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# HIGHLY ROBUST DOMAIN TRANSFORM BASED HEURISTICS WEIGHT AGE METHOD FOR IMAGE DE-BLURRING

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## Abstract

We proposed weighted average Fourier domain approach, with accumulated weights in Fourier spectrum magnitude for kernel estimation and to solve an inverse problem of image de-convolution. In most cases the main inconvenience of tackling this problem as a de-convolution and high computational burden, since the convolution model is not accurate or the kernel is not accurately estimated, the restored image will contain strong artifacts. Numerous recent approaches attempt to remove image blur due to camera shake, either with one or multiple input images, by explicitly solving an inverse and inherently ill-posed de-convolution problem. If the input takes a burst of images, which is generic in all modern digital cameras, we show that it is possible to combine them to get a clean sharp version. This is done without explicitly solving any blur estimation and subsequent inverse problem. Experiments with real time input data, we proved that the proposed Fourier burst accumulation algorithm achieves state of-the-art results an order of magnitude faster and yields better MSE and PSNR quality metrics.

**Index terms**: Multi-image de-blurring burst fusion, camera shake, low light photography, high dynamic range, Mean square error, Peak signal to noise ratio.

## 1. Introduction

Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal processing techniques to it.Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over 2-dimensions digital image processing may be modeled in the form of multidimensional systems.There are basically so many steps involved in processing of digital image some of them are given in below.

Image acquisition is the first process where in it involves preprocessing, such as scaling of images. Image enhancement is the process manipulating an image so that the result is more suitable than the original for specific application the word specific is important because it establish at the outset that enhancement technique are problem oriented. Image restoration is an area that also deals with improving the appearance of an image unlike enhancement, which is subjective, image restoration, is objective, in the sense that restoration technique tends to be based mathematical or probalisitic models of image degradation. Image compression deals with technique with reducing for storage required in saving an image, or the bandwidth required to transmit it. Image compression can be done using joint photographic experts group (JPEG) and moving pictures experts group(MPEG). Image segmentation procedures partition an image into its constituent parts or objects. Segmentation techniques' are of different types such as autonomous, rugged, weak or erratic.

## 2. Related Work

In blind motion de blurring from a single image using sparse approximation, J.F. Cai, H. Ji, C. Liu and Z. Shen [1] has presented a restoring of clear image from a single motion-blurred image due to camera shake has long been a challenging problem in digital imaging. In this new algorithm they presented to remove camera shake from a single image. The curvelet-based representation of the blur kernel also provides a good constraint on the curve-like geometrical support of the motion blur kernel, thus our method will not converge to the degenerate case as many other approaches might do.

The approach to remove motion blurring from a single image by formulating the blind blurring as a new joint optimization problem, which simultaneously maximizes the sparsity of the blur kernel and the sparsity of the clear image under certain suitable redundant tight frame systems (curvelet system for kernels and framelet system for images) has been presented. Without requiring any prior information of the blur kernel as the input, the proposed approach is able to recover high-quality images from given blurred images. Furthermore, the new sparsity constraints under tight frame systems enable the application of a fast algorithm called literalized Bregman iteration to efficiently solve the proposed minimization problem. However the main limitation of this approach is that the robustness against various noises is not achieved.It can only compute unit-pixel gradient and instable for heavily blurred image with rich textures.

In the approach of blind deconvolution using a normalized sparsity measure, blind de convolution is motivated by a fundamental re-analysis of the interaction between image regularizes and the effects of blur on the high frequencies in an image. The crucial component of our algorithm proposed by D. Krishnan, T. Tay and R. Fergus [2] is the introduction of a novel scale-invariant regularize that compensates for the attenuation of high frequencies and therefore greatly stabilizes the kernel estimation process. Blind image de convolution is an ill-posed problem that requires regularization to solve.

However, many common forms of image prior used in this setting have a major drawback in that the minimum of the resulting cost function does not correspond to the true sharp solution. Accordingly, a range of additional methods are needed to yield good results (Bayesian methods, adaptive cost functions, alphamatte extraction and edge localization). In this paper we introduce a new type of image regularization which gives lowest cost for the true sharp image. This allows a very simple cost formulation to be used for the blind deconvolution model, obviating the need for additional methods. Due to its simplicity the algorithm is fast and very robust. The number of iterations and regularization parameter are spatially variant setting. Externally we need to preprocess the input image. This method is not able to recover a reasonable kernel with high contrast images.

