Performance Evaluation of Super-Resolution Reconstruction Algorithms Based On Linear Magnifications

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Abstract

Super Resolution based Reconstruction of images produces a High Resolution (HR) image from multiple Low Resolution (LR) images by estimating the motion parameters and shifts in the LR images. The problem can be divided into two parts: an image registration part in which the motion parameters and shift between different frames of the same scene are estimated and the reconstruction part in which an HR image is reconstructed from the registered images. In this paper, we consider the second part of the problem: The reconstruction step. We have compared six different reconstruction algorithms which are Bi-Cubic Interpolation method, Iterated Back Projection (IBP) algorithm, Points onto Convex Sets (POCS), Robust Super-Resolution (RSR), Structured-Adaptive Normalized Convolution (SANC) and Populis-Gerchberg (PG) approach. The results are compared using Histogram Comparison Index (HCI) based on BHATTACHARYYA [23] distance which is a popular metric for color images comparisons. From an experimental evaluation, we find that SANC, POCS and Bi-Cubic Interpolation methods produce convincing results both under high and low magnification compared to other methods. On the other hand, PG algorithm and RSR degrade image quality on higher magnification.

Keywords*: Super-Resolution, Reconstruction Based Super-Resolution, Example Based Super-Resolution, Histogram Comparison Index, Image Registration*

1. Introduction

Super-Resolution (SR) is the process of creating an HR image from more than one image's by correctly estimating the motion parameters (registration process). In reconstruction based SR approaches, generally, a set of under sampled or aliased LR images are combined to construct an HR image. The reconstructed image has more details and resolving power than the original image. During the last two decades, various SR registration and reconstruction methods have been proposed in the literature [1][2][3][4][5][6][7][8][9][24], but there is very little work done regarding performance evaluation of limitation in resolving power [10].

This paper compares the results of Bi-Cubic Interpolation method, PG, SANC, RSR, IBP and POCS methods of the reconstruction algorithms on various magnifications by using Histogram Comparison Index (HCI) which is a useful metric for color image comparisons against other quality metrics [26]. Histogram comparison is less expensive, feasible and applicable across sensors [11].

Among the registration step or motion estimation step, a lot of algorithms have been proposed which can be found on [1][2][3][4]. In this paper, we use the Vandewalle et al.[1] approach. One advantage of this method is that it discards high-frequency components, where aliasing may have occurred, in order to be more robust [25]. It exploits the property that a shift in the space domain is translated into a linear shift in the phase of the image's Fourier Transform. In the same way, a rotation in the space domain is visible in the amplitude of the Fourier Transform [1][25]. Thus, the Vandewalle et al. [1] motion estimation algorithm first computes the images' Fourier Transforms and then determines the 1-D shifts in their amplitudes and phases to make them aliasing-free.

Among the reconstruction algorithms, the most widely used methods are Bi-Cubic interpolation method [18], Populis-Gerchberg algorithm [12][13], POCS [20][21] method, Robust Super-Resolution[5], Iterated-Back-Projection [19] and Structured-Adaptive Normalized Convolution [6]. From the experimental evaluation using HCI and visual analysis, the best performance is exhibited by POCS, Bi-Cubic Interpolation approach and Structured-Adaptive Normalized Convolution.

The rest of the paper is organized as follows: In section 2, a brief review of the existing work is given, followed by the reconstruction algorithms in section 3. Experimental results are explained in Section 4. Section 5 presents future work and concludes the paper.

2. Related Work

The primary motivation behind SR was the processing of satellite images in 1980's. A frequency domain method was developed by Tsai and Hang in 1984 [15]. In a broader domain, there are two SR classes: The Reconstruction Based Super Resolution (RBSR) and Example Based Super Resolution (EBSR). RBSR uses LR images to reconstruct an HR image. The EBSR however, uses learned correspondences of HR patches for prediction of HR image. Among the two classes of SR, RBSR is preferred over EBSR [16]. The image registration step in RBSR can be performed either in frequency domain or in spatial domain. The Vandewalle et al. [1] algorithm which we use is a frequency domain approach. It exploits the property that a shift in the space domain is translated into a linear shift in the phase of the image's Fourier Transform. In the same way, a rotation in the space domain is visible in the amplitude of the Fourier Transform [1][25]. The advantage of this method is that it discards high-frequency components, where the chances of aliasing are dominant, for robust SR [25].

