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# Remove Motion from the Camera is likely blast by Fourier Accumulation

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**Abstract**—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 deconvolution problem. If the photographer takes a burst of images, a modality available in virtually 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. The proposed algorithm is strikingly simple: it performs a weighted average in the Fourier domain, with weights depending on the Fourier spectrum magnitude. The method can be seen as a generalization of the align and average procedure, with a weighted average, motivated by hand-shake physiology and theoretically supported, taking place in the Fourier domain. The method's rationale is that camera shake has a random nature, and therefore, each image in the burst is generally blurred differently. Experiments with real camera data, and extensive comparisons, show that the proposed Fourier burst accumulation algorithm achieves stateof- the-art results an order of magnitude faster, with simplicity for on-board implementation on camera phones. Finally, we also present experiments in real high dynamic range (HDR) scenes, showing how the method can be straightforwardly extended to HDR photography.

## I. INTRODUCTION

ONE of the most challenging experiences in photography is taking images in low-light environments. The basic principle of photography is the accumulation of photons in the sensor during a given exposure time. In general, the more photons reach the surface the better the quality of the final image, as the photonic noise is reduced. However, this basic principle requires the photographed scene to be static and that there is no relative motion between the camera and the scene. Otherwise, the photons will be accumulated in neighboring pixels, generating a loss of sharpness (blur). This problem is significant when shooting with hand-held cameras, the most popular photography device today, in dim light conditions. Under reasonable hypotheses, the camera shake can be modeled mathematically as a convolution, v = u _ k + n, (1) where v is the noisy blurred observation, u is the latent sharp image, k is an unknown blurring kernel and n is additive white noise. For this model to be accurate, the camera movement has to be essentially a rotation in its optical axis with negligible in-plane rotation, see . The kernel k results from several blur sources: light diffraction due to the finite aperture, out-offocus, light integration in the photo-sensor, and relative motion between the camera and the scene during the exposure.

## II. RELATED WORK

Removing camera shake blur is one of the most challenging problems in image processing. Although in the last decade several image restoration algorithms have emerged giving outstanding performance, their success is still very dependent on the scene. Most image deblurring algorithms cast the problem as a deconvolution with either a known (non-blind) or an unknown blurring kernel (blind). See e.g., the review by Kundur and Hatzinakos where a discussion of the most classical methods is presented.

### A. Single Image Blind Deconvolution

Most blind deconvolution algorithms try to estimate the latent image without any other input than the noisy blurred image itself. A representative work is the one by Fergus et al.This variational method sparked many competitors seeking to combine natural image priors, assumptions on the blurring operator, and complex optimization frameworks, to simultaneously estimate both the blurring kernel and the sharp image. Fergus et al approximated the heavy-tailed distribution of the gradient of natural images using a Gaussian mixture. In the authors exploited the use of sparse priors for both the sharp image and the blurring kernel. Cai et proposed a joint optimization framework, that simultaneously maximizes the sparsity of the blur kernel and the sharp image in a curvelet and a framelet systems respectively. Krishnan et al. introduced as a prior the ratio between the _1 and the _2 norms on the high frequencies of an image. This normalized sparsity measure gives low cost for the sharp image. In the authors discussed unnatural sparse representations of the image that mainly retain edge information. This representation is used to estimate the motion kernel. Michaeli and Irani recently proposed to use as an image prior the recurrence of small natural image patches across different scales. The idea is that the cross-scale patch occurrence should be maximal for sharp images. Several attempt to first estimate the degradation operator and then applying a non-blind deconvolution algorithm.

