IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 18, Issue 4, Ver. IV (Jul.-Aug. 2016), PP 15-20
www.iosrjournals.org

Super-Resolution Reconstruction of Images using Total Variation Regularization and Wiener Filter Deconvolution

Amar Janjua[1], Tanuja Sarode[2]
[1]*(Student, University of Mumbai, India)*
[2] *(Associate Professor, Department of Computer Engineering, University of Mumbai, India)*

Abstract: *This paper presents a novel technique for reconstruction of High-resolution images from multiple Low-resolution images. A Multi-frame approach implements fusion of non-redundant information which was obtained from several low-resolution images of the same scene. Many papers have been published over last two decades proposing a variety of methods for enhancing resolution using the multi-frame approach. This paper reviews some of those proposed methods and addresses their various shortcomings. We propose two methods that are applicable to both gray-scale and colour images. One approach uses Total Variation Regularization for image recovery and deblurring, while the other method implements the use of Wiener filtering for denoising. These approaches also provide insight into solving the demosaicing problem. Simulation of the proposed methods confirm the effectiveness and superiority of our methods in comparison to the other super-resolution methods.*

Keywords: *Deblurring, Image Restoration, Multiframe, Regularization, Resolution Enhancement, Bilateral Filter, Super Resolution, Total Variation, Wiener Deconvolution*

I. Introduction

An image with a higher spatial resolution has a higher pixel density. This means that an image with higher resolution has superior level of detailing than an image with lower resolution. This is often desired in various day-to-day and specialized applications. However due to many limitations, i.e. Cost and Hardware, obtaining images with high resolution is not always feasible by replacing the image sensors. It is imperative to synthesize a new approach for increasing spatial resolution so as to overcome the manufacturing limits of sensor and optics.

Image super resolution is a method used to enhance the resolution of an imaging system in general image processing. A multi-frame approach to enhancing resolution involves generating a high-resolution image from several numbers of blurred and noisy low-resolution images of the same scene. This is achieved by fusing the non-redundant information from the multiple low-resolution images.

Super-resolution Reconstruction is a process that is computationally intensive. The early algorithms on super resolution had many limitations. Some methods were proposed without proper mathematical justification or were optimal for specific noise and data models. These algorithms produced poor results when they were tested on real images. On another front, performing single frame reconstruction to remove artifacts, often failed to completely remove such errors.

Many different methods of iterative nature have been proposed over the last 20 years (e.g. [1], [2] and [3]). Neither of these methods have considered noise models other than Gaussian noise, and regularization was either limited to Tikhonov regularization or was not implemented at all. Farsiu et al. [4] has proposed an algorithm for reconstruction of high-resolution images using Total-Variation [5] where the regularization method is based on Total-Variation. Despite being efficient, only single channel images are handled [4].

This paper uses L_1 norm, for both regularization and error handling. Regularization is essential for preserving edges and error handling provides robustness to errors and outliers. The proposed algorithm implements the generation of a better HR estimate and its regularization to improve the quality of the image. Image registration is done before the HR estimation begins. A constrained approach will enhance the quality if motion estimation and therefore result in more accurate reconstruction of the High Resolution images. The HR estimate is generated by using better interpolation techniques. Finally, regularization enhances the quality of the interpolated grid. We will show that our method performs better than what was proposed earlier[4].

This paper consists of V sections. Section II illustrates the background of this research and its related work. Section III describes the proposed method in its entirety along with the process of generating the HR estimate. Section IV illustrates the simulation setup and its results. Section V describes inferences and conclusions drawn from the experiments performed in its preceding section.

II. Related work

Many algorithms and approaches have been proposed to solve the problem of Super-resolution which is considered as an ill-posed problem. Many noise models have been considered by these algorithms. A popular class of methods include enhancements in the spatial domain. However, the methods developed initially were non-iterative and computationally expensive. Also approaching the problem in the frequency domain was not robust. Even though these methods are computationally cheap and intuitive, they are extremely susceptible to model errors. Besides all these methods could not carry out accurate motion estimation.

