Regularization based Super-Resolution Image Processing Algorithm Using Edge-adaptive Non-Local Means Filter

DaeOk Kim
Computer Science, Yonsei University
134 Shinchon-Dong,
Seodaemun-Gu, Seoul, Korea
+82-2-2123-2719
dokim2021@yonsei.ac.kr

Hyeran Byun
Computer Science, Yonsei University
134 Shinchon-Dong,
Seodaemun-Gu, Seoul, Korea
+82-2-2123-2719
hrbyun@yonsei.ac.kr

ABSTRACT

Super-Resolution (SR) image reconstruction is a technology to reconstruct multiple low-resolution images into one or multiple high-resolution images. As the use of digital camera is recently increasing, the advancement of super-resolution technology gets a great attention. In this study, we propose a regularization-based Super-Resolution algorithm that utilizes an Edge-adaptive Non-Local Means filter. We compare the result of image reconstruction through the algorithm that we proposed and that of image reconstruction through existing studies. As a result, we could verify that a better result would be obtained for regularization function when using an Edge-adaptive Non-Local Means filter rather than using a Non-Local Means filter. We could also obtain much higher PSNR(Peak Signal-to Noise Ratio) than using a Bilateral Total Variation(BTV) method.

Categories and Subject Descriptors

I.4.5 [**Computing Methodologies**] Image Processing and Computer Vision – Reconstruction**.** I.5.4 [**Computing Methodologies**] Pattern Recognition - Computer vision

General Terms

Algorithms, Performance, Verification, Reliability, Theory

Keywords

Super-Resolution, Regularization, Noise reduction, Non-Local Means filter

1. INTRODUCTION

High-resolution image means that the density of image pixel is high, and this is required by various fields such as medical image, satellite image, remote sensing and video surveillance. However, the quality and resolution of the digital images are subject to degradation due to the physical limit and noise of sensors during the image recording process that converts actual analogue world into digital one [1]. Fundamentally, the acquisition method of high-resolution image depends on the aspect of hardware.

ICUIMC(IMCOM)'13, January 17–19, 2013, Kota Kinabalu, Malaysia.

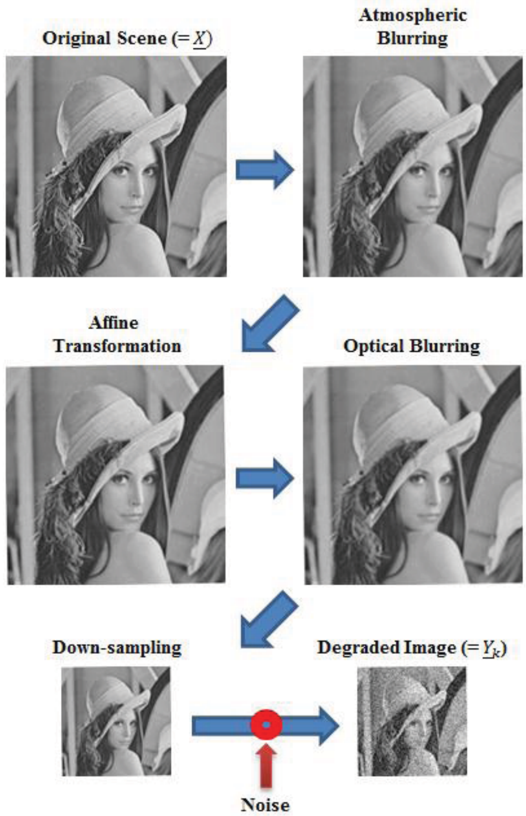

Figure 1. The block diagram of an imaging system.

For instance, enlarging chip size or reducing pixel size if for enlarging the capacity for image pixel. But reducing pixel size may result in the increase of scanning noise, and increasing chip size may result in the increase of capacitance.

This is also directly connected to the problem of increasing the manufacturing cost of image sensor. Therefore, researchers have been developing new technologies to make high-resolution image through one or multiple low-resolution images and this is called Super-Resolution Technology.

In this paper, we define the regularization function using an Edge-adaptive Non-Local Means filter in a regularized super-resolution image reconstruction process and propose a method of reconstructing high-resolution images.

The contents of this paper is as follows; In Chapter 1 and 2, we explore a method of creating image degradation model and a regularized multi-image super-resolution image reconstruction process, and analyze the problems caused by existing up-scaling method. In Chapter 3, in order to solve these problems, we propose an algorithm applied with regularization function newly defined. In Chapter 4, we validate the excellence of this algorithm through the result of experiment and make a conclusion of this paper.

