The Precision Exploration of Image Super-Resolution Applied into Motion Measurement

Ye Wei, Wenhui Hou, Wei Feng, Yi Jin, Chang’an Zhu

School of Engineering Science, University of Science and Technology of China, Hefei, People’s Republic of China

E-mail: jinyi08@ustc.edu.cn, weiy128@mail.ustc.edu.cn

Abstract. This paper proposes a new evaluation parameter of image super-resolution reconstruction quality, which is used to determine the influence of super-resolution reconstruction on motion measuring precision. Based on this new evaluation parameter, we respectively employ different algorithms of super-resolution reconstruction with different reconstruction scales, then calculate the motion measuring precision using the corresponding super-resolution image, analyze the impact of image super-resolution technology on the precision of image motion measuring. The experimental results show that only part of the super-resolution algorithms can improve the measuring precision slightly, and prove that under the background of image motion measurement, image super-resolution reconstruction method has the potential to apply to the actual measurement.

1. Introduction

It’s undeniable that the computer vision motion measurement has been increasingly popular and applied in recent years based on its non-contact measurement [1]. However, the computer vision measurement precision is mainly depends on the resolution of the camera. The camera with high resolution will bring the higher calibration accuracy. Namely, under the background of the same pixel error, the high accuracy of measurement can certainly be obtained with the high resolution image. However it’s upsetting that the price of the high resolution camera is not proportional to the resolution multiple of camera but far higher than that of low resolution camera. Besides, high resolution image often take up more storage space. Therefore, the image super resolution (SR) has very import application value and has been widely used in varieties of fields such as HDTV, video surveillance, remote sensing and medical image processing [2].

Existing SR algorithms can be classified into three categories: interpolation-based, reconstruction-based, and learning-based methods. Interpolation-based approaches, such as bilinear and bicubic interpolation, are the most commonly used methods in practice to upscale images. However, they tend to produce ringing and jagged artifacts as well as over-smoothing the critical structures such as edges [3], lead to the image blurring. In order to solve the above drawbacks, Li [4] proposed NEDI model which utilizes the similarity of the covariance matrix between the LR image and corresponding HR one to interpolate the pixels along the edges. Getreuer [5] introduces contour stencils for estimating the image contours and designing an edge directed color interpolation method.

By building an imaging model of the LR image, reconstruction based algorithms consider the image transformation in imaging, and look for the optimal estimation of the true HR image [6].
assume a simplified continuous imaging process and usually formulate the imaging process as a linear system. Among them, the frequency domain method is a pioneering approach [7]. The reconstruction based approaches do not exploit prior knowledge for potential effect improvement. What’s more, the high-frequency information often can't be reconstructed well with a large SR scaling factor. Hence, the reconstruction-based algorithms are limited in improving image resolution [8].

Finally, the learning-based approaches have become popular recently [9]. The learning procedure is used to supply prior knowledge to guide the SR reconstruction. This method can overcome many defects of the reconstruction-based approaches. And it mainly via structure analysis of image patches [10]. Also based on the image patches, Yang realized super-resolution and obtained a nice result via sparse representation which was named ScSR [11]. Similarly, the convolution neural network (CNN) was applied in this method by Dong [12]. But this method pays the price of large memory consumption. And if an external training database is used, noticeable artifacts often exist in the results when the specific image content does not match well with the training database. An alternative is to acquire the training set from the image itself based on local self similarities (LSS) [13], which can reduce memory consumption and achieve good results. LSS is based on research on image statistics that suggests image patches can be well-represented as a sparse linear combination of elements from an appropriately chosen over-complete dictionary. What’s more, the integration of several algorithms can make the result better, like the method named as A+ [14].

This paper tries to test the influence of the high-resolution image reconstructed from the low resolution image on the accuracy of the image motion measurement, especially in the tiny motion measurement by using the image super-resolution reconstruction algorithms. So we proposed a new evaluation parameter of image super-resolution reconstruction quality, and based on it, we investigate the effects in different reconstruction scales and shifts with different algorithms: Bicubic, Yang [13], A+ [14], Kim [10], ScSR [11] and SRCNN [12] by using the image in the database. The remainder of this paper is organized as follows. Section 2 explains the meaning of the new evaluation parameter, and gives the main process of the test. Section 3 presents the results of these tests. Finally, the conclusion is drawn in Section 4.