**B. Multi-Image Blind Deconvolution**

Two or more input images can improve the estimation of both the underlying image and the blurring kernels. Rav-Acha and Peleg claimed that "Two motion-blurred images are better than one," if the direction of the blurs are different. In the authors proposed to capture two photographs: one having a short exposure time, noisy but sharp, and one with a long exposure, blurred but with low noise. The two acquisitions are complementary, and the sharp one is used to estimate the motion kernel of the blurred one. Close to our work are papers on multi-image blindrecovered image. Having multiple input images improves the accuracy of identifying the motion blur kernels, reducing the illposedness of the problem. Most of these multi-image algorithms introduce cross-blur penalty functions between image pairs. However this has the problem of growing combinatorially with the number of images in the burst. This idea is extended in [3] using a Bayesian framework for coupling all the unknown blurring kernels and the latent image in a unique prior. Although this prior has numerous good mathematical properties, its optimization is very slow. The algorithm produces very good results but it may take several minutes or even hours for a typical burst of 8-10 images of several megapixels. The very recent work by Park and Levoy relies on an attached gyroscope, now present in many phones and tablets, to align all the input images and to get an estimation of the blurring kernels. Then, a multi-image non-blind deconvolution algorithm is applied. By taking a burst of images, the multi-image deconvolution problem becomes less ill-posed allowing the use of simpler priors. This is explored in where the authors adopted a total variation prior on the underlying sharp image. All these papers propose kernel estimation and to solve an inverse problem of image deconvolution. The main inconvenience of tackling this problem as a deconvolution, on top of the computational burden, is that if the convolution model is not accurate or the kernel is not accurately estimated, the restored image will contain strong artifacts (such as ringing).

### C. Lucky Imaging

A popular technique in astronomical photography, known as lucky imaging or lucky exposures, is to take a series of thousands of short-exposure images and then select and fuse only the sharper ones . Fried showed that the probability of getting a sharp lucky short-exposure image through turbulence follows a negative exponential. Thus, when the captured series or video is sufficiently long, there will exist such a frame with high probability.

## III. FOURIER BURST ACCUMULATION

### A. Rationale

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. Figure 1 shows several photographs 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 unidimensional regular random trajectories. This stochastic behavior will be the key ingredient in our proposed approach. Let F denote the Fourier Transform and ˆ k the Fourier Transform of the kernel k. Images are defined in a regular grid indexed by the 2D position x and the Fourier domain is indexed by the 2D frequency ζ . Let us assume, without loss of generality, that the kernel k due to camera shake is normalized such that _ k(x)dx = 1. The blurring kernel is nonnegative since the integration of incoherent light is always nonnegative. This implies that the motion blur does not amplify the Fourier spectrum:

### B. Fourier Magnitude Weights

Let p be a non-negative integer, we will call Fourier Burst Accumulation (FBA) to the Fourier weighted averaged image, where ˆ vi is the Fourier Transform of the individual burst image vi . The weight wi := wi (ζ ) controls the contribution of the frequency ζ of image vi to the final reconstruction u p. Given ζ, for p > 0, the larger the value of | ˆ vi (ζ )|, the more ˆ vi (ζ ) contributes to the average, reflecting what we discussed above that the strongest frequency values represent the least attenuated u components. The integer p controls the aggregation of the images in the Fourier domain.

## IV. ALGORITHM IMPLEMENTATION

The proposed burst restoration algorithm is built on three main blocks: Burst Registration, Fourier Burst Accumulation, and Noise Aware Sharpening as a post-processing. These are described in what follows.

### A. Burst Registration

There are several ways of registering images (see for a survey). In this work, we use image correspondences to estimate the dominant homography relating every image of the burst and a reference image (the first one in the burst). The homography assumption is valid if the scene is planar (or far from the camera) or the viewpoint location is fixed, e.g., the camera only rotates around its optical center. Image correspondences are found using SIFT features and then filtered out through the ORSA algorithm, a variant of the so called RANSAC method To mitigate the effect of the camera shake blur we only detect SIFT features having a larger scale than σmin = 1.8. Recall that as in prior art, see [25], the registration can be done with the gyroscope and accelerometer information from the camera.

### B. Fourier Burst Accumulation

Given the registered images {vi }M i=1 we directly compute the corresponding Fourier transforms { ˆ vi }M i=1. Since camera

**Algorithm 1** Aggregation of Blurred Images

**Input**: A series of images $\tilde{v}_1, \tilde{v}_2, \ldots, \tilde{v}_n$ of size $m \times n \times c^*$. An integer value $p$.