Farsiu et al.[4] proposed a robust and computationally efficient algorithm using L_1 norm, which was proved to be fast converging and superior to the other approaches. A mathematical justification has also been given attributing its superior performance over traditional approaches. However, this algorithm is limited to single channel pixel manipulation. In case of a colour image, the application of this method might result in discrepancies due to mosaicing effects that occur when a colour image is stretched spatially.

This paper attempts to address and overcome these issues. We propose a method that not only extended the algorithm proposed by Farsiu et al.[4] to colour images, it also provides a relief against mosaicing effects that occur in manipulation of colour images. Also a frequency domain based approach is suggested which is robust, computationally efficient and provides a balance between quality and execution time.

III. Proposed Method For Super-Resolution

A multi-frame reconstruction of high resolution images involves fusing information from within the low-resolution images which are obtained through image acquisition system. The result of such fusion produces a high-resolution image that has less blur and noise than the low-resolution images used to construct it.

1.1 Super Resolution as an Inverse Problem

The work of Super-Resolution algorithms is to reconstruct images of high-resolution from its corrupted acquisition by the constrained optical imaging system This is observed as in inverse problem, where the information source (high resolution image or HR image) is estimated from the data observed (low resolution image or LR image). Fig. 1 illustrates this inverse process. First, a forward model must be constructed to solve an inverse problem. The most common forward model for the problem of super-resolution is the linear model [6] which is given as:

$$y_k = D_k B_k M_k x + nk \qquad \forall k \in (1, p) \qquad (1)$$

Where y_k represents p LR images; matrix D down samples a HR image of dimensions N_1N_2 x $r_2N_1N_2$ into an aliased LR image of dimensions N_1 x N_2; matrix B_k represents blur matrix which is the point spread function (PSF) of the imaging system; M_k is a warping matrix that describes the motion that occurs during acquisition of the LR images; x is the desired HR image; and n_k is additional noise.

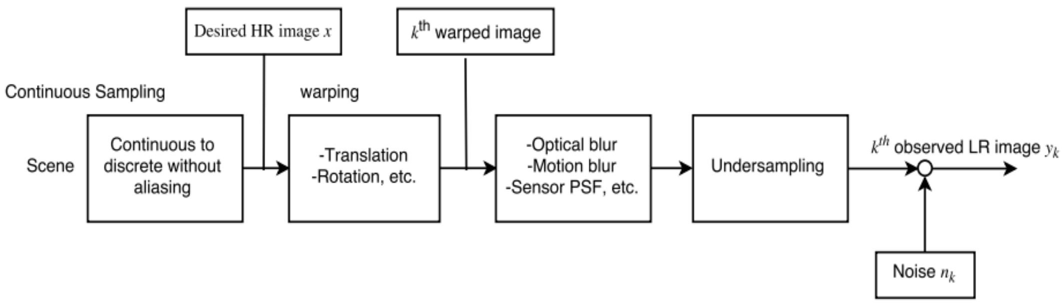


Fig. 1. Super-resolution observation model

Combining $D_kB_kM_k$ into an imaging system M, equation (1) takes the form:

$$Y = MX + N \qquad (2)$$

Where matrix Y is the data measured (single or collection of images), matrix X is the unknown but desired high resolution image or images, matrix N is the random noise inherent to any imaging system.

Armed with a forward model, a clean but practically naive solution to (2) can be achieved via the direct pseudo-inverse technique:

$$Y = \left(M^T M\right)^{-1} M^T Y \qquad (3)$$

An intrinsic difficulty with inverse problems is the task of inverting the forward model without amplifying the noise in the data measured. For a linear model, this results from the very large (almost infinity) condition number for the model matrix *M*. Solving the inverse problem, requires inversion of the effects of the system matrix *M*. This system matrix is ill-conditioned at best, thus making its stable inversion a challenge in itself. Therefore, for the problem of super-resolution, certain form of regularization becomes imminent in the cost function to constrain the space of solutions to a finite space and stabilize the problem.