The relationship (the observation model) between the original HR image and a set of LR images of the same scene which are aliased and corrupted by noise is described as follows [27]:

$$Y_{k=}DB_kM_kx + n_k \quad (1)$$

Where Y_k denotes the k low resolution images, D is a subsampled matrix. B_k on the other hand is blur matrix while M_k is the warp matrix and x is the ideal HR image that has to be recovered by performing all the processes mentioned in the equation of observation model. N_k is the additive noise which is usually modeled by Additive Gaussian white noise [28]. B_k and D simulate the averaging process performed by optical system and by the camera's CCD sensors[28]. M_k can be modeled by anything from simple transformation to translation and rotational motion in x and y-axis [17].

3. Super-Resolution Reconstruction Algorithms

In this section, we briefly describe the different reconstruction methods which have been used in performance evaluation.

3.1 Bi-Cubic Interpolation

Interpolation is the process of estimating the values of a continuous function from discrete samples [18]. Interpolation can be deployed in many image processing applications such as sub-pixel image registration in order to correct spatial distortions occurred, image magnification, image de-compression and as well as others. Of the many image interpolation techniques available Bi-Cubic interpolation [18] is the most common due to its smoother results and fewer interpolation artifacts. The general form for an interpolation function is [30]:

$$i(x) = \sum_k c_k l\,(\text{distance}_k) \quad (2)$$

Where $i(x)$ is the interpolation function, $l()$ is the interpolation kernel, distance_k is the distance from the point under consideration, x, to a grid point, x_k, and c_k are the interpolation coefficients. The c_k's are chosen such that $i(x_k) = f(x_k)$ for all x_k. It shows clearly that in the interpolated image the grid point should not be changed. The Bi-Cubic Interpolation method determines the grey level value from the weighted average of the 16 closest pixels to the specified input coordinates and assigns that value to the output coordinates [31]. Bi-Cubic Interpolation is internally implemented by performing one-dimensional cubic convolution in both directions [18]. For one-dimensional cubic interpolation, exactly four grid points are required to calculate the interpolation function, two grid points on one side of the point under consideration and two grid points on the other side. Given a point (x, y) to interpolate, where $x_k < x < x_{k+1}$ and, $y_k < y < y_{k+1}$, the general form of Bi-Cubic Interpolation is given as follows[18]:

$$i(x, y) = \sum_{l=-1}^{2} \sum_{m=-1}^{2} c_{j+l,k+m}\, u(distance_x) u(distance_y) \quad (3)$$

3.2 Points Onto Convex Sets (POCS)

The POCS method was introduced by Bregman [20] and Gubin et al [21]. This method does not take into account the rotation parameters and only considers the shift estimation parameters. Also, instead of cutting the high frequencies, which is a common pre-processing step in some of the reconstruction algorithms, it passes the image through a low-pass filter that approximates the camera's Point Spread Function (PSF) [14].

This method produces good results even on high magnification when the low resolution images have been properly registered.

3.3 Populis-Gerchberg(PG)

The PG algorithm is a modified version of POCS method. It places the given pixels on a HR grid, goes into the frequency domain to "cut" the high frequencies, and repeats the process until convergence[12][13].This procedure is an iterative algorithm, which approaches the solution by alternating between the spatial domain and the Fourier domain. There exists some constraints which should be imposed on the iterated solution such as the known boundary of the image and the known parts of the spectrum [32].

The performance of this algorithm sometimes suffer from degradation and periodic corruption due to the fact that this algorithm also does not take into account the motion parameters which results in garbled results at low magnification [32]. The details are provided in the results section.

3.4 Iterated Back Projection (IBP)

This method was proposed by Irani et al. [19]. This method starts with registration procedure and iteratively refines the displacement estimation. It also considers the blurring effect by using the Point Spread Function (PSF).

The IBP starts with a rough estimation of the HR image, and during its course of operation it iteratively adds to it a "gradient" image, which is calculated from the sum of the errors between each LR image and the estimated HR image[19][35].

The initial HR image can be generated from one of the LR images by decimating the pixels. It is then down sampled to simulate the observed LR images. In order to minimize the difference between the simulated and the given LR images, this back-projection process is iteratively repeated. The iterative process can better be described through the following equation [33]:

$$S^{k+1} = S^k - F^{BP}\,(HX - Y) \qquad (4)$$

Where $Y=\begin{bmatrix} y_1 \\ y_p \end{bmatrix}$ and $H=\begin{bmatrix} D_1 C_1 F_1 \\ D_p C_p F_p \end{bmatrix}$

F^{BP} is the back projection filter used by the algorithm, S^{k+1} is the improved HR image and S^k is the HR image after k iteration.