Recurrence of small image patches across different scales of a natural image has been previously used for solving ill-posed problems (e.g., super- resolution from a single image). In blind deblurring using internal patch recurrence [4] showed that how the multi-scale property can also be used for “blind-deblurring”, namely, removal of an unknown blur from a blurry image. While patches repeat ‘as is’ across scales in a sharp natural image, this cross-scale recurrence significantly diminishes in blurry images. We exploit these deviations from ideal patch recurrence as a cue for recovering the underlying (unknown) blur kernel. More specifically, we look for the blur kernel k, such that if its effect is “undone” (if the blurry image is de convolved with k), the patch similarity across scales of the image will be maximized. We report extensive experimental evaluations, which indicate that our approach com- pares favorably to state-of-the-art blind deblurring methods, and in particular, is more robust than them. The worst-case performanceis the highest error-ratio over the entire database. It measures the robustness of the methods. The method is more robustthan all competing approaches, in the sense that it rarely fails to recover the kernel with reasonable accuracy.

V. Garrel, O. Guyon and P. Baudoz, Lucky imaging technique [3] for AO-corrected images in the visible range is achieved by a selection based on the relative strength of signal for each spatial frequency in the Fourier domain, making a more efficient use of information contained in each frame. Realistic simulations show that our algorithm allows us to reach the diffraction limit in the visible range on an AO-equipped 8 m telescope and enhances the Strehl -ratio of an AO long exposure by a factor of up to 4.It outperforms the lucky imaging technique at an equivalent selection ratio. The fraction of selected data in simulation is also boosted from two to eight times for a given Strehl-ratio performance. These main operations can be used to describe any algorithm based on the lucky imaging principle of information selection into a set of frames. In the classic lucky imaging scheme, i.e., select, shift, and add, the preprocessing consists of the shift of individual frames. The selection of information is done by selecting frames according to a criterion estimating its quality.

In non-uniform deblurring for shaken images by O. Whyte, J. Sivic, A. Zisserman and J. Ponce [5], photographs taken in low-light conditions are often blurry as a result of camera shake, i.e. a motion of the camera while its shutter is open. Most existing deblurring methods model the observed blurry image as the convolution of a sharp image with a uniform blur kernel. However, the blur from camera shake is in general mostly due to the 3D rotation of the camera, resulting in a blur that can be significantly non-uniform across the image. A new parametrized geometric model of the blurring process in terms of the rotational motion of the camera during exposure has been proposed. This model is able to capture non-uniform blur in an image due to camera shake using a single global descriptor, and can be substituted into existing deblurring algorithms with only small modifications. it possible to model and remove a wider class of blurs than previous approaches, including uniform blur as a special case, and demonstrate its effectiveness with experiments on synthetic and real images.

## 3. Proposed Method

Edge is a fundamental feature of images, which contains abundant information and has been widely used in image registration, identification, segmentation and compression. Edge refers to the pixel set whose gray-level or gradient direction occurs abrupt change and usually manifests linear feature. By far, many approaches have been developed and applied in optical and SAR (synthetic aperture radar) images. There are mainly two sorts as follows: one sort is based on local gradient property, such as Prewitt, Sobel, Canny, zero-crossing operator, etc. These operators rely on the assumption that the noise is additive and white Gaussian and are mostly used in optical images. But they are limit to unit-pixel gradient and are highly sensitive to noise.

The other sort is based on local statistical property. They can restrain speckle noise effectively and are often used in SAR images. But the edge detected is wider and has lower position accuracy. Thus, the blurring kernels ki will be mostly different for different images in the burst. Hence, each Fourier frequency of uˆ will be differently affected on each frame of the burst. The idea is to reconstruct an image whose Fourier spectrum takes for each frequency the value having the largest Fourier magnitude in the burst. Since a blurring kernel does not amplify the Fourier spectrum (Claim 1), the reconstructed image picks what is less attenuated, in Fourier domain, from each image of the burst. Choosing the least attenuated frequencies does not necessarily guarantee that those frequencies are the least affected by the blurring kernel, as the kernel may introduce changes in the Fourier image phase.