2. RELATED WORK

2.1 Image Degradation Model

First, in order to execute the Super-Resolution image reconstruction, it is necessary to compose appropriate image quality degradation model that can imitates the physical procedure of creating an image. In the image sampling phase, there exist several image-quality degradation elements, for instance, object movement, blurring, down-sampling, etc. Regarding blurring, only optical blurring is focused in this paper because, in this limited imaging system of this paper, optical blurring gives more impact on images than atmospheric blurring [2]. The first thing to be done is to define image-quality degradation model through a mathematical approach with an image model that connects low-resolution image and high-resolution image. An appropriate image degradation model becomes the core of the SR algorithm. This becomes also the principle of every image reconstruction procedure. The details of the degradation model are shown in Figure. 1. In Figure. 1, X indicates original high-resolution image and Y indicates the result image of image degradation mode [8]. In other words, Y means multiple low-resolution images generated through degradation elements from X. It is defined as a Formula (1). $\underline{Y_k}$ is expressed as a set of low-resolution image, while m means the number of low-resolution images generated through the image degradation model. For example, $\underline{Y_{k,1}}$ indicates the low-resolution image of the first execution and $\underline{Y_{k,m}}$ indicates the low-resolution image of the m$^{\text{th}}$ execution.

$$\underline{Y_k} = \left[Y_{k,1}, Y_{k,2}, \ \ldots\ldots, Y_{k,m}\right]^T \qquad (1)$$

The mathematical formula for final image degradation model is defined as Formula (2).

$$\underline{\hat{Y}_k} = D_k H_k F_k \underline{X} + \underline{V_k} \qquad (2)$$

Blur matrix H_k is used for Point Spread Function (PSF) of camera sensor. D_k indicates the down-sampling procedure and the down-sampling matrix calculates the k^{th} image motion and blurring into high-resolution image. F_k indicates the moving matrix of the k^{th} image including the moving direction of horizontal and vertical axes. In this paper, in order to reflect the procedure for moving matrix, we use global movement. $\underline{V_k}$ indicates the Gaussian noise added on the down-sampled image.

2.2 Regularization-based approach

The high-resolution image responding reversely on the formula's basis can be analogized through the image degradation model defined in Formula (2). However, reverse transformation may cause ill-posed problems. As shown Figure. 2, even though multiple low-resolution images exist, pixel information might be insufficient to reconstruct the original image.

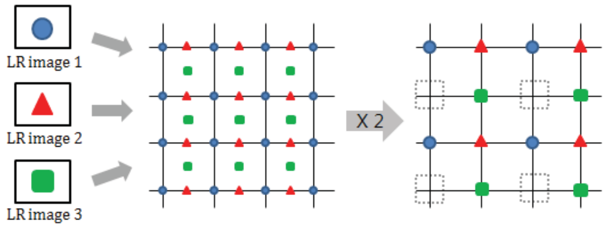

Figure 2. Basic super resolution reconstruction and ill-posed problem

Hence, the regularization-based approach solves the problem of reverse transformation by a solution that can analogize well-posed conditions using the advance information out of the formula (2). In this paper, CLS (Constrained Least Square) method was used to solve the same problem. This is defined as Formula (3) through minimizing Lagrange.

$$\underline{\hat{X}} = \arg\min_{\underline{X}}[\textstyle\sum_{k=1}^{N} \left\|D_k H_k F_k \underline{X} - \underline{Y_k}\right\|_2^2 + \lambda\left\|\gamma(\underline{X})\right\|_2^2 \quad , (3)$$

High-resolution image data can be obtained by finding a solution that minimizes the Formula (3). In this formula, λ is regularization parameter that will control the size of regularization function. In the Formula (3), $\sum_{k=1}^{N}\left\|D_k H_k F_k \underline{X} - \underline{Y_k}\right\|_2^2$ indicates the fidelity between degraded image and input image, and $\left\|\gamma(\underline{X})\right\|_2^2$ reflects the degree of image smoothness as high-frequency information of the image. [1] [6] [7]

The above method has a weakness that it cannot obtain noise reduction and edge preserving simultaneously. As a solution for this problem, Farsiu et al [2] proposed BTV (Bilateral Total Variation) model as regularization function. This is a regularization function from the combination of total variation and bilateral filter, and it is defined as shown in Formula (4). S_x^l and S_y^m indicate moving matrix, while l and m indicate the moving distance of pixel in direction of vertical and horizontal direction respectively, and α ($0 < \alpha < 1$) means weighting coefficient.