Tikhonov regularization [7] is employed widely as a form of regularization method, which has been driven from an analytic standpoint to substantiate certain specific mathematical factors of the estimated solution. Very little attention is given however to the consequences of such straightforward regularization on the super-resolution results. For example, higher frequencies in the solution are often penalized by regularization, opting for a smooth and hence blurry solution. Considering a statistical standpoint, regularization is included as a prerequisite about the solution. Using the Maximum A-Posteriori (MAP) estimator consequently causes emergence of a richer class of regularization functions, enabling us to understand the specifics of the particular application. Such robust methods, unlike the conventional Tikhonov penalty terms, are adept in carrying out adaptive smoothing considering the local structure of the image.

1.2 Proposed Method

This paper outlines the use of two methods for reconstructing images with high resolution. Both methods are applied as a series of similar steps with the difference lying in the reconstruction phase.
Fig. 2 illustrates how the image reconstruction is carried out from the multiple low resolution frames.

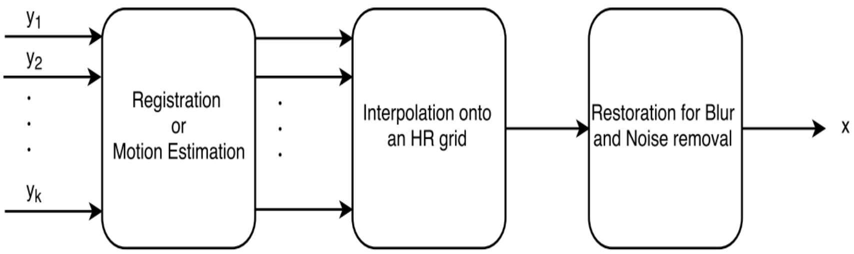


Fig. 2 Proposed method

1.2.1 Image registration:

The goal of image registration is to determine an alignment between sequences of successive image frames of the same scene. Image registration implements a motion estimation algorithm so as to improve the alignment based on a set of motion parameters. A global translational model is implemented as it is computationally efficient. Lucas-Kanade method [8] is used for measuring the optical flow, which is also less sensitive to image noise.

1.2.2 Calculation of initial HR estimate:

After the frames are registered, it is time to interpolate the image onto a higher-resolution grid. In this step, upsampling and warping is performed using *bicubic interpolation* and *lanczos interpolation*. These methods are computationally heavy, but they yield excellent results in terms of quality. The image frames are then combined using a median shift filter [9]. A median filter ensures that the computation is more robust to the outliers that might result from inaccuracies in image acquisition.

1.2.3 Regularization:

This constitutes the third block of Fig. 2. Image registration is considered a coarse method. The super-resolution process attempts to converge to a solution by minimization using steepest descent. This means that the solution is stable in presence of outliers and inaccuracies added to the image by inaccurate registration or noise.

1.2.3.1 Bilateral Total Variation based implementation:

The regularization terms [8][10] presented attempts to minimize the absolute difference between the estimated and several shifted versions of the initial estimate. This is referred to as *total variation (TV)*. This is implemented by using a bilateral filter and hence the name *Bilateral Total Variation(BTV).* The gradient is given by the following equation:

$$\hat{X}_{n+1} = \hat{X}_n - \beta \begin{Bmatrix} \sum_{k=1}^{N} F_k^T H^T D^T sign\left(DHF_k \hat{X}_n - \hat{Y}_k\right) \\ + \lambda \sum_{l=-P}^{P} \sum_{m=0}^{P} \alpha^{m+|l|} \left[I - S_y^{-m} S_x^{-l}\right] sign\left(\hat{X}_n - S_x^l S_y^m \hat{X}_n\right) \end{Bmatrix} \quad (4)$$

