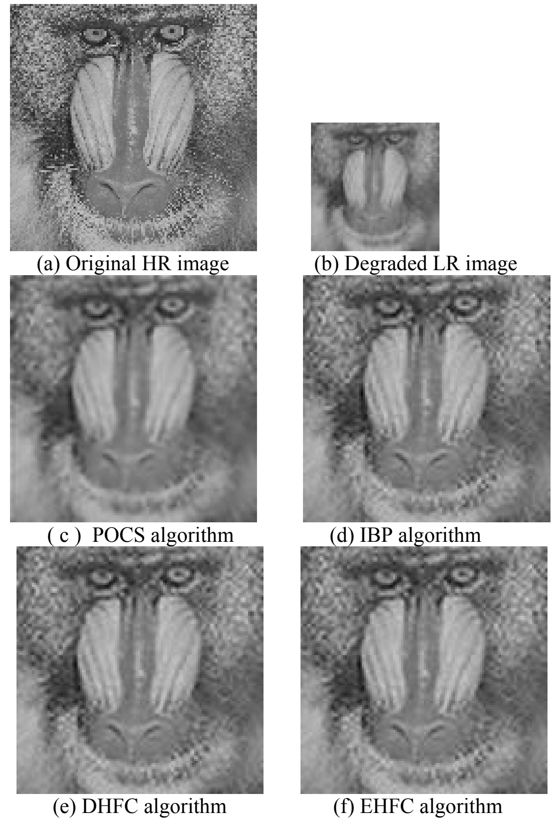


(a) Original HR image (b) Degraded LR image

(c) IBP algorithm (d) POCS algorithm

(e) DHFC algorithm (f) EHFC algorithm

Fig. 5 Reconstruction result comparisons of Lena

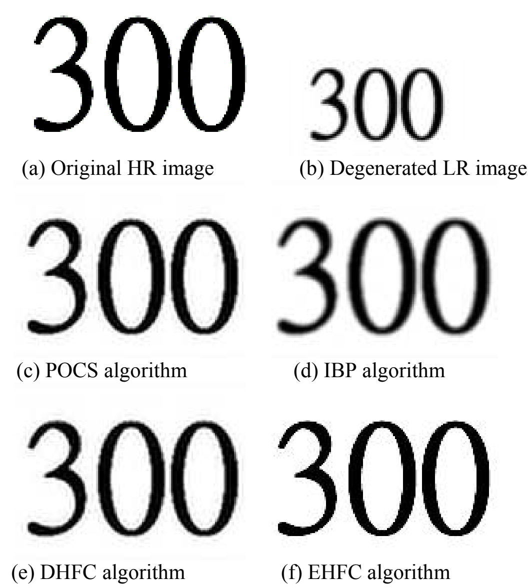


(a) Original HR image (b) Degraded LR image

(c) POCS algorithm (d) IBP algorithm

(e) DHFC algorithm (f) EHFC algorithm

Fig. 6 Reconstruction result comparisons of Baboon



(a) Original HR image (b) Degenerated LR image

(c) POCS algorithm (d) IBP algorithm

(e) DHFC algorithm (f) EHFC algorithm

Fig. 7 Reconstruction result comparisons of Number Text image

(a) Original HR image (b) Degraded LR image

(c) NN algorithm (d) BI algorithm

(e) BC algorithm (f) POCS algorithm

(g) IBP algorithm (h) DHFC algorithm

(i) EHFC algorithm

Fig. 8. Reconstruction result comparison of Chinese Text image

TABLE I
COMPARISONS IN PSNR (K=1000)

Algorithm / Experiment Image	NN	BI	BC	POCS	IBP	DHFC	EHFC
English Text	16.63	17.20	17.20	17.57	28.12	26.47	28.53
Number Text	18.61	19.16	19.64	19.53	48.35	42.58	56.59
Chinese Text	16.83	16.75	17.05	16.65	24.05	24.19	25.65
Lena	27.64	28.26	28.92	27.84	32.39	32.77	32.82
Baboon	21.29	21.35	21.54	21.31	22.42	22.47	22.49
David	31.63	33.78	35.89	30.31	43.23	43.54	43.93

Note: The number of maximum iterations is limited by 1000.

TABLE II
CONVERGENCE EFFICIENCY COMPARISON OF IBP, DHFC, EHFC

Algorithm / Test Image	Required Number of Iterations for IBP and HHFC to Produce Similar PSNR Value in DHFC Convergence			Required Number of Iterations for DHFC and EHFC to Produce Similar PSNR Value in IBP Convergence		
	DHFC	IBP	EHFC	IBP	DHFC	EHFC
English Text	50	98	40	1000	X	132
Number Text	114	358	81	1000	X	239
Chinese Text	338	X	94	1000	217	82
Lena	100	X	26	54	16	9
Baboon	100	X	47	51	23	14
David	10	X	5	50	8	4

Note: The number of maximum iterations is limited by 1000.

B. Analysis on Processing Efficiency and Calculation Complexity

From the results in Table II, in general image tests, the numbers of iterations required for EHFC method to achieve similar PSNR are only 1/10 to 1/4 of the number of IBP method. In addition, the PSNR is increased by about 0.4~0.7 db in EHFC method. In text images, the speed is accelerated by up to 5 folds and PSNR improvement about 1.2~8.3dB.

For instance, in the case of Lena with size 128x128, the computation time to do on iteration is 0.187125 sec. for IPB and 0.312325 sec. for EHFC, respectively. From Table 2, DHFC requires 9 iterations and IBP requires 54 iterations. Hence, the total computation time is 10.10475 sec. for IBP and 2.810925 sec. for EHFC, respectively. As a result, the ratio of the total computation time of EHFC to IBP = 1 : 3.545.

V. CONCLUSION

In addition to the basic IPB method, high frequency processing is especially emphasized in this work. LOG filter capturing the high frequency energy of images in every iteration process is used to improve the convergence iteration speed and the quality of reconstructed images. High frequency energy is compensated progressively during the iteration process.

The proposed EHFC algorithm can greatly decrease the required processing time in obtaining the visual quality similar to the result from IBP method. Alternatively, with the same computation time, EHFC algorithm can produce visual quality better than the one generated by IBP algorithm because the high frequency compensation operation. Further more, EHFC performs well in both general and text test images by estimating the lost information in high frequency and overcoming the early convergence problem. With the proposed EHFC algorithm, the speed is increased up to five folds and the reconstructed image gains 1.2~8.3dB in PSNR.

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