Partial differential equations (PDEs) have led to an entire new field in image processing and computer vision. Hundreds of publications have appeared in the last decade, and PDE-based methods have played a central role at several conferences and workshops. The success of these techniques is not really surprising, since PDEs have proved their usefulness in areas such as physics and engineering sciences for a very long time.

Images usually contain structures at a large variety of scales. In those cases where it is not clear in advance that which is the right scale for the depicted information it is desirable to have an image representation at multiple scales. Moreover, by comparing the structures at different scales, one obtains a hierarchy of image structures which eases a subsequent image interpretation. A scale-space is an image representation at a continuum of scales, embedding the image f into a family $\{T_t f \mid t \geq 0\}$ of gradually simplified versions of it, provided that it fulfils certain requirements [6].Most of these properties can be classified as architectural, smoothing (information-reducing) or invariance requirements. An important architectural assumption is recursively, i.e. for t = 0, the scale space representation gives the original image f, and the filtering may be split into a sequence of filter banks:

$$T_0 f = f,$$
$$T_{t+s} f = T_t(Tsf) \forall\, s, t \geq 0 \qquad (1)$$

Smoothing properties and information reduction arise from the wish that the transformation should not create artifacts when passing from fine to coarse representation. Thus, at a coarse scale, we should not have additional structures which are caused by the filtering method itself and not by underlying structures at finer scales. Camera shake originated from hand tremor vibrations has undoubtedly a random nature. The independent movement of the photographer hand causes the camera to be pushed randomly and unpredictably, generating blurriness in the captured image. The several photographs are taken with a digital single-lens reflex (DSLR) handheld camera. The photographed scene consists of a laptop displaying a black image with white dots. The captured picture of the white dots illustrates the trace of the camera movement in the image plane. If the dots are very small mimicking Dirac masses their photographs represent the blurring kernels themselves. As one can see, the kernels mostly consist of uni-dimensional regular random trajectories. This stochastic behavior will be the key ingredient in our proposed approach.

## 4. Weighted Fourier Domain Approach

### A. MATLAB GUI View:

These are the various tabs used in MATLAB GUI view as in figure 1 to perform the corresponding functions such as giving the input, display images, adding the noise, function calling and edge extraction and so on.

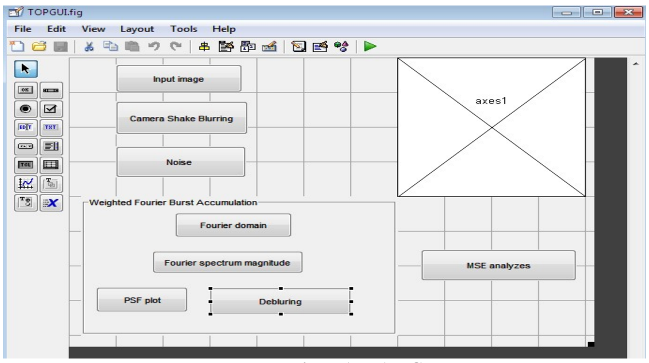


*Figure 1: MATLAB GUI*

### B. Input Image:

Here we use input image size of 256 x 256.input image should be gray scale image as shown in figure 2. Pixel ranges will 0 – 255 (8-bit).If it is a color image we convert that into gray scale image. A gray scale (or gray level) image is simply one in which the only colors are shaded of gray. The reason for differentiating such images from any other sort of color image is that less information needs to be provided for each pixel. In fact a `gray' color is one in which the red, green and blue components all have equal intensity in RGB space, and so it is only necessary to specify a single intensity value for each pixel, as opposed to the three intensities needed to specify each pixel in a full color image.Often, the grayscale intensity is stored as an 8-bit integer giving 256 possible different shades of gray from black to white.