$$\gamma_{BTV}(\underline{X}) = \textstyle\sum_{l=-P}^{P}\sum_{m=-P}^{P} \alpha^{|m|+|l|}\left\|\underline{X} - S_x^l S_y^m \underline{X}\right\|_1 \ (4)$$

Based on BTV regularization formula, the Lagrangian objective function for reconstructing a high-resolution image is defined as Formula (5).

$$\underline{\hat{X}} = \arg\min_{\underline{X}}[\textstyle\sum_{k=1}^{N}\left\|D_k H_k F_k \underline{X} - \underline{Y_k}\right\|_2^2 + \lambda\sum_{l=-P}^{P}\sum_{m=-P}^{P}\alpha^{|m|+|l|}\left\|\underline{X} - S_x^l S_y^m \underline{X}\right\|_1] \ (5)$$

Applying the edge and noise of each pixel in the result data of the above formula according to the property of each corresponding area separately, it could be verified that BTV method could obtain an image closer to the original image than the existing regularization method that uses high-frequency function.

3. PROPOSED WORK

In this paper, Non-Local Means filter was used as a regularization function for noise reduction and edge preserving. According to Antoni Buades [4], it was verified that Non-Local Means filter showed better performance in eliminating noise and protecting edge than Total Variation filter. This means that Non-Local Means filter has higher restoration ratio than existing noise eliminating method. As for Non-Local Means filter, if v, a noise image given, is $\{v(i)|i \in I\}$, Non-Local Means noise-eliminated image NL[v](i) can be expressed as Formula (6).

$$\mathrm{NL}[v](i) = \sum_{j\in \mathrm{I}} w(i,j)v(j) \quad (6)$$

$w(i,j)$ is induced as Formula (7) against $\mathrm{N_i}, \mathrm{N_j}$, a set of $\mathrm{N} * \mathrm{N}$ neighboring pixels for each pixel i, j .

$$\mathrm{w(i,j)} = \frac{1}{\mathrm{Z(i)}} \mathrm{e}^{-\frac{\|v(N_1)-v(N_2)\|_{2,\mathrm{a}}^2}{h^2}} \quad (7)$$

Z(i) is a regularization constant and defined as Formula (8).

$$\mathrm{z(i)} = \sum_j \mathrm{e}^{-\frac{\|v(N_1)-v(N_2)\|_{2,\mathrm{a}}^2}{h^2}} \quad (8)$$

In this formula, *h* is the factor that determines the weight of referential pixel in the search area, and *h* was used at a fixed value for the image noise eliminating filter of existing Non-Local Means method. This can eliminate noise and protect edge evenly in the whole area of image. However, in case just one *h* value is applied on the whole input image, edge and noise for each area, i.e., image characteristics are not reflected so that edge disappears in the area with much edge but with little noise, or noise is not eliminated in the area with little edge but with much noise. In other words, in case one *h* value is applied to whole input image, this causes the local structural information not reflected to the image so that it is hard to expect the performance of noise reduction locally optimized [5].

In this paper, we propose a method to improve the performance of Non-Local Means noise reduction regularization function by controlling the value of *h* depending on the local characteristics of input image.

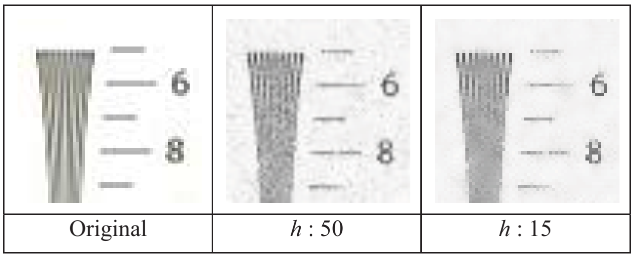

Figure 3. Cropped "PixelTest" image by different referential pixel weighted values. (*h*: referential pixel weighted value in Non-Local Means filter)

Figure. 3 is a screen for a specific area where an *h* value was applied evenly to all the areas in the image noise reduction filter of Non-Local Means method. If a high *h* value is applied to whole area, the image gets smooth but with a lot of noise. For Non-Local Means filter, it is difficult to distinguish neighboring edge and noise in an image. Hence, in this paper, we put different *h* values depending on the characteristics of each area. The characteristics of each area are the size of threshold value for each pixel. But improper threshold value comes out because original image contains noises. Therefore, noise should be eliminated first using Gaussian smooth kernel. The feature value for each area is regularized after being calculated into a threshold value through Sobel operator and applied as a referential pixel weighted value *h*. For an area with high threshold value, a low referential pixel weighted value is applied, and for an area with low threshold value, a high referential pixel weighted value is applied.