2. The new evaluation factor
There are mainly two evaluation factors for the quality of image super-resolution reconstruction which are Peak signal-to-noise ratio [15] and Structural SIMilarity [16]. Peak signal-to-noise ratio, often abbreviated as PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because the dynamic range of many signals are very wide, PSNR is usually expressed in terms of the logarithmic decibel scale. The Structural SIMilarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index can be viewed as a quality measure of one image compared with the other image whose quality is regarded as perfect.

In order to preferably evaluate the precision of image motion measurement with image super-resolution reconstruction algorithms, we propose the precision of SR in motion measurement, abbreviated as PRVM. To get the PRVM value of a algorithm utilized in a image, we need to know the accurate value of the motion. So the image displacement transformation is applied to simulate the motion of the image. The specific process can reference below, as shown in figure 1.
First of all, an original image P with high resolution is shifted by a presupposed value D, which is regarded as the image motion displacement in plane. And \( D = [\text{shift}_x \, \text{shift}_y] \). In order to research the effect of SR algorithms in tiny motion, the value should be supposed smaller than the general one. The shift is implemented by applying a linear phase on its FT, thus we have assumed that the image is wrap around (features leaving one side of the window reappear on the opposite side) and that the image is band-limited (interpolated by a sinc function). Cross-correlation image registration by DFTs (both the matrix-multiply DFT and the zero-padded FFT) shared the same assumptions.

Then the original image P and the shifted image DP are both conducted the sampling process with scale M to reduce their resolutions. The two new images LP_M and LDP_M are calculated by the registration algorithm \([17]\), which can obtain the shift values in the x and y directions respectively and can guarantee the accuracy of 0.001 pixel. So the shift values calculated from low resolution images are regarded as the measurement value in low resolution, written as \( L_x \) and \( L_y \). After that, we reconstruct the images with the SR algorithms and got the high resolution images SLP_M and SLDP_M respectively. Similarly, we calculate the shift values \( S_x \) and \( S_y \) from the new high resolution images.

At last, the PRVM of the algorithm utilized in this original image with presupposed shift D can be presented as

\[
PRVM = |S_x - \text{shift}_x| / \text{shift}_x \quad |S_y - \text{shift}_y| / \text{shift}_y
\]  

And the measure error in low resolution images can be calculated by

\[
Err = |L_x \cdot M - \text{shift}_x| / \text{shift}_x \quad |L_y \cdot M - \text{shift}_y| / \text{shift}_y
\]  

Obviously, only when the PRVM is smaller than the Err, the algorithm can be considered effective.

### 3. The results of research

Take the picture ‘Lena.jpg’ for example, we conducted 7 SR reconstruction algorithms on it to test the effects. The reconstruction scales selected were 2, 3, 4 respectively. The original picture and the sampled pictures in different scales were shown in figure 2. The solution of ‘Lena.jpg’ is 512X512, in order to better represent the effect, we narrowed all the pictures in 3 times in the following paper.
Figure 2. The original image and its sampled images in scale 2, 3, 4.

We set 3 shifts to simulate the different motions, shift 1 = [-5.7534  6.2157], shift 2 = [7.4702 - 2.0951], shift 3 = [1.1452  8.3576]. The values in x and y directions of Shift 1 are close while those of shift 2 and shift 3 were largely different in two directions. The shifted images are shown in figure 3.

Figure 3. The shifted images in different shift values

The SR algorithms selected are Bicubic, Yang [13], A+ [14], Kim [10], ScSR [11] and SRCNN [12]. And the reconstructed images of the sampled image with scale 2 are presented below in figure 4.

Figure 4. the reconstructed images by the figure 2(b) in different SR algorithms

3.1. The results of different scales and shifts
The first content we test is the effect of SR reconstruction scale on the measure precision. The reconstructed images of shift 1 in different scales are shown in figure 5.
Figure 5. The SR images of shift 1 in different scales and algorithms

The values of Errs with shift 1 in three scales are [0.06%, 0.23%], [0.41%, 0.98%] and [0.25%, 0.01%] respectively. And the PRVM values of different algorithms in different scales are calculated in Table 1, in which the effective algorithm results are bold.

| Bicubic | Yang   | A+    | Kim    | ScSR | CNNSR |
|---------|--------|-------|--------|------|-------|
| 2X      | 0.13%  | 2.06% | 1.41%  | 0.09%| 0.28% | 1.16% |
|         | 0.27%  | 2.30% | 1.85%  | 0.42%| 0.42% | 1.46% |
| 3X      | 0.64%  | 2.79% | 1.67%  | 0.56%| 0.92% | 1.37% |
|         | 0.85%  | 3.64% | 2.62%  | **0.78%**| 0.48%| 2.07% |
| 4X      | 0.34%  | 5.08% | 3.58%  | **0.01%**| 0.27%| 2.31% |
|         | 0.34%  | 4.94% | 3.27%  | 0.34%| 1.39% | 2.19% |

