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Image De-noising Using Improved Wavelet Coding: A super-resolution perspective

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Abstract: This paper proposes an improved wavelet coding for image de-noising in a super-resolution perspective. Here we present an improved version of wavelet based image de-nosing technique known as cycle-spinning to avoid the effect of Pseudo-Gibbs phenomena. With the thought of cyclic shift, this paper considers the relationship among each step of the whole reconstruction process, investigates the involved inverse translation and the average operation, and proposes two different image reconstruction methods. The experimental results indicate that these methods can eliminate the Pseudo-Gibbs phenomenon, and get better visual effects subjectively and higher PSNR value objectively.

Keywords: Super-resolution, cycle-spinning, image reconstruction

INTRODUCTION

In the process of image acquisition, there are many factors leading to the degradation of image quality, such as the limited resolution of cameras in time and space. Reducing the pixel size by sensor manufacturing techniques, increasing the chip size and the signal processing method are three ways to increase spatial resolution. The signal processing method can be divided into the reconstruction-based approach and the learning-based approach. The concepts and the methods of image super-resolution (SR) were firstly proposed by Harris and Goodman in the 1960s. It is a kind of the spatial resolution enhancement technology, which uses a single or multiple low-resolution (LR) images to obtain one clear high-resolution (HR) image through different algorithms. The SR image reconstruction method includes two steps: image registration and image reconstruction. Image interpolation is a kind of reconstruction methods, and its main methods include the interpolation method of cubic-spline, the interpolation method of sharpening Gaussian function, the Bayesian method and the learning-based approach. The other existing reconstruction algorithms are the frequency-domain method, the regularization method, the projection on convex set (POCS) method, ML-POCS hybrid method, iterative back projection(IBP) method, adaptive filtering method and the motionless reconstruction method. One application of SR technique is to use LR digital images captured by inexpensive digital camera/ camcorder to reconstruct the high quality image for printing. Other application is to scale the region of interest (ROI) in the field of monitoring, the court, science, medical treatment and satellite image. Another is to transform the low-definition signals with the NTSC format into the high-definition signals with the HDTV format. This paper uses the Cycle-Spinning method for SR image reconstruction. The second part introduces the relevant knowledge of the Cycle-Spinning method. The third section presents two improved algorithms. The fourth portion is the experiment results, and finally we present the conclusion.

2. Related Work:

2.1 Cycle-Spinning:

Cycle-Spinning technique was proposed by Coifman and Donoho, which was intended to eliminate the Pseudo-Gibbs phenomenon caused by imperfect alignment between the image features (such as discontinuous points) and the features of wavelet base function, that is to hop up and down at the special target level near the

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discontinuous points, showing the wave-like ripples in a region of the image. This method was originally used for de-noising, and translated the image by force to change location of the discontinuous points. After a series of processing, the inverse translation is preceded, as the equation (1) is as follows;

$$\bar{T}\left(x;(S_h)_{h\in H}\right) = Ave_{h\in H} S_{-h}\left(T\left(S_h(x)\right)\right) \quad (1)$$

The formula is described by words: the average [translation, de-noising, inverse translation], where *H* represents a series of data set with translation in the time domain, *h* is one translation, -*h* denotes the inverse translation of *h* , *S* is the translation operation, *T* represents the de-noising operation, *Ave* denotes the average operation. We extend its idea and replace the above de-noising operation *T* with the Super-resolution image reconstruction.

2.2 Image Enhancement Using Cycle-Spinning:

Temizel used the Cycle-Spinning method for image enhancement. Its specific steps are: use the wavelet-domain zero-padding (WZP) method firstly to generate a HR image *y* from a LR image *x* with the size of $m \times n$. The generation process is regarded *x* as the low-frequency coefficients through the discrete wavelet decomposition of *y*, instead the all-zero matrix with the high-frequency coefficients and then carry out the inverse discrete wavelet transform (DWT), as the equation (2) is shown as follows;

$$\hat{y}_0 = W^{-1}\begin{bmatrix} x_{m,n} & 0_{m,n} \\ 0_{m,n} & 0_{m,n} \end{bmatrix} \quad (2)$$

Do the operation of spatial translation, wavelet transform and high-frequency coefficients remove for the generated y_0 , and take the final low-frequency coefficients as the multiple LR images x_i , where $i \in \{1,2,3,4,\ldots. N\}$, N presents the translation times in the horizontal and vertical direction (-*k*, -*k*) , (-*k* +1, -*k*), (-*k* +1, -*k*+1),.....(0,0),…., (*k* -1, *k* -1) , (*k* -1, *k*), (*k*, *k*), N = (2*k*+1) (2*k*+2).