Here, λ is a regularization weight determining the importance of the bilateral TV term as compared to the data fidelity term. The spatial decay constant, α, ranges from 0 to 1 and controls the relevance of more distant pixels. Higher values give blurrier results, requiring pixels to be more similar to their distant neighbours. β is a scalar measure defining the step-size in the direction of the gradient. The kernel radius, *P*, is normally fixed at 2. $S^l{}_x$ and $S^m{}_y$ are shift operators that shift the image to the right by *l* pixels and down by *m* pixels, respectively. The matrices *F*, *H*, *D*, *S*, and their respective transposes are interpreted as image operators such as shift, blur, and decimation

1.2.3.2 Wiener Filter based implementation:

Murli et al. [11] focuses on the computational aspects of Wiener filter, which was introduced long before Bilateral Total Variation was conceived. Wiener filter can be regarded as a Tikhonov Regularization method which is applied in the Fourier domain where the regularization parameter is equal to the square-root of the signal to noise ratio. Wiener filters are extremely efficient to remove noise to provide a finer quality of the desired signal.

3.2.4 Solving the demosaicing problem

A colour image is typically represented by combining three separate monochromatic images. Here, each pixel reflects a data measure one for each of the colour bands, Red, Blue and Green. In practice, to reduce production cost, various digital cameras have only one colour measurement (red, green, or blue) per pixel. The sensor array is a grid of CCDs(Charge Coupled Devices), each made sensitive to one colour by placing a colour-filter array (CFA) in front of the CCD. The values of the missing colour bands at every pixel are usually constructed by means of some form of interpolation methodology from neighbouring pixel values. This process is known as *colour demosaicing*.

Supporting the regularization component [8], a computationally efficient estimation method to fuse and demosaic a set of low-resolution frames (which may have been colour-filtered by any CFA) resulting in a colour image with higher spatial resolution and reduced colour artifacts is proposed. The BTV based algorithm solves this using the classical approach [12] while Wiener filter implements a more implicit method [11].

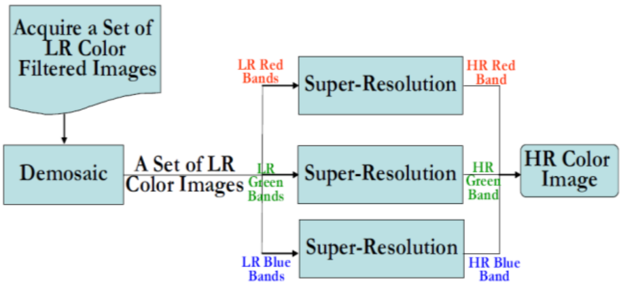


Fig. 4 Classical approach(BTV)

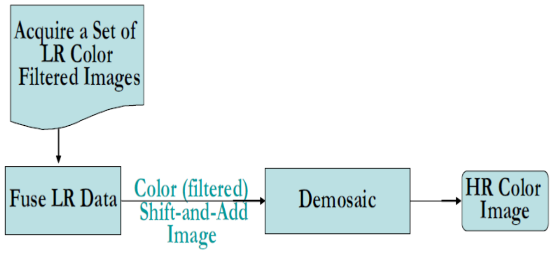


Fig. 5 Implicit method(Wiener)

IV. Experimental Validation

In this section, the proficiency of the proposed methods is calculated by means of experimentation on real data. Following subsections illustrate the entire process:

1.3 Experimental Setup

The entire process is implemented in MATLAB 8.5.1(R2015a) on a 64-bit Windows 10 machine with 2.20 GHz Intel core i3 processor and 3GB RAM.

The image parameters are as follows:

1) All images used are 256 x 256 resolution. These are considered to be the High Resolution images. Both colour and grayscale images are used. The images are first decimated into 128 x 128 resolution by convolution with noise and blur. These are reconstructed into high resolution of 256 x 256 using

i) Total Variation Regularization.

ii) Wiener Filter Regularization.
iii) Total Variation Regularization with Bilateral Filter.
2) For Total Variation Regularization, separate functions are executed for Grayscale and Colour images. This illustrates the implementation of solution to demosaicing as explained in the previous section.
3) Wiener Filter Deconvolution is directly implemented for both grayscale and colour images alike.
4) Total Variation Regularization with Bilateral Filter is implemented by extending the algorithm used for total variation and applying a bilateral filter to it.