Similarly, the PRVM values with shift 2 and shift 3 are presented in Table 2 and Table 3 respectively.

| Bicubic | Yang   | A+    | Kim    | ScSR | CNNSR |
|---------|--------|-------|--------|------|-------|
| 2X      | 0.49%  | 1.23% | 0.71%  | 0.29%| 0.51% | -0.69%|
|         | 0.25%  | 5.89% | 4.74%  | 1.48%| 0.64% | 4.11% |
| 3X      | 1.33%  | 2.02% | 1.09%  | **0.98%**| 1.58%| **1.03%**|
|         | 4.48%  | 7.43% | 4.44%  | 3.89%| 8.11% | 3.25% |
| 4X      | 1.14%  | 2.47% | 1.40%  | 0.29%| 1.90% | 1.12% |
|         | 2.98%  | 11.78%| 9.21%  | **0.37%**| 3.86%| 6.90% |

| Bicubic | Yang   | A+    | Kim    | ScSR | CNNSR |
|---------|--------|-------|--------|------|-------|
| 2X      | 1.58%  | 4.94% | 2.84%  | **0.42%**| 2.43%| 3.71% |
|         | 0.51%  | 1.61% | 1.47%  | 0.39%| 0.58% | 1.17% |
| 3X      | **3.06%**| 13.72%| 13.56%| 7.89%| 9.40% | 8.01% |
|         | 1.59%  | 1.68% | **0.44%** | 1.57%| 2.41%| **0.63%**|
| 4X      | 13.16%| 16.24%| 13.03%| 13.33%| 16.41%| 9.67% |
|         | 0.49%  | 3.34% | 2.67%  | 0.52%| 0.93% | 1.95% |

The data shows that the image measurement has a certain accuracy under the low resolution in image measurement, but it is arbitrary to conclude that the SR reconstruction algorithms can improve the precision of the measurement only from the above data. In order to better compare the impact on the results of different reconstruction scales, we classify the above data according to the reconstruction scale, and accumulate the effective times under the same reconstruction scale. The results are shown in Table 4.
Table 4. The effective times of different algorithms in different scales for ‘Lena.jpg’

|       | Bicubic | Yang  | A+   | Kim  | ScSR | CNNSR |
|-------|---------|-------|------|------|------|-------|
| 2X    | 0/6     | 0/6   | 0/6  | 1/6  | 0/6  | 0/6   |
| 3X    | 2/6     | 0/6   | 1/6  | 2/6  | 1/6  | 2/6   |
| 4X    | 0/6     | 0/6   | 0/6  | 2/6  | 0/6  | 0/6   |

In table 4, each algorithm is conducted 6 times measuring calculations for each scale. And what can be seen from table 4 is that, for image ‘Lena. JPG’, all kinds of SR reconstruction algorithms can’t improve the results obviously, including Kim [12] algorithm is slightly better than other algorithms. The reconstruction scale does not evidently effect on the reconstruction of the algorithm. Similarly, the classification of the shift is implemented, and the corresponding results of each shift in both directions are shown in table 5.

Table 5. The effective times of different algorithms in different shifts for ‘Lena.jpg’

|       | Bicubic | Yang  | A+   | Kim  | ScSR | CNNSR |
|-------|---------|-------|------|------|------|-------|
| Shift 1 | 0/3     | 0/3   | 0/3  | 1/3  | 0/3  | 0/3   |
| Shift 2 | 0/3     | 0/3   | 0/3  | 1/3  | 0/3  | 1/3   |
| Shift 3 | 1/3     | 0/3   | 0/3  | 1/3  | 0/3  | 0/3   |

From table 5, we can get that, just for image ‘Lena. JPG’, the motion of the different direction doesn’t affect the SR reconstruction’s influence on the accuracy of measurement. In general, it is not adequate to get the effective conclusion merely rely on the results of one image, so we need to test more image data.

3.2. The results of different images

In order to guarantee the validity of the results, we choose 4 images from BSD500 database to conduct this test which are: ‘8086.JPG’, ‘64061.JPG’, ‘257098.JPG’ and ‘372019.JPG’. Via accumulating all the images results, the classification results according to the reconstruction scale are shown in table 6.