In case the result of calculation using Sobel mask is that threshold value is δ, the formula for the referential pixel weighted value of Edge-adaptive Non-Local Means filter is defined as Formula (9).

$$h = \frac{255-\delta}{nor} + min \quad (9)$$

"*nor*" is a constant for normalization and "*min*" is the minimum h. Referential pixel weighted value *h* is substituted to Formula (7) and (8) so as to calculate the noise eliminating filter NL[v](i) of Formula (6).

Noise eliminating filter NL[v](i) composes Formula (10), similar to Formula (5), in order to regularize the result image to be reconstructed.

$$\underline{\hat{X}} = \arg\min_{\underline{X}} [\sum_{k=1}^{N} \rho\left(\underline{\hat{Y}_k}, D_k H_k F_k \underline{X}\right) + \lambda(\mathrm{NL}[\underline{X}])] \quad (10)$$

In order to estimate result images, a method of estimating $\underline{\hat{X}}$ through repetitive revision applying Gradient descent type method.

4. EXPERIMENTS

In this paper, a comparison analysis with other algorithm was conducted to verify the performance of the proposed algorithm. The items of other algorithm are as follows.

1. Bicubic interpolation
2. Tikhonov regularization [1]
3. Bilateral Total Variation regularization [3]

The conditions of performance comparison test were as follows. For Tikonov regularization method, Laplacian kernel was used as regularization function and -0.03 was applied as regularization parameter. The values $\lambda = 0.003, \mathrm{P} = 2, \alpha = 0.7$ of Bilateral Total Variation regularization function was applied. The block size of Edge-adaptive Non-Local Means regularization function proposed in this paper is 5 * 5, Gaussian smooth mask size is 5 * 5, min of referential pixel weighted value *h* is 20 and *nor* is 0.7. The pixel size of low-resolution image is 128 * 128 and the magnification factor of super-resolution reconstruction image is double, 256 * 256. In this paper, the quantitative comparison value of the result data for each algorithm is calculated with Peak signal to noise-ratio (PSNR).

In this paper, the quantitative comparison value of the result data for each algorithm is calculated with Peak signal to noise-ratio (PSNR). It is most easily defined via the mean squared error (MSE). Given a noise-free m * n monochrome image, and its noisy approximation K, MSE is defined as Formula (11).

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \quad (11)$$

PSNR formula is defined as Formula (12).

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (12)$$

MAX_I is the maximum possible pixel value of the image.

