International Journal on Applications in Engineering and Technology
Volume 2: Issue 5: May 2016, pp 15-19. www.aetsjournal.com ISSN (Online) : 2455 - 0523

Aggregation Of Blurred Images Through Weighted Fba To Remove Camera Shake

K.Gayathri , Dr.P.Marikkannu

Abstract - Many algorithms were designed to remove image blur due to camera shake, either with one or multiple input images, by using the deconvolution problem. If the photographer takes a burst of images, a modality available in virtually all modern digital cameras, it is possible to combine all the images to get a clean sharp version. This algorithm does not use blur estimation or its inverse problem. The proposed algorithm is strikingly simple where the average weight is calculated using Fourier domain which depends on the Fourier spectrum magnitude. Here, burst of images are taken into an account and each image in the burst is blurred differently. The proposed Fourier burst accumulation algorithm shows that one can obtain a sharp image by combining all the images together which is blurred differently. This can be implemented in modern smart phones.

Keywords: Camera shake, Deconvolution, Fourier spectrum magnitude, Fourier burst accumulation.

I. INTRODUCTION

A. Photography and Camera Shake

Capturing the images in low-light environment is the most challenging experience in photography. The principle of photography is accumulating more number of photons in the sensor. In general, to get a better quality image the more photons should reach the surface and this will also reduce the photonic noise. However,this follows a rule that the scene to be photographed should be static and that there should not be any motion between the scene and the camera. This may lead to accumulation of photons to the other pixels which may result in blurriness. This is common in photography while taking the images using hand-held cameras. This is also possible if the images are taken in low light conditions.

The camera shake can be defined mathematically as a convolution,

$$v=u\text{-}k+n \quad \text{equation 1}$$

where in equation(1) v represents the noisy blurred observation, u is he latent sharp image, k is an unknown blurring kernel and n is the additional noise. The rotation should be in optical axis with in-plane rotation as negligible to get an accurate result. The kernel k results from several blur sources: light diffraction, out-of-focus and light integration in the photo-sensor, and relative motion between the camera and the location. To get enough photons, the camera needs it capture light for a period of tens to hundreds of milliseconds. Usually blur kernel represents the handshakes while taking the picture.

With the availability of accurate gyroscope and accelerometers in, for example, phone cameras, free registration can be possible by rendering the whole algorithm very efficient for on-board implementation. Indeed, one could envision a mode transparent to be the user, where every time he/she takes a picture, it is actually a burst or multiple bursts with different parameter each. The set is then processed and only the result is saved.

B. Digital Image Processing

Digital image processing is used to enhance image features which can be used to attenuate and extract more information about the enhanced image. Images are produced by a variety of sources which may be still and video camera, X-ray devices purposes from all the fields. Often the raw image is not directly suitable for this purpose and so they must be processed. Such processing called image enhancement and when an observer extracts the information from the source it is called image analysis. Usually Image enhancement is done by chemical or electronic means while the analysis part is done by the humans or by electronic means.

Transforming different sets of data into a single system is called as Image registration. Data may be from different sources like photographs, sensors, times, depths or viewpoints. It is mostly used in various fields like medical imaging, automatic target recognition, brain mapping and also for compiling and analyzing images from satellites. Registration is used to integrate or compare the data from different sources.

In this paper ***Section (2),***deals with the various other methods used for removing the blurriness in the image either with a single or multiple images. ***Section(3),***focuses on the proposed method for removing the blurriness using burst of images and ***Section(4),***explains the Analysis and Results of the proposed model which is been developed in Matlab where the image registration is done.

II. LITERATURE SURVEY

In most of the deconvolution algorithms the estimation is done with the latent image without any other input than the noisy blurred image itself. A similar work which was the one by Fergus *et al.*[02]. This helps in combining natural image priors, assuming the blurring operator and optimizing complex frameworks for estimating the blurring kernel as well as the sharp image. The camera rotation was taken to be negligible and the assumption was made to be a uniform camera blur.

The next technique is by taking two images into an account, where one for estimating the image and other as the blurring

K.Gayathri , Information Technology , Anna University Regional Campus CBE , India (Email : gayathri2018@gmail.com)
Dr.P.Marikkannu , Information Technology , Anna University Regional Campus CBE , India (Email :pmarikkannu@gmail.com)

kernel. Rav-Acha and Peleg[03] in their work proved that two images would be better than one, if the blur in the image occurs in different direction. In this two photographs are captured in which one image having a short exposure time while the other with long exposure time. The image having short exposure time will be noisy while the other which is taken in long exposure time will be with low noise but blurred. From the two images the sharper image is used to estimate the blurred one.