**Output** : The aggregated image $u_p$

$w = \text{zeros}(m, n)$; $\hat{u}_p = \text{zeros}(m, n, c)$;

**for** *image* $i$ *in* $\{1, \ldots, n\}$ **do**

*Burst Registration*

$M_i = \text{SIFT}(\tilde{v}_i, \tilde{v}_1)$ ; *$M_i$ set of corresponding points.*

$H_i = \text{ORSA}(M_i)$ ; *$H_i$ dominant homography in $M_i$.*

$v_i = \tilde{v}_i \circ H_i$ ; *Image resampling.*

*Fourier Burst Accumulation*

$\hat{v}_i = \text{FFT}(v_i)$;

$w_i = \frac{1}{c}\sum_{j=1}^{c} |\hat{v}_i^j|$; *Mean over color channels*

$w_i = G_\sigma w_i$ ; *Gaussian smoothing*

$\hat{u}_p = \hat{u}_p + w_i \cdot \hat{v}_i$; *Weighted Fourier accumulation*

$w = w + w_i$;

$u_p = \text{IFFT}(\hat{u}_p / w)$;

*Noise Aware Sharpening (Optional)*

$\bar{u}_p = \text{DENOISE}(u_p)$;

$\bar{u}_p^s = 2\bar{u}_p - G_\rho \bar{u}_p$; *Gaussian sharpening, $\rho \in [1, 3]$*

$u_p = \bar{u}_p^s + \delta(u_p - \bar{u}_p)$; *Add a fraction of removed noise, $\delta = 0.4$*

*[*] c is the number of color channels, typically 3. The color channels of v are denoted by $v^j$, for $j = 1, \ldots, c$. All the regular operations (e.g. $+, /, \cdot$) are point-wise.*

### C. Noise Aware Sharpening

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. Thus, we first apply a denoising algorithm (we used the NLBAYES algorithm [38]2), then on the filtered 2A variant of this is already available on camera phones, so we stay at the level of potential on-board implementations. image we apply a Gaussian sharpening. To avoid removing fine details we finally add back a percentage of what has been removed during the denoising step. The complete method is detailed in Algorithm 1.

### D. Memory and Complexity Analysis

Once the images are registered, the algorithm runs in O(M · m · logm), where m = mh × mw is the number of image pixels and M the number of images in the burst. The heaviest part of the algorithm is the computation of M FFTs, very suitable and popular in VLSI implementations. This is the reason why the method has a very low complexity. Regarding memory consumption, the algorithm does not need to access all the images simultaneously and can proceed in an online fashion. This keeps the memory requirements to only three buffers: one for the current image, one for the current average, and one for the current weights sum.

## V. CONCLUSION

We presented an algorithm to remove the camera shake blur in an image burst. The algorithm is built on the idea that each image in the burst is generally differently blurred; this being a consequence of the random nature of hand tremor. By doing a weighted average in the Fourier domain, we reconstruct an image combining the least attenuated frequencies in each frame. Experimental results showed that the reconstructed image is sharper and less noisy than the original ones. This algorithm has several advantages. First, it does not introduce typical ringing or overshooting artifacts present inmost deconvolution algorithms. This is avoided by not formulating the deblurring problem as an inverse problem of deconvolution. The algorithm produces similar or better results than the state-of-the-art multi-image deconvolution while being

significantly faster and with lower memory footprint. We also presented a direct application of the Fourier Burst Accumulation algorithm to HDR imaging with a hand-held camera. As a future work, we would like to incorporate a gyroscope registration technique, see [25], to create a realtime system for removing camera shake in image bursts. A very related problem is how to determine the best capture strategy. Giving a total exposure time, would it be more convenient to take several pictures with a short exposure (i.e., noisy) or only a few with a larger exposure time (i.e., blurred)? Variants of these questions have been previously tackled in the context of denoising/ deconvolution tradeoff. We would like to explore this analysis using the Fourier Burst Accumulation principle.

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