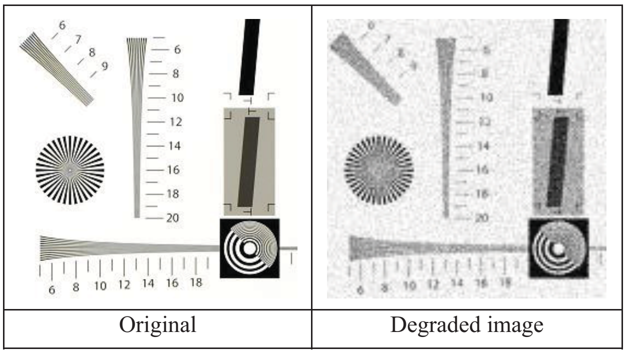

Figure 4. Reconstruction results of the "PixelTest" image

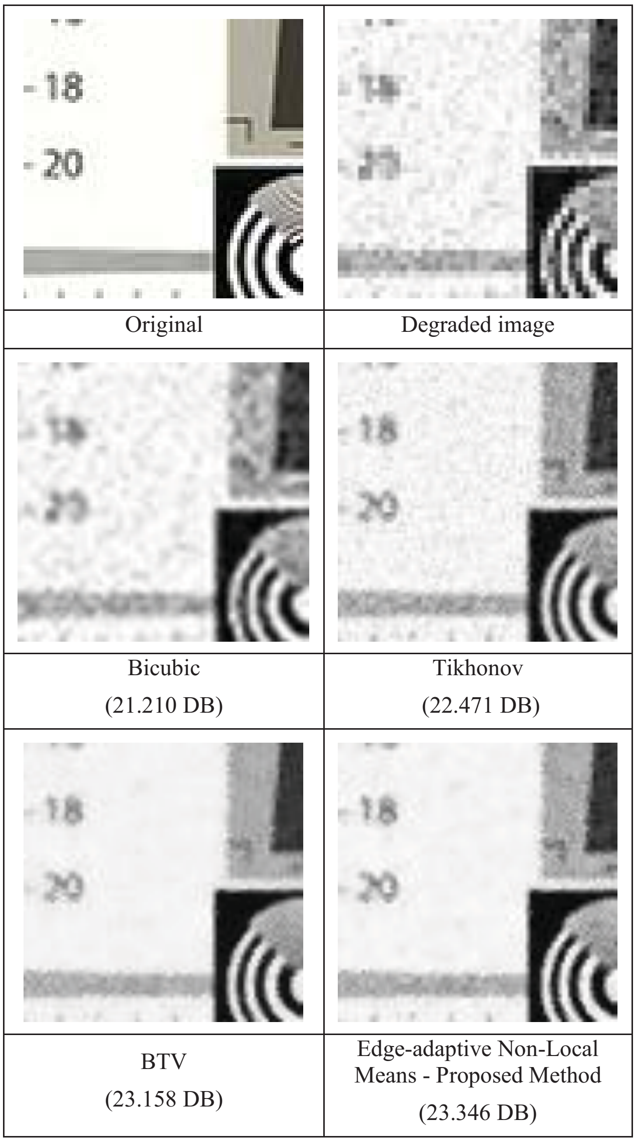

Figure 5. Detailed regions cropped from (Figure 4) Reconstruction results of the "PixelTest" image and PSNR (peak-signal noise ratio) data.

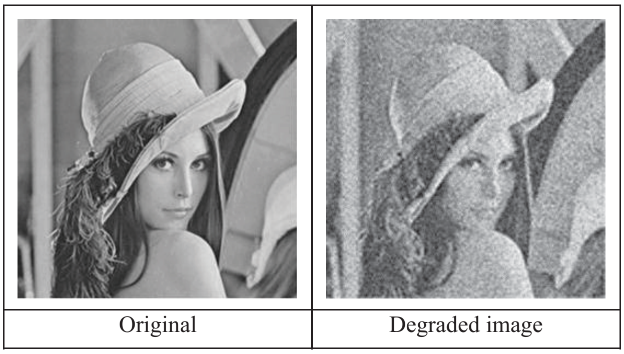

Figure 6. Reconstruction results of the "Lena" image

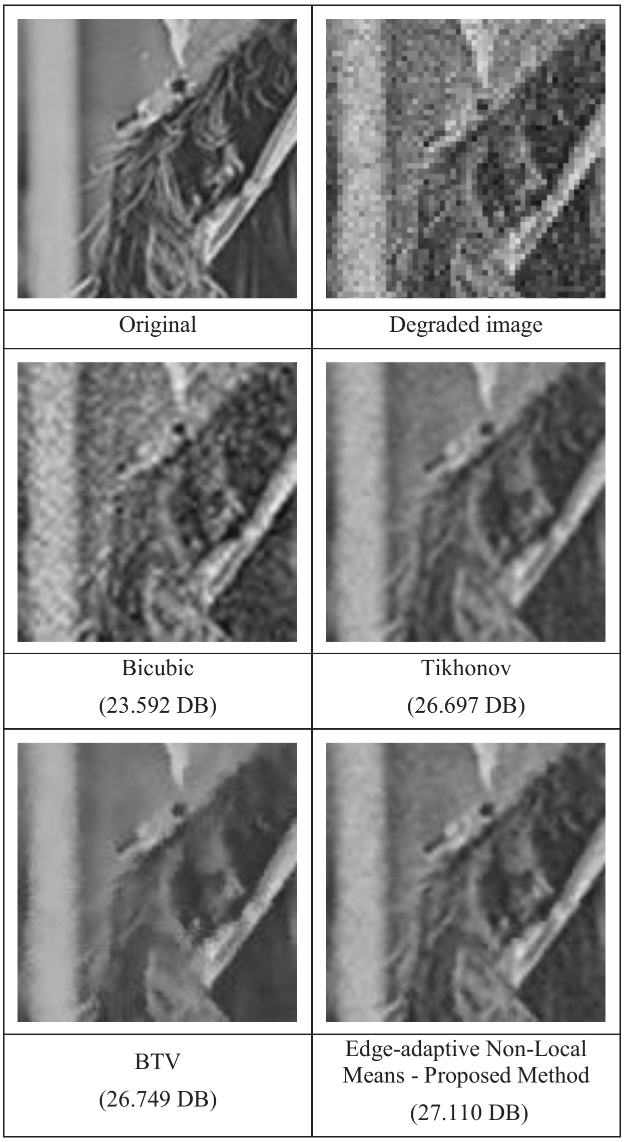

Figure 7. Detailed regions cropped from (Figure 6) Reconstruction results of the "Lena" image and PSNR (peak-signal noise ratio) data.