A technique in astronomical photography, which is also known as lucky imaging or lucky exposure, is done by taking a series of thousands of short-exposure images. This is followed by selecting and fusing the sharper ones[04]. The probability of getting a sharp lucky short-exposure image through turbulence follows a negative exponential. Thus, when the capture series or video is sufficiently long, there will exist such a frame with high probability. Classical selection techniques are based on the brightness of the brightest speckle. The number of selected frames is chosen to optimize the tradeoff between sharpness and signal-to-noise ratio required in the application.

Removing the blurriness caused by camera shake is called Image deblurring has been studied in this paper [8]. Some algorithms were more expensive but, here, to make the deblurring more robust and tractable, multi-image approaches are followed which capture and combine multiple frames. Two approaches are compared: align-and-average and multi-image deconvolution.It is also clear from the paper that by increasing the exposure time beyond certain threshold the deconvolution becomes unbeneficial.

Modern cameras like Canon EOS 7D and also Pointgrey Grasshopper have 14-bit sensors. The paper [10] presents a theoretical analysis and a practical approach to get a reliable HDR imaging from a camera which is in motion by exploiting these new cameras with high-resolution quantization. A unified probabilistic formulation that allows to analytically comparing two HDR imaging alternatives:

- Deblurring a single blurry but clean image and
- Denoising a sequence of sharp but noisy images.

It is analyzed that the uncertainty occurs while estimating the HDR image. The paper concludes that multi-image denoising offers a more reliable solution. The sharp HDR imaging is obtained by combining the optical flow and the image denoising algorithms. Handheld cameras can be used for complex scenes with large depth variation.

III. PROPOSED METHOD

In the proposed system burst of images are taken into account where each image is blurred differently. The weighted average in the Fourier domain is performed for each image. Reconstruction of an image is done by combining the least attenuated frequencies in each frame. It does not introduce typical ringing or overshooting artifacts present in most deconvolution algorithms. Noise reduction is done at the last to obtain sharper and noise free image.

A. System Architecture

The architecture for the proposed FBA method is explained in the Fig 1.

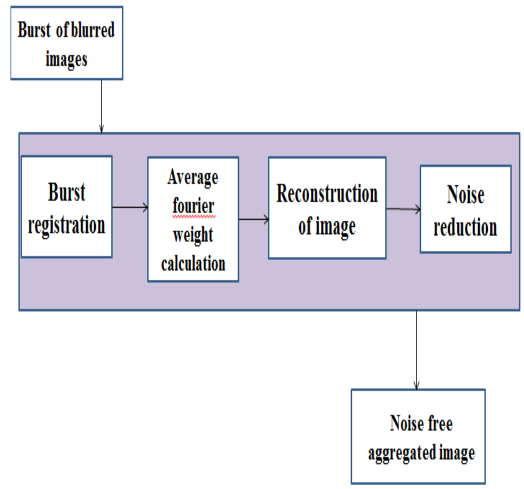

Fig. 1. Architecture diagram for the proposed system

The proposed architecture in Fig. 1 shows that the input is taken as the burst of blurred images. In the processing part, first the images are registered and the average fourier weight calculation is done. The reconstruction of image is done by replacing the least attenuated frequency with the higher frequency. The blurriness at last is removed by reducing the noise. The output obtained is the noise free aggregated image. The final step of the method is the complexity analysis where the time taken is analyzed.

B. Implementation

The five steps included in the project are registration of images, FBA calculation, and reconstruction of an image, noise reduction and complexity analysis.

The burst of blurred images are taken as an input and SIFT feature detection is followed to register the images. The process of aligning two or more images of the same scene by taking one image as the reference image and the other image as the fixed image is called as the Image registration. The transformations are done to align with the reference image.

1) Scale Invariant Feature Transform

The objects contain interesting points which is called as the features. The features can be extracted to provide description to the object. The description can be used locate the object among many objects. The set of features are provided by the SIFT features that are not affected by rotation and object scaling. It allows the object to be recognized within the environment. The SIFT algorithm contains 4 steps to extract the features. They are explained below:

2) Detecting Scale Space Extrema

In this stage the filtering can be done to identify locations and scales from different views of same object. The function used to achieve this is called scale space function. By assuming it with Gaussian function the scale space function is defined by:

$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$ equation (2)

where in equation(2) * is the convolution operator, $G(x, y, \sigma)$ represents the Gaussian in variable scale and $I(x, y)$ represents the input image.