Employ the above wavelet-domain zero-padding method to generate *N* high-resolution images $\hat{y}_i$ from all the low-resolution images $\hat{x}_i$, take the average operation after the inverse translation, and get the final reconstructed image HR. This method uses the LR images with different numbers. The experimental results prove that if $k = 2$, the peak signal to noise ratio (PSNR) of reconstructed image is the highest, referring this value in our experiment. In this paper, the wavelet Daubechies 9/7 is used, whose length of the decomposition and reconstruction filters are 9 and 7 respectively, and it is the bi-orthogonal wavelet filters with the symmetrical structure.

2.3 SR Reconstruction Using Cycle-Spinning:

Multi-frame SR reconstruction based on Cycle-Spinning is similar to Section 2.2, different from the initial input images, as equation (3) as follows;

$$f_t(x,y) = f_{t-1}\left(x + s^x_{t-1,t}(x,y),\, y + s^y_{t-1,t}(x,y)\right) \quad (3)$$

where $f_{t-1}(x, y)$ and $f_t(x, y)$ are the two successive frames in the time t-1 and t, $s^x_{t-1,t}(x,y)$ and $s^y_{t-1,t}(x,y)$ represent the displacement represent the displacement of the two successive frames in the horizontal and vertical direction respectively. This paper assumes that the continuous sequences imply the translations, completing the process from $\hat{x}_i$ to $\hat{y}_i$ in Section 2.2, so it constructed the multi-frame SR image reconstruction framework based on Cycle-Spinning.

3. Algorithm description:

The first step of analysis the SR image reconstruction is to establish the observation model using the formula, describing how to get the original HR image the from the observed LR images. The proposed observation model is divided into the static image model and video sequence model. This paper uses the former. The desired HR image y_k can be obtained by the observed LR image x through the distorted matrix W_k with the noise n_k. While the distorted matrix contains the sub-sampling D, the blur B_k, and the motion M_k , there are $y_k = W_k x + n_k$, k=1, 2, 3, 4, ……p and $W_k = D B_k M_k$.

3.1 ***Two Key Factors:***

Integrated the above applications, we find that each step has a certain relationship between each other in the entire reconstruction process of Cycle-Spinning, in which there are two key factors. One is the inverse translation. Because translation and the inverse translation are always in pairs, the objects of processing should be the same kind. Specifically, if the beginning translation is used for the LR images, then the following inverse translation should also correspond to the LR images; HR image has no exception. However, Yan's algorithm in Section 2.3 did not follow this equivalence principle. Thus, we change the location of the inverse translation operation in our experiment. The other is the average operation. Coifman and Donoho in Section 2.1 gave us the framework for the average operation after the operation of the translation and the inverse translation, not indicating whether to do it immediately after the inverse translation or only at the end. We believe that the average operation is a kind of more ideal method to eliminate the errors through a series of operations, so it should be placed in the final step. The experiment behind verify our hypothesis.

3.2 Algorithm Steps:

The difference of our two methods is the position of average operation. For the input images, we discuss the details in the experiment of the Part Four.

3.2.1 Cycle-spinning reconstruction method-1 (CSR1):

Yan proposed a method to simulate the framework proposed by Temizel and add the assumptions of the input N LR images containing the translation, place the inverse translation before the average operation, but not consider the corresponding relationships between the translation and the inverse translation, namely, this pair-wise operation should precede the same object. The translation operation of Temizel is in the HR image, so the inverse translation operation should aim at the HR image. But that of Yan is implied in the LR images, so the inverse one should be in the LR images, rather than in the HR image. Therefore we place the inverse translation operation of Yan after the LR images, short for CSR1. The specific steps describes below, as shown in Figure 1.