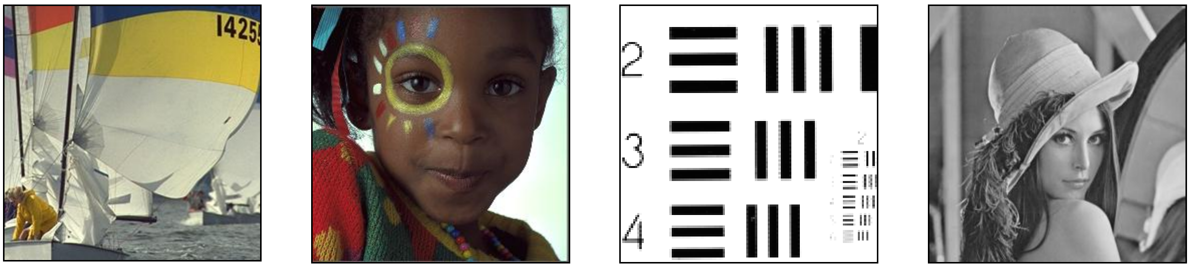
1.4 Execution Parameters

The image set here consists of 2 images of each type. “sail.png” and “eye.png” are used as colour images, whereas “lena.png” and “cartap.png” are used as grayscale images. These images are decimated into lower resolutions using interpolation and noise is added to them.

Noise Parameters: Two types of noises are used. Standard Noise and Gaussian Noise. These images are tested for different values of the noise parameters which here is spread value (σ for additive Gaussian noise and θ for standard noise). The noise parameters take the values 1,3 and 5.

Magnification factor achieved is 2 (This is because a 128 x 128 image is resized into an image of higher resolution of 256 x 256).

Test set includes the following images:



(a) “sail.png” **(b) “eye.png”** **(c) “cartap.png”** **(d) “lena.png”**

Figure 6(a) – (d) Test images used in the experiment.

These images are each tested with the given algorithms. The runtime of the algorithms is also calculated. The following section gives the results of the given algorithms.

1.5 Results

The quality of the output is measured by comparing the reconstructed images with the original high-resolution that were decimated. This output is measured in terms of *peak signal-to-noise ratio(PSNR)* and execution *runtime*.

Peak Signal to Noise Ratio (PSNR): It is an expression for the ratio between the maximum possible power of a signal and the power of noise that affects the quality of its representation. Because many signals have a very extensive dynamic range, the PSNR is usually expressed in terms of the logarithmic decibel scale.

Runtime: It is the time elapsed from the initiation of execution to completion, when the output image is produced. Depending on the number of processes running in background, the runtime values may vary. All open applications were closed before starting MATLAB. Since the output images printed on paper look similar, it is more appropriate to compare the results by tabulating the output parameters (i.e. PSNR and runtime).

1.5.1 Total Variation Regularization

Table 1. Results of TV regularization

Image	Noise level (θ)	PSNR (dB)	Runtime(seconds)
Lena	1	49.85	0.006
	3	25.28	0.006
	5	16.54	0.006
Cartap	1	37.56	0.006
	3	28.75	0.006
	5	25.06	0.008
Sail	1	22.80	0.72
	2	16.69	0.97
	3	13.21	1.21
Eye	1	23.00	0.68
	2	17.05	0.95
	3	13.59	1.17

1.5.2 Wiener Filter

Table 2. Results of Wiener Filter Regularization

Image	Noise level (σ)	PSNR (dB)	Runtime(seconds)
Lena	1	93.20	0.47
	3	79.65	0.35
	5	79.47	0.34
Cartap	1	93.21	0.39
	3	75.67	0.36
	5	76.54	0.33
Sail	1	93.51	0.97
	3	77.88	0.94
	5	77.84	0.95
Eye	1	93.27	0.94
	3	81.50	1.02
	5	81.30	1.05

