Camera Shake Removal using Weighted Fourier Burst Accumulation and NLmeans Denoising

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Abstract

Taking photos under dim lighting conditions using a hand-held camera is very challenging. If the camera is set to a large exposure time, the image is blurred due to camera shake. On the other hand, if it is taken with a short exposure time, the image is dark and noisy. Various approaches try to remove image blur due to camera shake, either with one or multiple input images. Blur introduced in an image from camera shake is mostly due to the 3D rotation of the camera. This results in a blur kernel which is non-uniform throughout the image. In this method a new algorithm is proposed which do not estimate the blur kernel instead use an align and average like technique. Burst images are considered because each image in the burst is blurred differently. The proposed algorithm performs a weighted average, for the burst images, in the Fourier domain, with weights depending on the Fourier spectrum magnitude. Rationale is that camera shake has a random nature, and therefore, each image in the burst is generally blurred differently. First, the burst of images are registered. Then, for that image correspondences are considered to estimate the dominant homograph relating every image of the burst and a reference image (the first one in the burst).Image correspondences are found using SURF algorithm. Then, Fourier Burst Accumulation is done channel by channel using the same Fourier weights for all channels. Then a noise removal is done using NLMEANS denoising algorithm and finally, a Gaussian sharpening is done on the filtered image. To avoid removing fine details, a percentage of what has been removed during the denoising step is added back finally. Experiments with real camera data show that the proposed burst accumulation algorithm achieves faster and better results.

Keywords- DE blurring, SURF algorithm, Burst registration, NLMeans DE noising

I. INTRODUCTION

The basic principle of photography is: When light is incident on an object to be captured, the reflected photons get accumulated on the sensor of the camera, an image is formed. The image will have good quality when more photons will reach the surface of the sensor within the exposure time. One can experience that if there is movement of scene or camera, the photons will be accumulated in the neighbouring pixels resulting in a blurred photograph. An image is said to be blurred if one can notice the shaky effect in the image. The shaky effect to an image is due to motion of the subject or the imaging device. Also blurring can be caused due to incorrect focus. Motion blur is the apparent streaking of rapidly moving objects or a movie or animation.

Many of the favourite photographs of most of the amateur photographers are spoiled due to camera shake. For the photographers who capture some unforgettable moments, cannot be recaptured under controlled conditions or repeated with different camera settings — if camera shake occurs in the image for any reason, then that moment is “lost”. This is one of the major problems faced by the photographers. So obtained image is a blurred image. 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 neighbouring 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. Camera shake, in which an unsteady camera causes blurry photographs, is a chronic problem for photographers. The explosion of consumer digital photography has made camera shake very prominent, particularly with the popularity of small, high-resolution cameras whose light weight can make them difficult to hold sufficiently steady.

In spite of the tremendous progress in image DE blurring, several challenges remain unsolved. The first challenge occurs in telephoto and low-light imaging where the effects of camera shake manifests itself as large blur kernels. Unfortunately, the performance of state of-the-art DE blurring algorithms degrade significantly as the size of the blur kernel increases. The second challenge is in DE blurring scenes that are noisy or contain saturated regions, both of which occur in low-light scenes. While there has been research addressing denoising low-light imagery and telephoto imaging, their treatment does not consider blur due to camera shake.

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 DE blurring algorithms cast the problem as a DE convolution with either a known (non-blind) or an unknown

blurring kernel (blind).The camera shake can be modelled mathematically as a convolution = u * k + nowhere v is the noisy blurred observation, u is the latent sharp image, k is an unknown blurring kernel and n is additive white noise.

Basically the camera can move in three directions i.e. x, y, z directions. Depending upon the position of camera, out of these one will be optical axis and other two will form planes of rotation. If the camera movement is in its optical axis with negligible in plane rotation [1], the above model will be accurate. There are many sources which give rise to blurring kernel. For example light diff rated due to the finite aperture, or out of focus, light accumulation in the photo-sensor and relative motion between the camera and the scene during the exposure. In the situation, the scene is static and the user/camera has correctly set to focus, the blurring kernel may result from hand tremors or due to vibrations or movements of the device on which camera is mounted e.g. the camera mounted on satellite may capture

Blurred images. Now a day there is setting in cameras as well as mobile phones to take burst of images. Thus the camera shake originated from vibrations is essentially random. Thus we can say that the movement of the camera in each image of the burst is different and independent of each other. Thus the blur in one frame will be different from the one in another image of the burst. [2]. this is the basic concept used in this paper.