The stable keypoint locations can be detected by using various techniques. One of the technique is DOG (Difference Of Gaussian) which is done by locating scale space extrema, $D(x, y, \sigma)$. The computation is done by finding the difference between two images. $D(x, y, \sigma)$ is given by:

$D(x, y, \sigma) = L(x, y, k\sigma)\ L(x, y, \sigma)$equation (3)

The equation (3) is used to detect the local maxima and minima of $D(x, y, \sigma)$. Here, each point is compared and if this value is the minimum or maximum then this point is an extrema.

3) Localizing The Keypoints

In this stage more points which have low contrast or poorly localized on an edge are eliminated. Removing the extrema with low contrast is by finding the point which has the function value at z below the threshold value. The large curvature and the small curvature in the difference of Gaussian function is to be noted. This helps to remove the extrema based on poor localization. If the difference calculated is low then the keypoint is rejected.

4) Assigning The Orientation

The keypoint orientation can be found by following these steps:

- The Gaussian smoothed image was computed.
- The gradient magnitude was computed.
- The orientation was computed and assigned.
- From the orientations of sample points form an orientation histogram.
- Use the highest peak in the histogram to create a keypoint with that orientation.
- Multiple orientations can also be assigned and the 3 values can be used to interpolate the peak position.

5) Keypoints descriptors

By making use of the gradient data the keypoint descriptors can be created. It is also used to create many histograms centered on the keypoint. The keypoint descriptor contains 128 elements which consist of 16 histograms which can be aligned in a 4x4 grid, with 8 orientation bins each. The resulting vector are called SIFT keys which are used to identify all the possible objects in an image

6) Weighted FBA

The image is represented in the pixel format and the fourier weight is calculated for each image and the average FBA is found. The frequencies are replaced with the higher frequency in order to remove the blurriness and produce a clear image.

7) Noise Reduction

The final step is reducing the noise by using the Salt and Pepper noise method. The output is obtained as the noise free aggregated image. Below gives the brief description of noise. Noise is nothing but the result of errors in the image. The pixel values do not reflect the true intensities of the real scene. Filtering can be used to remove the noise. Averaging filter is used for removing grain noise from a photograph. **Imfilter**is the N-D filteringof multidimensional images. The syntax is given as:

B=imfilter(A,h) equation (4)

The equation (4) filters the multidimensional array A with the multidimensional filter h. A can be logical or a non-sparse numeric array of any else and dimension. It computes each element of the output B using double precision floating point. Imfilter truncates output elements that exceed the range of the given type and rounds fractional values.

gpuarray B = imfilter(gpuarrayA,h) equation (5)

The equation (5) performs the operations on a GPU. It contains a logical or a non-sparse numeric array of any class and dimension and also requires parallel computing toolbox.

B = imfilter (B, options) equation (6)

The equation (6) performs multidimensional filtering according to the specified options.

IV. ANALYSIS AND RESULTS

The result produced here is the output of feature transform using SIFT and the image registration. The sample output of the clear image obtained at the end of this experiment is also shown in this paper.

Fig. 2 shows the detection of scale space extrema which is the first step in the scale invariant feature detection. Here the difference of Gaussian was calculated and displayed.

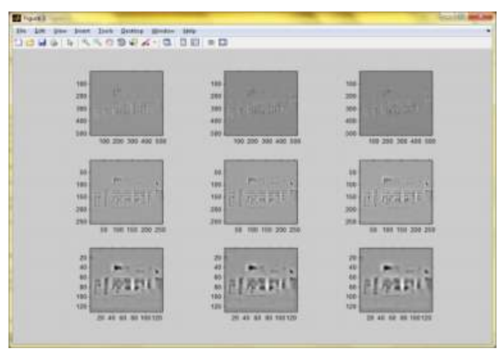

Fig. 2 Scale space extrema detection

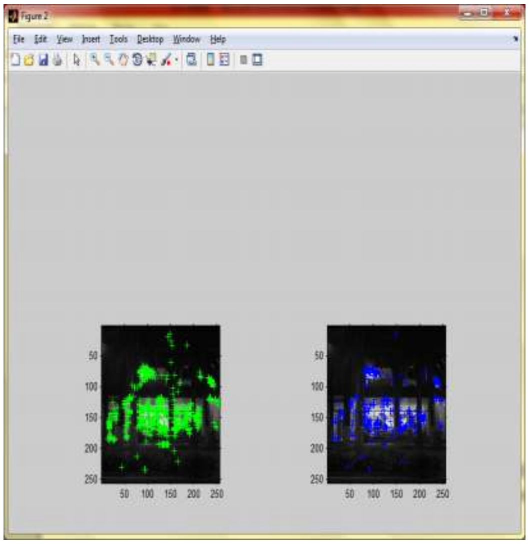

Fig. 3 Keypoint detection

Fig. 3 is the screenshot of finding the detection and description of keypoints.

