A New Weighted Average Filter for Removing Camera Shake

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ABSTRACT
Image blurring is one of the major problems in the field of digital image processing. Generally, camera shake causes blurring. As a result, uneven blur kernel is present in the image which is random in nature. Therefore, every image in the burst is blurred in a different way. Deblurred image can be obtained using single image or multiple images. A clean sharp image is recovered by fusing the group of images without calculating the blurring kernel. In this paper, a new technique called a new weighted average filter is introduced for removing camera shake using single or multiple images. This technique takes a burst of images and calculates a weighted average in the Discrete Wavelet domain, where the weights of images depend on their Discrete Wavelet Spectrum magnitudes.

Keywords
Blur, burst, Discrete Wavelet

1. INTRODUCTION
The basic principle of photography is accumulation of photons in the sensor. When more photons reach the surface of the sensor during a given exposure time, the quality of the image increases. If the scene to be captured or camera moves, the photons will accumulate in the neighboring pixels. As a result, a blurred image occurs. Under reasonable hypotheses, the mathematical model of camera shake can be given as

$$v = u * k + \eta$$

Where v is noisy blurred observation, u is the latent sharp image, k is an unknown blurring kernel and n is additive noise. There are many sources which give rise to blurring kernel: light diffraction due to the finite aperture, out of focus, light accumulation in the photo-sensor and relative motion between the camera and the scene during the exposure. There is a setting in present cameras and also in mobile phones so that they can take a burst of images. The camera shake originated from vibrations is essentially random. Therefore, in each image of the burst, camera moves differently and independent for different images. Hence the blur is different from the one in another image of the burst. In this algorithm, a burst of images is combined. While aggregating of images, less blurred images of each frame are taken into consideration to build a sharper and less noisy image compared to all the images in the burst. The algorithm is simple to understand and also to implement. Its takes a series of images as input which are registered and computes the weighted average of the Discrete Wavelet coefficients of the images from the burst of images. The remaining of this paper is organized as follows. Section II explains how an aggregation of burst of images can be combined in Discrete Wavelet domain to reconstruct a sharper image. Section III details the algorithm implementation. Section IV presents experimental results.

Deblurring algorithms can be classified into two groups: single image-based algorithms, multiple image-based algorithms.

Single image deblurring:
The problem of restoring the sharp image [8] from a single blurred image can be done using image deconvolution if the blur kernel is shift-invariant. Image deconvolution is divided into non-blind (known kernel) and blind (unknown kernel) cases. In non-blind deconvolution case, kernel is known. Therefore sharp image is recovered using blur kernel. In blind deconvolution, kernel is not known. First, the kernel is estimated and then the sharp image is recovered.

Multi image deblurring:
In this method [4-7], sharp image and blurring kernels are estimated using two or more images. Hence two images are taken using different exposure timings. Short exposure image is a sharp image with noise content. Long exposure image is a blurred one with less noise. Now motion kernel of blurred one is estimated using sharper one.

Lucky imaging:
This method [9-12] is used in astronomical photography, a series of thousands of short-exposure images are taken by this method. The resultant image is obtained by fusing only the sharper ones.

2. DISCRETE WAVELET BURST ACCUMULATION
Camera shake generated because of hand vibrations is random [1-3]. When the camera is handheld, the independent movement of the photographer's hand causes the camera to be moved randomly. As a result, a blurred captured image will occur.

M is the number of images in the burst of same scene u.

$v_{i=}k_i + \eta_i$, for i= 1,…,M.

Due to the reason of blurring kernels is different for different images in the burst of images; different blurred images are occurred. Therefore, the Discrete Wavelet Transform of each frame of the burst is different. In the proposed system an image is to be reconstructed whose Discrete Wavelet spectrum takes the largest valued Discrete Wavelet magnitude in the burst? Thus the reconstructed image picks up what is less attenuated.

A. Discrete wavelet magnitude weights
Let p be a non-negative integer. Weights of images can be calculated as,

$$w_i(\xi) = \frac{|v_i^{\wedge}(\xi)|^p}{\sum_{j=1}^{M} |v_j^{\wedge}(\xi)|^p}, \quad (1)$$

$$\mathrm{u_p}\,(\mathrm{x}) = \mathrm{E}^{-1}\left(\sum_{\mathrm{i=1}}^{\mathrm{M}} \mathrm{w_i}(\xi)\,.\,\mathrm{v_i^{\wedge}}(\xi)\right)(\mathrm{x}) \quad (2)$$

Where $v_i^{\wedge}$ is the Discrete Wavelet transform of individual burst imagev_i, u_p is the reconstructed image. P value is explained in [15]. E denotes Discrete Wavelet transform.

B. Equivalent point spread function

By using the weights of images in (1), the reconstructed image u_p can be obtained by the convolution between sharp image u and average kernel k_{DWBA}.

$$u_p = u * k_{DWBA} + \bar{n}, \quad (3)$$

Where$k_{DWBA}(x) = E^{-1}\left(\sum_{i=1}^{M} w_i(\xi)\,.\,k_i^{\wedge}\,(\xi)\right)(x)$,

Where $\bar{n}$ is weighted average of the input noise? The DWBA kernel obtained is the final point spread function (PSF). The Discrete Wavelet aggregation works better if DWBA kernel is closer to Dirac function. The average kernel is constructed from least attenuated frequencies in the burst, given by the weights of images. Since convolution kernels are arbitrary, these may introduce phase distortion in the images. Therefore, the average DWBA kernel may not be closer to Dirac function. Blurring kernels k_i are estimated using sharp reference image u_{ref}, by minimizing the least squares distance to the blurred acquisitionv_i, namely,

$\left|\left|u_{ref} * k_i - v_i\right|\right|$. [13]

3. ALGORITHM IMPLEMENTATION

The proposed algorithm is built on three main blocks: Burst Registration, Discrete Wavelet Burst Accumulation and Noise Aware Sharpening as a post processing.