Imaging sensor vendors and camera makers have been competing on megapixels and price. The cost of the sensor is most dependent on the size of the die, so designers have crammed more pixels into smaller dice by shrinking the pixel size. Each pixel has a somewhat fixed overhead of space required for circuitry, so as the overall size is reduced, the light sensitive area of each pixel gets smaller. As the light-sensing areas become smaller, the signal-to-noise ratios get smaller as well. To bring the signal-to-noise ratio up to an acceptable level requires a longer exposure [3]. This presents a problem for hand-held photography, since a long exposure will result in motion blur that limits the resolution of the photograph. If the loss in resolution due to motion is greater than the pixel sampling resolution, a higher resolution image could have been obtained with larger pixels and a shorter exposure.

Capturing satisfactory photos under low light conditions using a hand-held camera can be a frustrating experience. Often the photos taken are blurred or noisy. The brightness of the image can be increased in three ways. First, to reduce the shutter speed. But with a shutter speed below a safe shutter speed (the reciprocal of the focal length of the lens, in the unit of seconds), camera shake will result in a blurred image. Second, to use a large aperture. A large aperture will however reduce the depth of field. Moreover, the range of apertures in many cameras is very limited. Third, to set a high ISO. However, the high ISO image is very noisy because the noise is amplified as the camera's gain increases. To take a sharp image in a dim lighting environment, the best settings are: safe shutter speed, the largest aperture, and the highest ISO. Even with this combination, the captured image may still be dark and very noisy.

Recovering a high quality image from a very noisy image is no easy task as fine image details and textures are concealed in noise. Denoising [Portilla et al. 2003] cannot completely separate signals from noise. On the other hand, DE blurring from a single blurred image is a challenging blind DE convolution problem - both blur kernel (or Point Spread Function) estimation and image DE convolution are highly under-constrained. Moreover, unpleasant artifacts (e.g., ringing) from image DE convolution, even when using a perfect kernel, also appear in the reconstructed image.

There are several debluring algorithms such as: Non-uniform DE blurring: Whyte [1] analysed that the observed image uses current DE blurring methods with the uniform kernel as the convolution of sharp image. In terms of the rotational velocity of the camera, the parameterized geometric algorithm has been used. The camera shake removal has the two different algorithms: Blind DE blurring and DE blurring with noisy / blurry image. Blind DE blurring is the process of estimating both the true image and the blur from the degraded image characteristics, using partial information about the imaging system. Along with uniform blur, wide range of blur can be removed by this algorithm. The blur kernel can be estimated and obtain the sharp image by "DE convolving" the blurry image. The uniform blur can be removed by applying within a multistate framework. Richardson- Lucy algorithm is used for DE convolution. The causes of blur are the size is inversely proportional to the depth of the scene. The 10 rotation represent the smaller motion of the camera.

Multi-Image Denoising: T.Buades[4] described that the photos that are taken by using hand held camera under low light condition is more problematic .The motion blur is caused by using long exposure and the noisy image is caused due to short exposure. In this method complex image processing chain algorithm is efficiently used for denoising the multi images. This algorithm includes various techniques like noise estimation, video equalization. The non-parametric camera noise can be estimated efficiently. Image fusion is the technique that is used for the combination of multiple images into single image. There are various methods for image denoising that are used to remove or separate noise from the image. Object/ image retrieval, scene parsing are the major application in the image matching.

Multi-image blind DE blurring: The author, H.Zhang [5] studied that the blur kernels, levels of noise and unknown latent image can be coupled by using Bayesian-inspired penalty function which is used to solve multi-image blind DE convolution. There are no essential parameter for recovering quality image, whereby the relative concavity is adapted by the coupled penalty function, which contain potentially both blurry and noise images. The sharp and clean images can be estimated by using the multi-image blind DE blurring. $y_l = k_l * x + n_l$, k_l is a Point Spread Function (PSF), $*$ is the operator for convolution , and n_l is a Gaussian noise term with covariance $\lambda_l I$ [6].The premature convergence is avoided by the penalty function, which is highly desirable and course structure can be accurately identified.

Blind motion DE blurring: Motion blurring, is complex to remove by using the technique called blind DE blurring. The clear image with high quality is recovered by Multi frame approach. The author, Boracchi[7] analysed that the clear image can

be restored and blur kernel can be identified from the given blurred images by using the approach called alternative iteration. Accurate estimation of blur kernel and minimization problem can be efficiently solved by the linearized Bergmann iteration. Short shutter speed is used to produce a clear image with the limited light. Non blind DE convolution and blind convolution are the two different types of image DE convolution problem. Non blind DE convolutions mainly focus on an ill-conditioned problem, and the solution for the problem is reversing the effect of convolution on the blurred image. The problems in blind DE convolution such as blur kernel and clear image is unknown and can be resolved by infinite solution, one can be under constrained.

