SATELLITE IMAGE SUPER RESOLUTION USING GRADIENT-PRIOR

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ABSTRACT

Super-resolution (SR) has been used in the realm of remote sensing to improve the resolution of an image and get more detailed spatial information than the original image captured by the sensor on the acquisition device. Several SR methods with different approaches, only focusing on sharpening the edges and forgetting non-edge areas. One of the SR methods that utilize prior gradients, can produce high resolution (HR) images in a short time and produce sharp images for non-homogeneous areas. But for areas that tend to be homogeneous, a lot of noise appears. This problem will affect the remote sensing process due to the amount of noise that arises. This paper offers to use dynamic weighting on the gradient prior that will reduce the noise on the homogeneous area, while still able to maintains to produce the sharp edges in non-homogeneous areas. An experimental comparison is conducted on both homogeneous and non-homogeneous area using the previous method and the proposed method.

Index Terms— Image super-resolution, dynamic weighting, gradient-based, gradient prior, image reconstruction.

1. INTRODUCTION

The super-resolution has a function to produce an image that has a higher resolution (HR) and better quality such as a sharper gradient detail compared to the original image that has a low resolution (LR). There are currently 3 approaches to perform super-resolution: interpolation-based, learning-based and reconstruction-based methods.

In the interpolation-based category, the well-known methods are bilinear and bicubic interpolation[1]. These method using fixed kernels to predict the unknown pixels of higher resolution. This method has become a standard and have been widely used but has drawbacks such jaggy edges, ringing effect, and blur of image details. In a learning-based approach, the high-frequency details of a low-resolution image are cloned based on the correlations between the low-resolution and high-resolution image patches in a training set[2-4]. This approach can obtain satisfactory results; however, the high-resolution details cloned by that kind of method cannot be guaranteed to provide real details of high-resolution images. The performance of this approach highly relies on the similarity between the training set and the testing set. In addition, the results are sensitive to the training set. In the reconstruction-based method, a set of low-resolution images of the same scene are registered with sub-pixel accuracy, and the generation of the high-resolution image is formulated as an optimization problem[5]. In addition, the statistical edge information was utilized as constraints in the optimization of SR generation[6-10]. In [7, 9], a gradient profile prior describing the shape and sharpness of image gradients were introduced in the image reconstruction. In[6], a statistical edge dependency relating certain edge features of two different resolutions was employed. In [8] solved the deconvolution process and reconstruction optimization efficiently in the frequency domain. In addition, [11] getting HR image details by fast deconvolution using gradient prior. It employs interpolation method such as bicubic as initial HR image then perform a deconvolution process to sharpen the image. It is fast and perform well but sometimes create a lot of noise.

This paper proposes an image super-resolution scheme by introducing a dynamic weighting to gradient prior to adjust to various types of conditions in the SR process. The contributions of the proposed scheme include: 1) We proposed a gradient-based adaptive super-resolution which is adjusted to the map based on homogeneity area. 2) Having dynamic weight of the gradient prior, we can reduce the noise that appears after the super-resolution process and keeps maintaining of gradient profile sharpness along edges.

2. METHODOLOGY

In general, the mechanism in the proposed method, the LR input will be calculated the variance and the mean value. These two values will produce VMR ratio which will correlate to the weighting of the gradient. This weight value will be used for the next SR process.

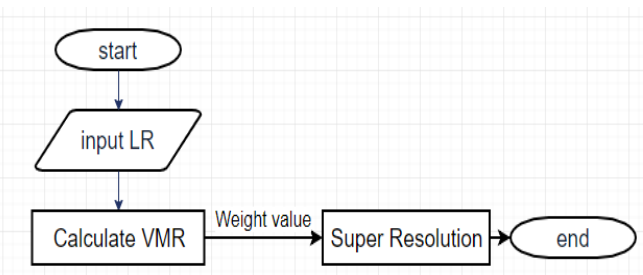

Figure 1. Flowchart of the SR process.

2.1. Variance to Mean Ratio

A map described as a visualization of the point pattern. To describe the pattern quantitatively, two approaches are used, based on points density and points separation. Point Density approach using Quadrat Analysis based on observing the frequency distribution or density of points within a set of grid squares. Point interaction approach using Nearest Neighbor Analysis based on distances of points one from another. The first approach examines first order effects and the second approach examines second order effects[12].