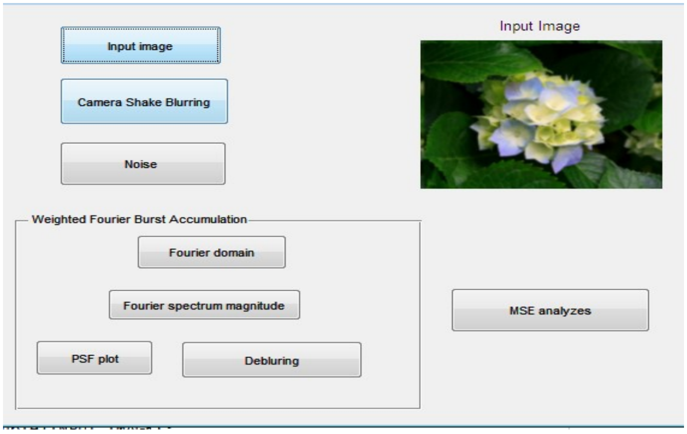


*Figure 2: Input Image*

### C. Blurred Input:

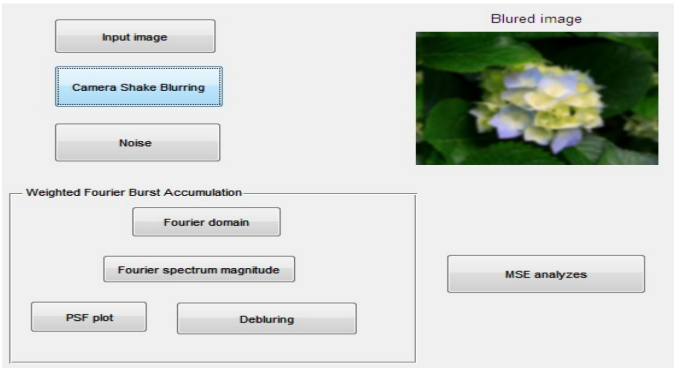


*Figure 3: Blurred Input*

### D. Noisy Input:

The input image can be any of class uint8, uint16, int16, single, or double.The mean and variance parameters for 'Gaussian' noise types should always be specified if the image were of class double as shown in figure 4. If the input image is in any other class adds noise according to the specified type and parameters, and then converts the noisy image back to the same class as the input.

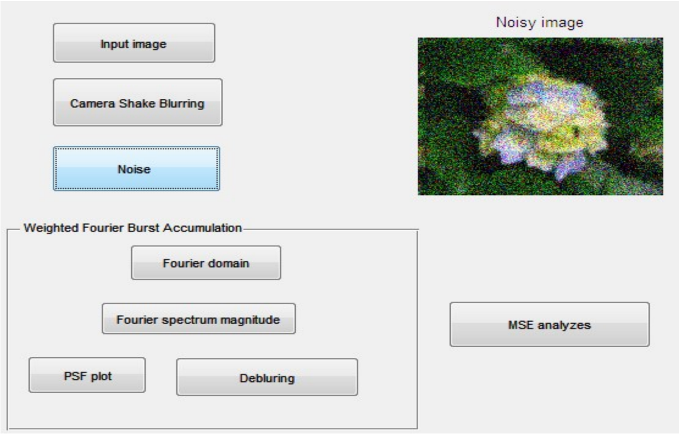


*Figure 4: Noisy Input*

## 5. Experimental Results

### A. De blurred image

In image processing and computer vision, they offer several advantages. Deep mathematical results with respect to well-posedness are available, such that stable algorithms can be found. PDE-based methods are one of the mathematically best-founded techniques in image processing. They allow a reinterpretation of several classical methods under a novel unifying framework. This includes many well-known techniques such as Gaussian convolution, median filtering, dilation or erosion. This understanding has also led to the discovery of new methods. They can offer more invariance's than classical techniques, or describe novel ways of shape simplification, structure preserving filtering, and enhancement of coherent line-like structures. The PDE formulation is genuinely continuous. Thus, their approximations aim to be independent of the underlying grid and may reveal good rotational invariance.