Image restoration from motion blur: J.Flusser [8] studied that restoration algorithm is used to remove the motion blur based on blur amount. The identification of best balance is very difficult in restoration task. In case of the arbitrary motion, performance of restoration can be analysed by the DE blurring algorithm such as point spread function and monte-carlo approach. The restoration performance is based on the three relevant DE convolution algorithms: the Anisotropic LPA-ICI DE blurring, Sparse Natural Image Priors DE convolution, and the Richardson-Lucy DE convolution [9]. The motion is measured the hybrid imaging system by using the first algorithm. The inversion of blur is done by Richardson-Lucy DE convolution; the motion information is used compute the blur PSF. The noise parameters are estimated by Anisotropic LPA-ICI and the Lucy Richardson DE convolution and the noise model can implicitly addressed by Sparse Natural Image Priors DE convolution. The three DE convolution is used for increasing the quality of the image restored during exposure time.

The camera shake can be removed from a single image based on an assumption that all image blur can be described as a single convolution; i.e., there is no significant parallax, any image-plane rotation of the camera is small, and no parts of the scene are moving relative to one another during the exposure. The blur kernel is estimated and then using this blur kernel a DE convolution algorithm is used to estimate the latent or the original image.

While taking pictures, if the camera is set to a long exposure time, the image is blurred due to camera shake. On the other hand, the image is dark and noisy if it is taken with a short exposure time but with a high camera gain. By combining information extracted from both blurred and noisy images, produce a high quality image that cannot be obtained by simply denoising the noisy image, or DE blurring the blurred image alone. If the photographer takes a burst of images, a modality available in virtually all modern digital cameras, it is possible to combine them to get a clean sharp version. The blur in one frame will be different from the one in another image of the burst. A multi-image DE blurring algorithm called Blur Burst is used to overcome the limitation of single-image DE blurring, especially in the context of large blurs due to camera shake. Obtaining a few blurry images opportunistically provides blur profiles that are not aligned; this makes the DE blurring problem well-conditioned.

In the proposed methodology, Camera shake originated from hand tremor vibrations which are essentially random are considered. This implies that the movement of the camera in an individual image of the burst is independent of the movement in another one. Thus, the blur in one frame will be different from the one in another image of the burst. The method is built on this basic principle which presents an algorithm that aggregates a burst of images (or more than one burst for high dynamic range), image correspondences are found using SURF features. Then, Fourier Burst Accumulation is done channel by channel using the same Fourier weights for all channels. The weights are computed by arithmetically averaging the Fourier magnitude of the channels before the low pass filtering. A denoising algorithm, NLMEANS, is done in order to remove the noise, then the filtered image is sharpened using Gaussian sharpening.

II. RELATED WORKS

In [10] Alex Rav-Acha et.al proposes a method which proves that when two motion-blurred images are available, having different blur directions, image restoration can be improved substantially. Two images of the same scene, having motion blur in different directions, prove to preserve large amount of information of the original scene. This method does not require a prior knowledge regarding to the blur PSF or even its direction, and does not assume any relation between the image displacement and the motion blur. Due to the motion blur, the motion parameters are pre-computed, up to a small translation. Then the PSFs of the two images are recovered simultaneously, and the image is restored using an iterative scheme.

The blur functions usually have much smaller supports than their inverses, enabling the restoration of wider blurs. Both images are used together with their recovered PSFs) to restore the original image. This results in a better restoration and robustness to noise. Regularization is incorporated in the algorithm, providing improved treatment of noise. It is easier to incorporate regularization when the recovery of the blur functions and the image restoration are done separately. This method is not suitable for image DE blurring for the images that has the motion blur degradation is always in the same direction, example the images taken from a moving car.

In [11] Rob Fergus et al. proposed a method that remove camera shake from a single photograph by adopting a method which will first estimate the blur kernel of the input blur image. The estimation process is performed in a coarse-to-fine fashion in order to avoid local minima. Then, by using the estimated blur kernel, a standard DE convolution algorithm is applied to estimate the latent or unblurred mage.

In this method, the user supplies four inputs to the algorithm: the blurred image, a rectangular patch within the blurred image, an upper bound on the size of the blur kernel (in pixels), and an initial guess as to orientation of the blur kernel (horizontal or vertical).The blur kernel K and the latent patch image Lp are estimated from the given grayscale blurred patch P.The method approximate the full posterior distribution and then compute the kernel K with maximum marginal probability.

This method selects a kernel that is most likely with respect to the distribution of possible latent images, thus avoiding the over fitting that can occur when selecting a single best estimate of the image.a Multi-scale approach is used for estimation of blur kernel. To ensure a correct start to the algorithm, manually specify the initial 3x3 blur kernel The size of the blur encountered is small then that are hard to resolve if the algorithm is initialized with a very large kernel. Conversely, large blurs will be cropped if too small a kernel is used. Hence, for operation under all conditions, the approximate size of the kernel is a required input from the user. Finally, two blur kernels are estimated from that user need to select the appropriate one.Next, image reconstruction s done. This method remove the effects of camera shake from seriously blurred images but this is time consuming since it requires the participation of the user to select the kernel size, estimated kernel .etc.There are a number of common photographic effects such as saturation, object motion, and compression artifacts are not considered so it reduce the robustness.