This method produces poor results on low magnification, partly due to ill-posed nature of the problem and partly due to arbitrary choice of back-projection filter. On high magnification, it produces good results mainly due to incorporation of multiple iterations. The results section discusses the images reconstructed using the algorithm on various magnifications.

3.5 Robust Super-Resolution Algorithm (RSR)

RSR Algorithm enhances the performance of IBP by incorporating a robust median estimator [5]. Due to this additional step, the resolution can be improved resulting into more accurate estimates of HR images especially in the presence of outliers. The outliers may be due to inaccurate blur models or moving objects or noise.

Since aliasing occurs in the regions having higher frequencies, so by treating each pixel in the estimated solution independently, it is ensured to improve the enhancement in the regions of high frequencies as aliasing is the main source of information for resolution enhancement [34]. The pixel-wise median therefore performs better.

3.6 Structured-Adaptive Normalized Convolution (SANC)

This algorithm was proposed by Tuan Q. Pham et al. [6]. It uses Normalized Convolution (NC) [22] to reconstruct an HR image from a set of several LR images. In this method of reconstruction the local signal is approximated through a projection onto a subspace spanned by a set of basis functions.

The innovation of the approach lies in its adaptive applicability extending along local linear structures for gathering more samples of the same modality for better analysis. This method in turn improves signal-to-noise ratio resulting into reduction of diffusion across discontinuities [36]. To minimize the effect of outliers that might be caused by occasional mis-registration or dead pixels, robust signal certainty is also incorporated by the SANC [6].

This algorithm may be expensive in terms of computation time due to the extra pass performed by it against noise but we are not considering the complexities of algorithms nor comparing the algorithms on complexity here.

4. Experimental Results

This section discusses the experimental results for the six SR approaches. All these results are obtained using Vandewalle [1] Algorithm as the registration algorithm. The SR approaches are based on SR software Version 2.0† [37].

We use HCI [26][11] based on BHATTACHARYYA distance [23] measurement for comparing the results of the different reconstruction algorithms. The normalized histograms of the results of different algorithms are compared with the normalized histogram of the original image. High HCI value means low similarity to the original image and low HCI value stands for high similarity.

The results of reconstruction algorithms are compared for two different image data sets and magnification factors and the images have been zoomed for visual purposes where required.

Figure 1(a) shows one out of four original images used for SR. Reconstruction algorithms are compared in presence of aliasing artifacts that are dominant in the images, For example Figure 1. Each reconstruction algorithm achieves a different HCI which shows its similarity with the original image.

As shown in the Figure 1(c), magnification factor can have adverse effects on some of the algorithms such as the Populis-Gerchberg (PG) [12][13]. It suffers from severe periodic data corruption when subjected to high magnification factor and therefore giving highest HCI. The best performance is exhibited by Structured-Adaptive Normalized Convolution (SANC) [6] shown in Figure 1 (d) on all magnification factors and also by the Bi-cubic Interpolation method shown in Figure 1(b). In Figure 1 (b)(d), the aliasing artifacts are completely removed. The Iterated Back Projection (IBP)[12][13] algorithm results shown in Figure 1(g) are garbled at low magnification factors and so is the case of Robust Super-Resolution(RSR) [5] algorithm shown in Figure 1(f). Also the aliasing artifacts are not completely removed by these algorithms.

POCS[20][21]on the other hand doesn't suffer from any degradation or data corruption of images on any magnification factor but rather produces smoother results as shown in Figure 1(e). However the HCI is higher compared to SANC and Bi-Cubic Interpolation methods.

† The software is provided by Martin Vetterli (from http://lcav.epfl.ch/software/superresolution)