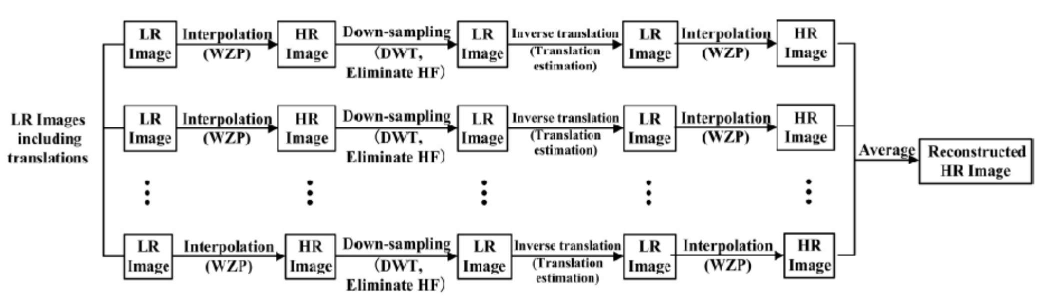

Fig. 1: The flow chart of CSR1

a) Do the interpolation operation for multiple LR images. The input images are viewed as low-frequency coefficients of DWT after the interpolation. The three high-frequency coefficients have the same size with the zero matrices of the low-frequency coefficients, and do the inverse DWT to get the interpolated HR image.

b) Do the down-sampling operation for multiple interpolated HR images. Down-sampling method is to do the DWT, rounding the high-frequency coefficients, only leaving the low-frequency coefficients as the down-sampling LR images.

c) Do the translation estimation for multiple down-sampling LR images, and select the first image as a reference image.

d) Do the inverse translation for multiple down-sampling LR images.

e) Do the interpolation operation after the inverse translation of multiple LR images, and the interpolation method is the same in the first step.

f) Do the average operation for multiple down-sampling LR images, and get the final reconstructed image HR.

3.2.2 Cycle-spinning reconstruction method-2 (CSR2):

The Cycle-Spinning frame proposed by Coifman and Donoho only stated that the average operation was after the inverse translation operation, and the exact location was not clear. In other words, the average operation can be anywhere between the inverse translation and the final results. Thus, we put it after the location of the inverse translation, short for CSR2, and the specific steps are described below, as shown in Figure 2.

a) Do the interpolation operation for multiple LR images. The input images are viewed as low-frequency coefficients of DWT after the interpolation. The three high-frequency coefficients have the same size with the zero matrices of the low-frequency coefficients, and do the inverse DWT to get the interpolated HR image.

b) Do the down-sampling operation for multiple interpolated HR images. Down-sampling method is to do the DWT, rounding the high-frequency coefficients, only leaving the low-frequency coefficients as the down-sampling LR images.

c) Do the translation estimation for multiple down-sampling LR images, and select the first image as a reference image.

d) Do the inverse translation for multiple down-sampling LR images.

e) Do the average operation for multiple LR images after the inverse translation, and obtain the average LR image.

f) Do the interpolation operation for this average LR image, and get the final reconstructed image HR. The interpolation method is the same as (1) in CSR1.

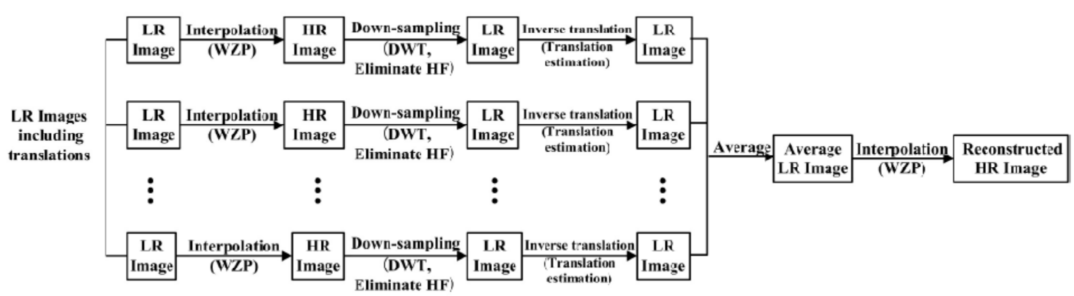

Fig. 2: The flow chart of CSR2

4. Experimental results:

We conduct an experiment with the above two methods. The standard test image Lena.tiff with the size of 512×512 is chosen. In condition of accurate translation, the wavelet transform used in the experiment is