Table 6. The effective times of different algorithms in different scales

|       | Bicubic | Yang  | A+   | Kim  | ScSR | CNNSR |
|-------|---------|-------|------|------|------|-------|
| 2X    | 7/30    | 5/30  | 8/30 | 11/30| 10/30| 10/30 |
| 3X    | 10/30   | 6/30  | 10/30| 11/30| 10/30| 12/30 |
| 4X    | 10/30   | 5/30  | 8/30 | 15/30| 8/30 | 15/30 |

From table 6, we can get that with the increasing of the reconstruction scale, the image reconstructed by SR algorithms become more suitable than the original low resolution image for image measurement, especially the effects of algorithm Kim [10] and CNNSR [12] are more noticeable. According to this trend, it is presumable that the image of SR reconstruction can partly improve the precision of image measurement in the condition of high reconstruction scale. Statistics of all images results of different motion direction are shown in table 7.
Table 7. The effective times of different algorithms in different shifts

|        | Bicubic | Yang  | A+   | Kim  | ScSR | CNNSR |
|--------|---------|-------|------|------|------|-------|
| Shift 1| 2/15    | 3/15  | 4/15 | 5/15 | 1/15 | 6/15  |
|        | 5/15    | 0/15  | 1/15 | 6/15 | 6/15 | 7/15  |
| Shift 2| 6/15    | 7/15  | 11/15| 6/15 | 6/15 | 11/15 |
|        | 4/15    | 2/15  | 1/15 | 4/15 | 2/15 | 3/15  |
| Shift 3| 4/15    | 1/15  | 3/15 | 8/15 | 6/15 | 3/15  |
|        | 6/15    | 2/15  | 6/15 | 7/15 | 6/15 | 7/15  |

It’s very easy to find the difference between row ‘Shift 2’ and row ‘Shift 3’ in table 7. And it illustrates that the SR reconstruction images with a large shift is superior to the small one in the displacement measurement. Therefore, in the context of tiny motion measurement, the applicability of the image SR reconstruction is limited.

For different images, the influence of the image with 6 SR reconstruction algorithms is explored. The results are shown in table 8.

Table 8. The effective times of different algorithms for different images

|        | Bicubic | Yang  | A+   | Kim  | ScSR | CNNSR |
|--------|---------|-------|------|------|------|-------|
| Lena   | 2/18    | 0/18  | 1/18 | 5/18 | 1/18 | 1/18  |
| 8086   | 6/18    | 5/18  | 7/18 | 7/18 | 5/18 | 11/18 |
| 64061  | 6/18    | 5/18  | 6/18 | 7/18 | 7/18 | 9/18  |
| 257098 | 5/18    | 1/18  | 4/18 | 5/18 | 4/18 | 5/18  |
| 372019 | 8/18    | 5/18  | 8/18 | 13/18| 10/18| 11/18 |

As can be seen from the table 8, the applicability of SR algorithm is also different for different images. We can see that all sorts of algorithms are unsatisfactory for ‘Lena.JPG’, however the good results can be obtained for ‘372091.JPG’. Compare these two images, we found that the boundaries in the image ‘372091.JPG’ is more obvious than ‘Lena.JPG’. So we can speculate that the SR reconstruction algorithm can significantly optimize the image measurement for the image with clear edges.

In general, the SR reconstruction algorithm, can improve the precision of image measurement on a certain extent, and the performance of algorithm Kim [10] and CNNSR [12] is more outstanding.

4. Conclusions

In this paper, we sample and reconstruct the simulated motion images through the usage of image super-resolution reconstruction algorithm, and establish a new evaluation mechanism for the precision of image motion measurement. And we try to test the value of image super-resolution reconstruction in the field of image measurement. The results show that the super-resolution image reconstruction can only improve the motion measurement precision of the image in the image measurement on a certain extent.

The results show that the reconstruction images do not affect the accuracy of measurement significantly within a certain range of image reconstruction magnification, but there is a tendency that the effects would be better when the reconstruction scale increased; The main motion direction don’t effect on the accuracy of measurement. The error for small displacement measurement is larger than the big displacement, which illustrates that the SR reconstruction is not suitable for micro motion measurement; The influence of all kinds of super-resolution reconstruction algorithm on image measurement precision is random. And the edge information contrast in the image has great effect. The image with big edge information contrast is more suitable for SR reconstruction algorithm.
Among all the compared algorithms, the effects of algorithm Kim [10] and SRCNN [12] are better. In general, it requires further processing and optimization if you want to apply image super-resolution algorithm to image motion measurement process.

For the practical application of the SR reconstruction on the motion measurement, we plan to improve the preprocessing process and find the best parameters of the applied SR reconstruction algorithms. The next work will be better in real measurement.

5. References

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