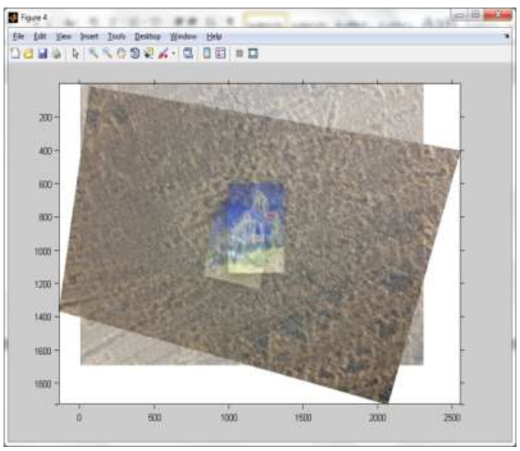

Fig. 4 Image registration

In the Fig. 4, the screenshot of the transformation of unregistered image with the base image is shown.

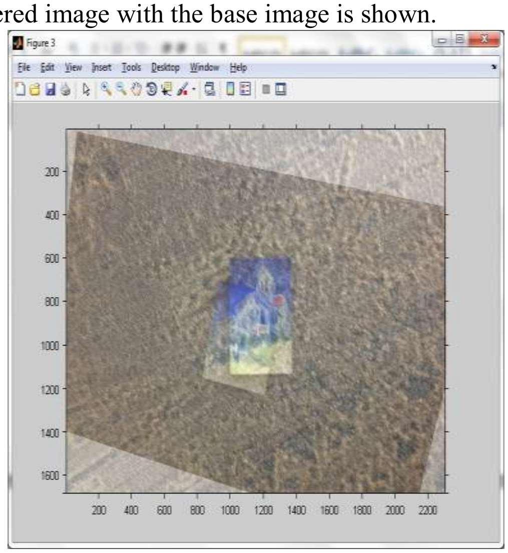

Fig. 5 Base image as gray scale image.

Fig.5 is the screenshot of differentiating the base image and unregistered image by making the base image as gray.

Fig.6 Average fourier weight of the image

The weighted average for the fourier burst calculation was done and the average weight was displayed in the fig. 6

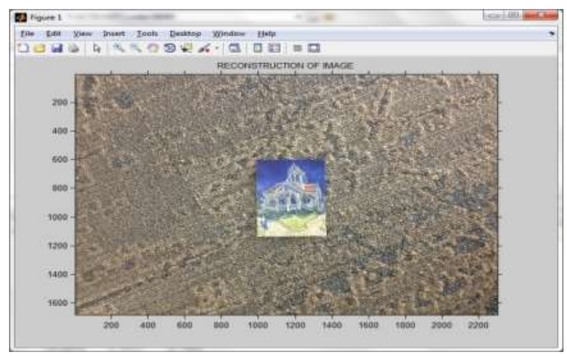

Fig 7 Reconstructed image

The image after reconstruction using the average weighted FBA is shown in the fig.7 which contains some noise in the image.

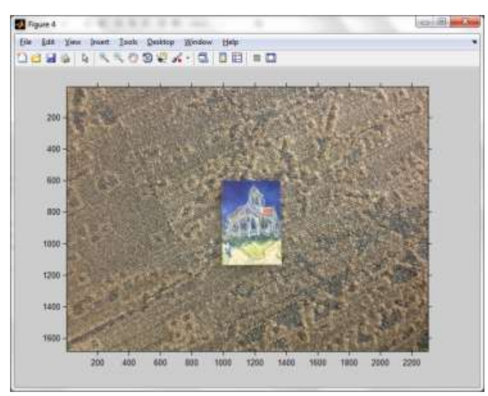

Fig. 8 Noise free aggregated image

The image after applying the median filtering is shown in the fig.8. This image is the noise free aggregated image which is considered as an output of the system.