One of the methods in Quadrat Analysis is variance / mean ratio(VMR), which has the following characteristics: 1) For uniform distribution, the variance is zero. 2) For a random distribution, the variance and mean are the same. 3) For a clustered distribution, the variance is relatively large. Then these characteristics are used as a basis for determining homogeneity.

The VMR calculated using the following formula:

$$\frac{\sum_{i=1}^{n} X_i^2 - [(\sum X)^2 / N]}{N-1} \tag{1}$$

2.2. Gradient-based Adaptive Super Resolution

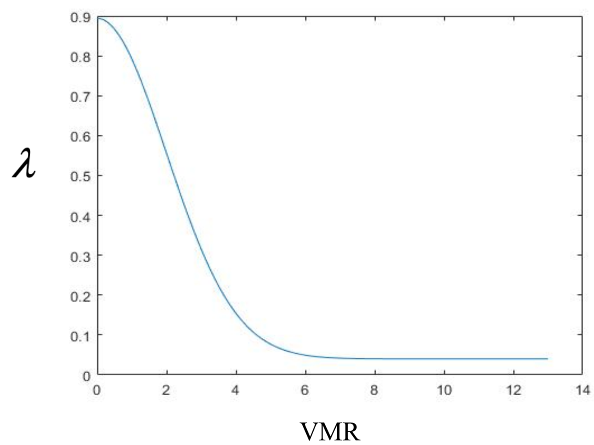

Figure 2. Correlation between λ and VMR

Super-resolution method based on[11]. HR denotes as a high-resolution image, LR as a low-resolution image. First, up-sampled LR using bicubic interpolation. The up-sampling result is denoted as $\tilde{H}$. By utilizing gradient prior from $\tilde{H}$, we have G_x as gradient values of the horizontal direction and G_y as gradient values of the vertical direction. The estimated high-resolution image, denoted as $E(H^*)$, from LR can be calculated

$$E(H^*) = \| f \otimes H^* - \tilde{H} \|_2^2 + \lambda(\| \partial_x H^* - G_x \|_2^2 + \| \partial_y H^* - G_y \|_2^2) \tag{2}$$

where λ is a weight. The equation is transformed into the frequency domain as

$$F(H^*) = \frac{\overline{F(f)} \circ F(\tilde{H}) + \lambda \overline{F(\partial x)} \circ F(G_x) + \lambda \overline{F(\partial y)} \circ F(G_y)}{\overline{F(f)} \circ F(f) + \lambda \overline{F(\partial x)} \circ F(\partial x) + \lambda \overline{F(\partial y)} \circ F(\partial y)} \qquad (3)$$

Adaptive gradient means the gradient value can be changed according to image conditions whether the image is a homogeneous area or not. Its value can be change through weight or λ value. A homogeneous area such as water area needs a bigger λ value to smooth and reduce the noise that emerges after the super-resolution process. On the contrary, the non-homogeneous area needs smaller λ value to strengthen the gradient to get sharper edges.

VMR value is used to define homogeneity. Under some conditions, the VMR value that involves variance are finite, stated that the averages of samples of observations of random variables independently obtained from independent distributions converge in distribution to the normal[13]. To satisfy this condition, we use Gaussian Normal Distribution to correlate VMR value and λ. The formula:

$$f_g(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad (4)$$

where μ is the mean, σ is the standard deviation and σ^2 is the variance.

3. RESULT AND DISCUSSION

In order to get better correlation, we set some parameter in the Gaussian Normal Distribution as follows: $\mu = -0.01$, $\sigma = 2$. Because $0 < \lambda < 1$, we add $\lambda * \pi + 0.05$ to prevent $\lambda = 0$. The degree of homogeneity is determined by the VMR value. The result from observing 100 map images, the correlation of VMR and λ values can be seen in **Figure 2**.

Table 1. VMR and λ values

VMR	Lambda	VMR	Lambda	VMR	Lambda
12.604	0.040	6.674	0.043	1.876	0.588
7.169	0.041	5.039	0.075	2.724	0.376
1.748	0.621	4.272	0.126	2.69	0.383
13.354	0.040	2.012	0.552	0.902	0.810

Using the dynamic value of λ, super-resolution process tested on both homogeneous and non-homogeneous area. The λ value from **Table 1** produces the highest PSNR value shown in **Figure 3**. We took samples many λ values from **Table 1** then choose another value, A1-A5 is gradually different values bigger than λ, and B1-B5 is gradually different values smaller than λ. It proves than VMR process can assign λ a value which tends to give better result in the highest PSNR.