Daubechies 9/7. We add Gaussian noise (average value = 0, variance = 0.01) to the image, and make the known translation operation. We set the translation as (0, 0), (0, 0.5), (0.5, 0), (0.5, 0.5) respectively in our experiment, and keep its value in order to use in the inverse translation. The results of experiment are shown in Figure 3 and Table 1.

Table 1: The PSNR (dB) values using different SR methods

Lena Image/Methods	Yan	CSR1	CSR2	IBP	POCS
PSNR (dB)	24.9131	26.1368	25.9381	19.2728	23.6794

In the Figure. 3, we can tell the two methods we proposed are much better than IBP and POCS algorithm in the subjective vision effect, and our methods eliminate the Pseudo-Gibbs phenomena obviously. In the Table. 1, it shows that the PSNR value of our methods is higher distinctly, which is totally in accord with the subjective vision effect. In the Figure. 4, we can visualize the graphical representation of the PSNR values for various different super-resolution methods.

Conclusion:

This paper analyzes the previous methods that make image reconstruction using Cycle-Spinning, studies the similarities of these methods, and proposes two improved algorithms. This improve is based on the hypothesis that several LR input images is the low-frequency coefficients of HR image after DWT. Considering the corresponding relationship and the average operation between the inverse translation and the translation, this paper make the super-resolution image reconstruction in the wavelet domain using Cycle-Spinning, and the results of experiment prove the feasibility of these methods. The next work can concentrate on the following aspects. This paper researches on the relationship between each step of the reconstruction process, and some further study should be discussed, such as the importance level of every step, the usage of the input images, the differences between wavelet base function, the algorithms of translation estimation, adding the rotation factor into the Cycle-Spinning model, extending this method from the image reconstruction to the reconstruction of video sequences and developing a complete system with the GUI interface by integrating each step.

Fig. 3: Final results of Lena Image

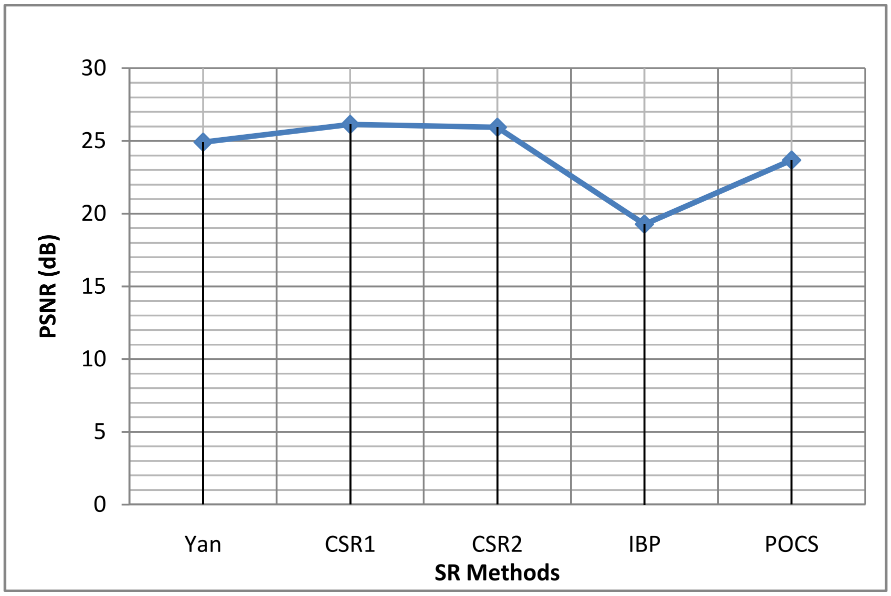

Fig. 4: PSNR of Lena image for different SR methods

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