1. **Burst registration**

There are so many ways of registering images [14]. In this work, out of total blurred images only less blurred images are taken for registration.

2. **Discrete Wavelet Burst Accumulation**

$\{v_i\}_{i=1}^{M}$ are the given registered images then we can calculate directly the Discrete Wavelet transforms $\{v_i^{\wedge}\}_{i=1}^{M}$. Due to camera shake motion kernels does not vary spatially, their Discrete Wavelet spectrum magnitudes vary very smoothly. Therefore, $|v_i^{\wedge}|$ is low pass filtered before computing the weights, that is, $|\bar{v}_i^{\wedge}| = G_\sigma |v_i^{\wedge}|$, where G_σ is Gaussian filter of standard deviation σ. The strength of the low pass filter must depend on the assumed motion kernel size(the smaller the kernel the more regular its Discrete Wavelet spectrum magnitude). In this algorithm implementation, we set $\sigma = \min(m_h, m_w)\,/k_s$, where k_s =50 pixels and the image size is $m_h \times m_w$ pixels.

The final Discrete Wavelet burst aggregation is

$$\mathrm{u_p} = \mathrm{E}^{-1}\left(\sum_{\mathrm{i=1}}^{\mathrm{M}} \mathrm{w_i}.\,\mathrm{v_i^{\wedge}}\right),\quad \mathrm{w_i} = {|\bar{\mathrm{v}}_\mathrm{i}^{\wedge}|^\mathrm{p}} \Big/ {\textstyle\sum_{\mathrm{j=1}}^{\mathrm{M}} |\bar{\mathrm{v}}_\mathrm{j}^{\wedge}|^\mathrm{p}} \quad (4)$$

3. **Noise aware sharpening**

For sharpening of reconstructed image, unsharp masking process is used.

Algorithm

1. Take a series of blurred images.

$$v_i; 1 \le i \le n$$

2. Find kernels k_i out of v_i blurred images. For this, take the sharpest image among 'v_i' blurred images as reference image that is u_{ref}.

$$v_i = u_{ref} * k_i + n$$

n: White noise

3. Weights are estimated based on the Discrete Wavelet spectrum magnitudes of all the images.

$$w_i(\xi) = \frac{|\bar{v}_i^{\wedge}(\xi)|^p}{\sum_{j=1}^{M} |\bar{v}_j^{\wedge}(\xi)|^p}$$

P: Non-negative integer

M: Number of images of the same scene 'u'

$v_i^{\wedge}$: Discrete Wavelet transform of v_i

Discrete Wavelet magnitudes of blurred images represented by $|v_i^{\wedge}|$ are low pass filtered before computing the weights.

$$|\bar{v}_i^{\wedge}| = G_\sigma |v_i^{\wedge}|$$

G_σ: Gaussian filter of standard deviation σ

4. Final reconstructed image

$$u_p(x) = \sum_{i=1}^{M} IDWT[w_i(\xi) v_i^{\wedge}\,(\xi)](x)$$

5. To get better visualization of reconstructed image, apply image sharpening using unsharp masking filter. An unsharp mask cannot create additional detail but it enhances the appearance of the detail.

4. EXPERIMENTAL RESULTS

In this paper, ten blurred images are taken and applied weighted average filter using FFT and DWT. The results were computed using p=1 and the results were compared.

Fig1: Group of ten blurred images

Fig2: FFT output

Fig3: DWT output

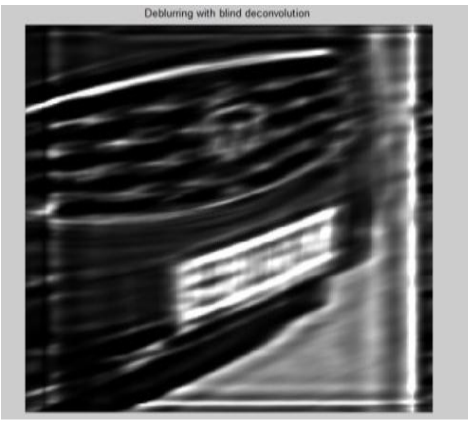

Fig4: Blind deconvolution output

PSNR comparison of different methods

S.NO	Method	Image	PSNR
1	FFT	rice	26.29
		moon surface	31.00
		cameraman	25.95
		car	26.65
		underwater	32.60
2	DWT	rice	28.69
		moon surface	32.83
		cameraman	28.82
		car	27.09
		underwater	34.19
3	Blind-deconvolution	rice	22.84
		moon surface	25.01
		cameraman	22.36
		car	20.81
		underwater	26.07

5. CONCLUSION

In this paper, proposed a new weighted average filter for removing image blur from multiple images using DWT. The original image is reconstructed from a group of its blurred images without calculating the blurring kernels. The advantage of this technique is that it does not introduce any ringing effects which are present in many deconvolution algorithms. This technique gives sharper and less noisy image than all the burst of remaining images. The proposed technique gives better PSNR than the existing FFT based technique. The simulation results show that this technique gives better results than that of the multi image deconvolution technique. The proposed technique can also be implemented using Discrete Cosine Transform.

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