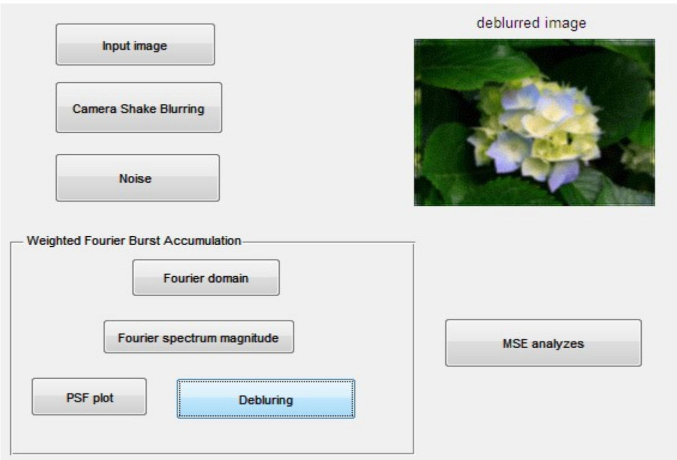


*Figure 5: Reconstructed Output Image*

While the results of the Fourier burst accumulation are already very good, considering that the process so far has been computationally non-intensive, one can optionally apply a final sharpening step if resources are still available. The sharpening must contemplate that the reconstructed image may have some remaining noise as shown in figure 5. To avoid removing fine details we finally add back a percentage of what has been removed during the de-noising.

### B. Parameters Extraction:

It is evident that the method based on FFT accumulation performs much better than the Gaussian based scheme when processing the noisy images as shown in figure 6.

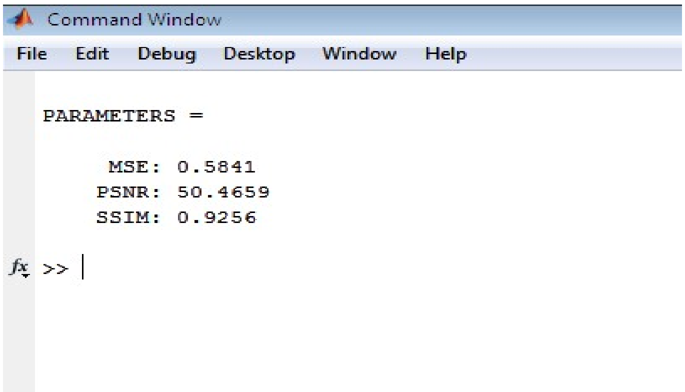


*Figure 6: Edges after Gaussian Smoothening*

PDE-based image processing techniques are mainly used for smoothing and restoration purposes. Many evolution equations for restoring images can be derived as gradient descent methods for minimizing a suitable energy functional, and the restored image is given by the steady-state of this process. Typical PDE techniques for image smoothing regard the original image as initial state of a parabolic (diffusion-like) process, and extract filtered versions from its temporal evolution. The whole evolution can be regarded as a so-called scale-space, an embedding of the original image into a family of subsequently simpler, more global representations of it. Since this introduces a hierarchy into the image structures, one can use a scale-space representation for extracting semantically important information.

## 6. Conclusion

In this project we presented a domain transformation based algorithm to remove the camera shake blur in an image burst. The FFT algorithm is built on the idea of spectrum magnitude in that each image in the burst is generally differently blurred; this being a consequence of the random nature of hand tremor. The weighted average in the Fourier domain, we successfully reconstruct the de blurred image combining the least attenuated frequencies in each frame. MATLAB Experimental results showed that the reconstructed image is sharper and less noisy than the original ones. And also, it is not produce ringing or overshooting artifacts present in most de convolution algorithms.

## 7. References

[1]. J.-F. Cai, H. Ji, C. Liu and Z. Shen, “Blind motion deblurring from a single image using sparse approximation,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2009, pp. 104–111.
[2] D. Krishnan, T. Tay and R. Fergus, “Blind deconvolution using a normalized sparsity measure,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2011, pp. 233–240.
[3] V. Garrel, O. Guyon and P. Baudoz, “A highly efficient lucky imaging algorithm: Image synthesis based on Fourier amplitude selection,” Pub. Astron. Soc. Pacific, vol. 124, no. 918, pp. 861–867, 2012.
[4]T. Michaeli and M. Irani, “Blind deblurringusing internal patch recurrence,” in Proc. IEEE Eur. Conf. Comput. Vis. (ECCV), Sep. 2014, pp. 783–798
[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]F. Gavant, L. Alacoque, A. Dupretand D. David, “A physiological camera shake model for image stabilization systems,” in Proc. IEEE Sensors, Oct. 2011, pp. 1461–1464.