(a) Original image

Linear Magnification	× 1	× 2	× 3	× **4**
HCI	0.0754	0.0641	0.0644	0.0643

(b) Bi-Cubic Interpolation result

Linear Magnification	× 1	× 2	× 3	× 4
HCI	0.0754	0.2569	0.2410	0.2804

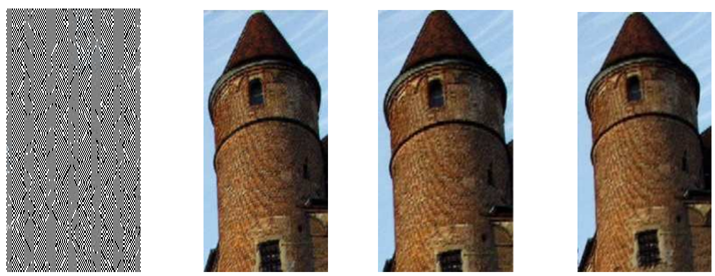
(c) Populis-Gerchberg(PG) result

Linear Magnification	× 1	× 2	× 3	× 4
HCI	0.0624	0.0614	0.0642	0.0657

(d) Structured- Adaptive Normalized Convolution(SANC) result

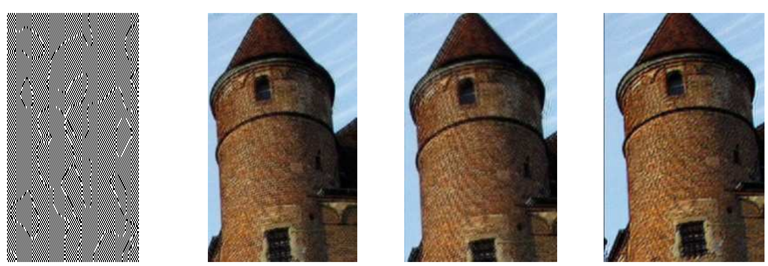
Linear Magnification	× 1	× 2	×3	× 4
HCI	0.0754	0.0746	0.0798	0.0940

(e) POCS result



Linear Magnification	×1	×2	×3	×4
HCI	0.9016	0.1563	0.1029	0.0984

(f) Robust Super-Resolution (RSR) result



Linear Magnification	×1	×2	×3	×4
HCI	0.9507	0.2146	0.2148	0.1320

(g) Iterated Back Projection (IBP) result

Figure 1: Comparison of Reconstruction Algorithms: (a) Original Image (b) Bi-Cubic Interpolation results with HCI range between 0.06 and 0.07 (c). Populis-Gerchberg results with HCI range of 0.07 to 0.28 (d) Normalized Convolution results with HCI range of 0.062 to 0.65 (e) POCS results with HCI range of 0.07 to 0.09 (f) Robust Super-Resolution results with HCI of 0.90 for low magnification and range of 0.15 to 0.09 for high magnification (g) Iterated Back Projection results with HCI of 0.95 for low magnifications and having range of 0.21 to 0.13 for higher magnification.

The reconstruction algorithms have also been compared on true RGB color images that result in the same pattern as exhibited on data set 1. The PG Algorithm suffers from severe periodic degradation on higher magnification factors shown in Figure 2(c). The SANC and POCS methods outperform the IBP and RSR Algorithms shown in Figure 2(d) and Figure 2(e). The images are compared only on high magnification factors where the degradation and other corruption caused by reconstruction algorithms are more visible to human eyes.

The Structured-Adaptive Normalized Convolution (SANC) approach, POCS and Bi-Cubic Interpolation methods outperform the Iterated Back Projection (IBP), Populis-Gerchberg (PG) and Robust Super-Resolution (RSR) methods on high magnifications by producing more convincing results. Thus by carefully registering the low resolution images, the Structured-Adaptive Normalized Convolution (SANC), POCS and Bi-Cubic Interpolation methods could be exploited for optimized results in Super-Resolution applications.

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(a). Original Image

(b).Bi-Cubic Interpolation result

(c).Populis-Gerchberg result

(d).Structured-Adaptive NC result

(e). POCS result

(f). Robust SR result

(g). Iterated Back Projection result

Figure 2: Comparison of Reconstruction Algorithms: (a) Original image (b) Bi-Cubic Interpolation results with HCI 0.0698 (c). Populis-Gerchberg results with HCI 0.4275 (d) Structured-Adaptive Normalized Convolution results with HCI 0.0653 (e) POCS results with HCI 0.0688 (f) Robust Super-Resolution results with HCI 0.1184 (g) Iterated Back Projection results with HCI 0.1343.

5. Conclusion

By comparing different Super-Resolution Reconstruction Algorithms we found that Structured-Adaptive Normalized Convolution (SANC), POCS (Points Onto Convex Sets) and Bi-Cubic Interpolation methods produce best results both under high and low magnification factor compared to Populis-Gerchberg (PG), Iterated Back Projection

(IBP) and Robust Super-Resolution (RSR) methods, resulting in better visual results and HCI index. On the other hand, Populis-Gerberg Algorithm and Robust Super-Resolution methods suffer from degradation of images on higher magnification.

Future work related to this paper may include mapping of a particular Registration Algorithm to a particular Reconstruction Algorithm for better visual appearance and good HCI results that could be applied to particular applications such as surveillance videos and object detection from SR images.

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