The left image in Figure. 4 is the original image of "PixelTest" and the right image is a degraded image. In this experiment, one high-resolution image is reconstructed out of 4 degraded images. Figure. 5 shows the cropped images of reconstructed images. Similarly, the left image in Figure. 6 is the original image of "Lena" and the right image is a degraded image. Figure. 7 is the result screen of executing the reconstruction processes of each algorithm with 4 degraded images. These data showed that the image reconstruction using the Edge-adaptive Non-Local Means regularization function produced a better result.

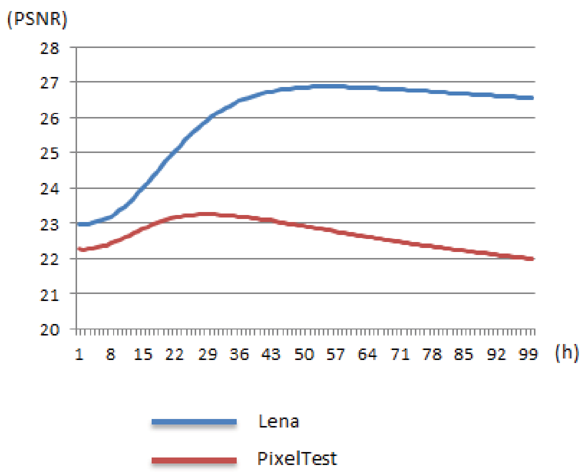

Figure 8. PSNR variation graph by different referential pixel weighted value *h* in regularization function.

In this paper, instead of applying *h* value to whole area during the execution of Non-Local Means regularization function, each *h* value was applied depending on the size of threshold value of each area. Figure. 8 is a graph of PSNR variation according to the variation of the referential pixel weighted value *h* of "Lena" image and "PixelTest" image. As for "Lena" image, when *h* is 55, PSNR value becomes 26.873, the highest value. As for "PixelTest" image, *h* is 29, PSNR value becomes 23.247, the highest value. The result of using the regularization method proposed in this paper was better than existing methods as the PSNR values were 27.110 and 23.346 respectively.

5. CONCLUSIONS

Multi-image super-resolution algorithm is one of the most important issues in image processing. This paper shows a better image can be obtained using Edge-adaptive Non-Local Means regularization function than using existing methods. However, in consideration of the fact that regularization parameter cannot be calculated automatically and the execution of regularization process takes a lot of time, future study is to complement the algorithm proposed with more efficient calculation form.

6. REFERENCES

[1] Nhat Nguyen, Peyman Milanfar, Senior Member, IEEE, and Gene Golub, 2001. A Computationally Efficient Superresolution Image Reconstruction Algorithm. IEEE Transactions on Image Processing, VOL. 10, NO. 4.

[2] S.C. Park, M.K. Park and M.G. Kang, 2003. Super - resolution image reconstruction: a technical overview. IEEE Signal Processing magazine, pp. 21-36.

[3] Robinson, M.D. Elad, M. Milanfar, P. 2004. Fast and robust multiframe super resolution. Image Processing, IEEE Transactions on, page. 1327 – 1344.

[4] A. Buades, B. Coll and J.M. Morel. 2005. A non-local algorithm for image denoising. IEEE Int.Conf. on Computer Vision and Pattern Recognition, vol. II, 60–65.

[5] j.salmon. 2010. On Two Parameters for Denoising With Non-Local Means. IEEE Signal Process, Lett, vol, 17, no, 3, pp. 269-272.

[6] L. Zhang, H. Zhang, H. Shen and P. Li. 2010. A super-resolution reconstruction algorithm for surveillance images. in Int. J. Signal Processing, vol. 90, no. 3, pp. 848-859.

[7] Qiangqiang Yuan, Liangpei Zhang, Huanfeng Shen, and Pingxiang Li. 2010. Adaptive Multiple-Frame Image Super-Resolution Based on U-Curve. IEEE Transactions on Image Processing, VOL. 19, NO. 12.

[8] Xuelong Li, Yanting Hu, Xinbo Gao, Dacheng Tao, and Beijia Ning. 2010. A multi-frame image super-resolution method. Signal Processing, vol. 90, no. 2, pp. 405 –414.