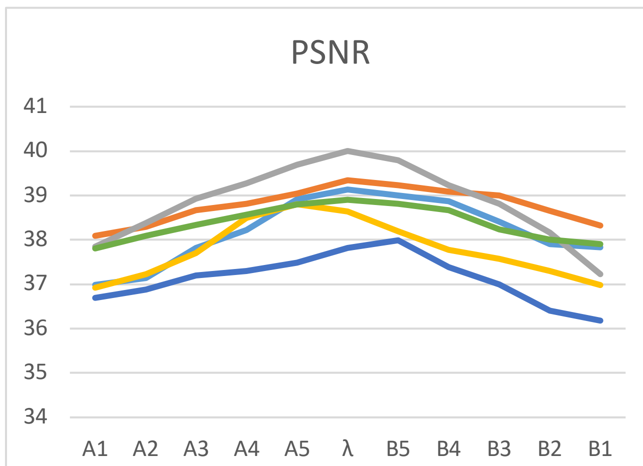

Figure 3. PSNR value with various λ value

Satellite images are taken from Formosat-5 provided by Satellite Image Division, National Space Organization, Taiwan. The first image is a multispectral image contains 4 bands with size 5616x4937 pixels. For multispectral image, only RGB band processed. The second image is grayscale one band with size 2000x2000 pixels.

In the experiment, the first image cropped into 822x804 pixels in the homogeneous area. The result is shown in **Figure 4** and the evaluation shown in **Table 2**.

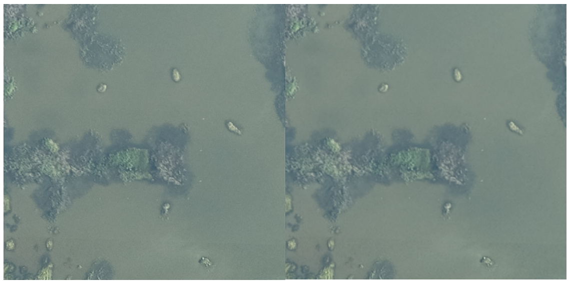

Figure 4. SR result. Left:[11] ; right: proposed method

Table 2. VMR and λ values

Method	Run time (s)	RMSE	PSNR
[11]	0.8	3.2326	37.9397
Proposed Method	0.59	2.8173	39.1342

According to the result in **Figure 5**, the proposed method reduces noise that appears after the super-resolution process, especially for the homogeneous area, compares with[11]. In the non-homogeneous area, the proposed method still improves with sharp edges. Time executions are 0.27s and 0.29s for the original and proposed method, respectively.

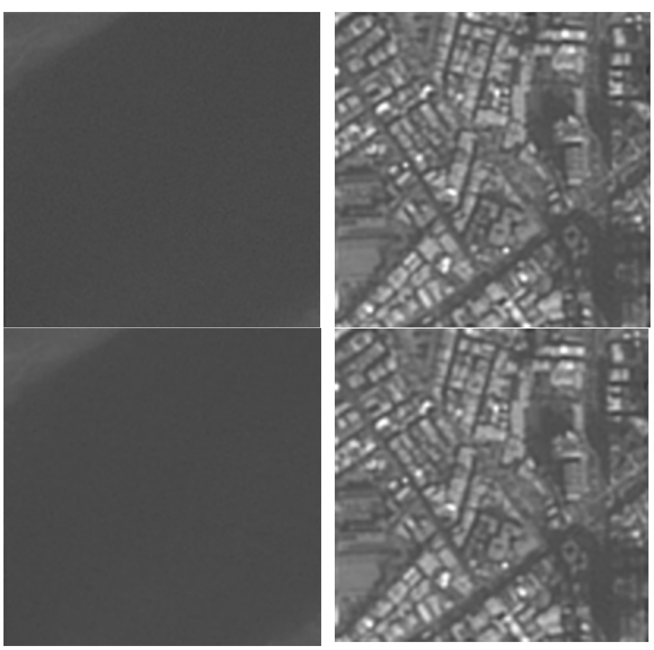

Figure 5. Left: Homogeneous regions; right: non-homogeneous regions, top: result from the related study, bottom proposed method result

4. CONCLUSION

The proposed method, based on the adaptive weight value of the gradient prior can reduce the noise that emerges from the super-resolution process in the homogeneous area. Meanwhile, when applied for the non-homogeneous area, the proposed method can maintain the edge sharpness of the image. Time execution between the two methods has no significant difference.

5. REFERENCES

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