1.5.3 Total Variation Regularization with Bilateral Filter

Table 3. Results of BTV Regularization

Image	Noise level (θ)	PSNR (dB)	Runtime(seconds)
Lena	1	76.00	2.62
	3	77.87	2.65
	5	80.20	2.65
Cartap	1	78.21	2.62
	3	79.01	2.57
	5	82.15	2.56
Sail	1	78.17	6.18
	3	78.11	5.89
	5	77.24	6.38
Eye	1	78.11	5.90
	3	78.69	6.15
	5	79.73	6.40

V. Conclusion

Resolution enhancement has garnered a wide interest among research scholars over the years. This is a result of the need for high-resolution images which is affected by the limitations of hardware in image acquisition. In this paper, the proposed methods are adept in reconstructing high-resolution images from noisy and blurry low-resolution images. The total variation based regularization is a robust technique which gives good results in terms of quality, and application of a bilateral filter improves the results drastically. Besides these algorithms are extended for colour images thereby solving the demosaicing problem.

To summarize, it is important to achieve a balance between quality of output and the subsequent efficiency of the algorithm. Wiener deconvolution proves to be very efficient as a reconstruction model for our purpose. Utilization of bilateral filter works slower for colour images. An in case of total variation, the algorithm works relatively slower for colour images. However, Wiener filter regularization works consistently.

References

[1]. S. Lertrattanapanich and N. K. Bose, High resolution image formation from low resolution frames using Delaunay triangulation, IEEE Trans. Image Processing, vol. 11, pp. 1427–1441, Dec. 2002.
[2]. M. Elad and Y. Hel-Or, A fast super-resolution reconstruction algorithm for pure translational motion and common space invariant blur, IEEE Trans. Image Processing, vol. 10, pp. 1187–1193, Aug. 2001.
[3]. M. Irani and S. Peleg (April 1991), Improving resolution by image registration, CVGIP: Graph. Models Image Process., vol. 53, pp. 231–239.
[4]. S. Farsiu, D. Robinson, M. Elad, and P. Milanfar, Fast and robust multi-frame superresolution, IEEE Trans. Image Processing, vol. 13, pp. 1327–1344, Oct. 2004.
[5]. Y. Li and F. Santosa, A computational algorithm for minimizing total variation in image restoration, IEEE Trans. Image Processing, vol. 5, pp. 987–995, June 1996.
[6]. S. Park, M. Park and M. Kang, Super-resolution image reconstruction: a technical overview, IEEE Signal Processing Magazine, vol. 20, no. 3, pp. 21-36, May 2003.
[7]. M. Elad and A. Feuer, Restoration of single super-resolution image from several blurred, noisy and down-sampled measured images, IEEE Trans. Image Processing, vol. 6, pp. 1646–1658, Dec. 1997.
[8]. B. Lucas and T. Kanade, An iterative image registration technique with an application to stereo vision, Proc. of DARPA Image Understanding Workshop, pp. 121–130, 1981.
[9]. S. Farsiu, D. Robinson, M. Elad, and P. Milanfar, Robust shift and add approach to super-resolution, Proc. of the 2003 SPIE Conf. on Applications of Digital Signal and Image Processing, pp. 121–130, Aug. 2003.
[10]. C. Tomasi and R. Manduchi, Bilateral filtering for gray and color images, Proc. of IEEE Int. Conf. on Computer Vision, pp. 836–846, Jan. 1998.
[11]. A. Murli, L. D'Amore and V. De Simone, The Wiener filter and regularization methods for image restoration problems, Image Analysis and Processing, 1999. Proceedings. International Conference on, Venice, 1999, pp. 394-399.
[12]. A. Zomet and S. Peleg, Multi-sensor super resolution, in Proc. of the IEEE Workshop on Applications of Computer Vision, pp. 27–31, Dec. 2001.