TWO CONDITIONS FOR OBTAINING THE NOISE FREE IMAGE:

1. PSNR(Peak signal noise ratio) should be maximum.
2. MSE(Mean square error) should be minimum.

Table 1 Results of MSE and PSNR of various noise

CONDITIONS	SALT AND PEPPER NOISE	GAUSSIAN NOISE	POISSON NOISE	SPECKLE NOISE
MSE	34.9704	36.4897	43.5104	35.2005
PSNR	49.5591	42.1692	46.6193	39.7780

Four types of noise were implemented for the image to remove the noise. Each noise produces its own MSE and PSNR value which is shown in the tabular form in the table1. From the results it is clear that the noise that satisfies the above two conditions is the salt and pepper noise. It produces minimum MSE and maximum PSNR. MSE is the mean square error and PSNR is the peak signal to noise ratio.

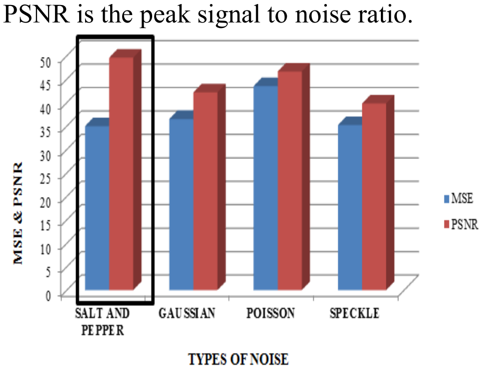

Fig. 9 MSE and PSNR values for different noise

The MSE and PSNR values produced while removing noise with various types of noise is shown in fig.9. Four types of noise were implemented for the image to remove the noise. From the figure, it is clear that the noise that satisfies the above two conditions is the salt and pepper noise. It produces minimum MSE and maximum PSNR. MSE is the mean square error and PSNR is the peak signal to noise ratio.

V. CONCLUSION

The proposed method is designed to remove the camera shake blur in an image burst. The main idea is that each image in the burst is generally differently blurred. By doing a weighted average in the Fourier domain, image is reconstructed by combining the least attenuated frequencies in each frame. It does not follow any typical ringing or overshooting artifacts present in most algorithms. Formulation of an inverse problem is avoided by the deblurring problem.

Gyroscope registration technique can be used to create a real time system for removing camera shake in image bursts as a future work. The best capture can be obtained by determining the total exposure time and also total exposure time will be given which would be more convenient to take short exposure pictures.

REFERENCES

[1] Delbracio, M.; Sapiro, G., "Removing Camera Shake via Weighted Fourier BurstAccumulation," in *Image Processing, IEEE Transactions on* , vol.24, no.11, pp.3293-3307, Nov. 2015
[2] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman, "Removing camera shake from a single photograph," *ACM Trans.Graph.*, vol. 25, no. 3, pp. 787 794, 2006.
[3] A. Rav-Acha and S. Peleg, "Two motion-blurred images are better than one," *Pattern Recognit.Lett.*, vol. 26, no. 3, pp. 311–317, 2005.
[4] N. M. Law, C. D. Mackay, and J. E. Baldwin, "Lucky imaging: High angular resolution imaging in the visible from the ground," *Astron.Astrophys.*, vol. 446, no. 2, pp. 739–745, 2006.
[5] O.Whyte, J. Sivic, A. Zisserman, and J. Ponce, "Non-uniform deblurring for shaken images," *Int. J. Comput. Vis.*, vol. 98, no. 2, pp. 168–186, 2012.
[6] T.Buades, Y. Lou, J.-M. Morel, and Z. Tang, "A note on multi-image denoising," in *Proc. Int. Workshop Local Non-Local Approx. Image Process. (LNLA)*, Aug. 2009, pp. 1–15.
[7] H. Zhang, D. Wipf, and Y. Zhang, "Multi-image blind deblurring using a coupled adaptive sparse prior," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2013, pp. 1051–1058.
[8] S. H. Park and M. Levoy, "Gyro-based multi-image deconvolution for removing handshake blur," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2014, pp. 3366–3373.
[9] A. Ito, A. C. Sankaranarayanan, A. Veeraraghavan, and R. G. Baraniuk, "Blurburst: Removing blur due to camera shake using multiple images," *ACM Trans. Graph.*, to be published.
[10] L. Zhang, A. Deshpande, and X. Chen, "Denoising vs. deblurring:HDR imaging techniques using moving cameras," in *Proc. IEEE Conf.Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2010, pp. 522–529.
[11] D. G. Lowe, "Distinctive image features from scale-invariant keypoints,"*Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, 2004.