In [6] Jian Sun et.al proposes a method in which a high quality image is reconstructed using an input image and a noisy image. Blurriness is due to the convolution of bluer kernel and the original image. For noisy image a denoised image loses some fine details in the denoising process, but preserves the large scale, sharp image structures. Denoised image is a very good initial approximation to original image for the purpose of kernel estimation. Once kernel is estimated, it can be used to non-blindly DE convolute the DE blurred image, which unfortunately will have significant artifacts, e.g, ringing effects. Instead of recovering DE blurred image direct.The residual image can be reconstructed from a residual DE convolution using a residual blurred image. The residual blurred image is obtained by subtracting the convolution of denoised image and the kernel from the blurred image. Iterative kernel estimation is used for estimation of kernel. The residual DE convolution lessened the ringing effects, but cannot fully eliminate them .To avoid the ringing artifacts, a gain-controlled RL algorithm is used.

By formulating the image DE blurring problem using two images, developed an iterative DE convolution algorithm which can estimate a very good initial kernel and significantly reduce DE convolution artifacts. No special hardware is required. This method assumes a single, spatial-invariant blur kernel. For spatial-variant kernel, it is possible to locally estimate kernels for different parts of the image and blend DE convolution results.

In [12] Aseem Agarwala et.al proposes a method that computes a deblurred image using a unified probabilistic model of both blur kernel estimation and DE blurred image restoration. Method starts with an analysis of sources of error in blind and non-blind deconvolution. One of the major problems in latent image restoration is the presence of ringing artifacts. Ringing artifacts are visible around strong edges. Ringing artifacts are dark and light ripples that appear near strong edges after deconvolution. They are Gibbs phenomena from an inability of Finite Fourier basis functions to model the kind of step signals that are commonly found in natural images. A reasonable number of finite Fourier basis functions can reconstruct natural image structures with an imperceivable amount of loss. The method unifies blind and non-blind DE convolutions into a single MAP formulation. Then an algorithm for motion DE blurring then iterates between updating the blur kernel and estimating the latent image. Next, MAP problem is transformed to an energy minimization problem that minimizes the negative logarithm of the probability. It is done by first optimizing the latent image and then optimizing the kernel function. The iteration of the DE blurring algorithm continues until a convergence is occurred. This method builds unified models that solve non-blind and blind DE convolution problems. The optimization scheme re-weights the relative strength of priors and likelihoods over the course of the optimization. This methods also emphasis on the local prior in order to suppress ringing artifacts which might induce incorrect image structures and confuse the kernel estimation. But this method failed, when the blurred image is affected by blur that is not shift-invariant, e.g. From slight camera rotation or non-uniform object motion.

In [13] Sunghyun Cho .et.al. Presents a fast DE blurring method that produces a DE blurring result from a single image of moderate size in a few seconds. It incorporates both latent image estimation and kernel estimation in an iterative DE blurring process by introducing a novel prediction step and working with image derivatives rather than pixel values. In the prediction step, simple image processing techniques is used to predict strong edges from an estimated latent image, which will be solely used for kernel estimation. With this approach, a computationally efficient Gaussian prior becomes sufficient for DE convolution to estimate the latent image, as small DE convolution artifacts can be suppressed in the prediction. For kernel estimation, the optimization function is formulated using image derivatives, and accelerate the numerical process by reducing the number of Fourier transforms needed for a conjugate gradient method.

The method for kernel estimation shows faster convergence than the method including pixel values. In the output the sharp edges have been significantly enhanced, revealing the object shapes and structures more clearly. But the method has got certain disadvantages. The DE blurring method consists of simpler steps. This simplicity may incur degradation of the deblurring quality. The prediction depends on local features rather than global structures of the image. If an image has strong local features inconsistent with other image regions, method may fail to find a globally optimal solution.

In [14] Filip Sroubek et.al proposes a new algorithm for motion DE blurring using multiple images. First roughly estimates the PSFs by minimizing a cost function incorporating a multichannel PSF regularization term and an l1 norm-based image scarcity regularizer.This step generates reasonable, but blurry PSFs, which can be viewed as the latent ones convolved by a common, hidden, and spurious kernel. A refinement step based on the PSF scarcity and positivity properties is then carried out to DE convolve the estimated PSFs.Finally the output image is computed through a standard non-blind multichannel DE convolution procedure. ALM and IRLS are implemented to efficiently optimize the cost functions involved in this system. In most of the cases the PSFs corresponding to two given images are estimated and assumed to be close to the latent image. But these estimated blurs are often share a common, and unidentified PSF that goes unaccounted for. That is, the estimated PSFs are themselves “blurry”. While this can be due to any number of other blur sources including shallow depth of field, out of focus, lens aberrations, diffraction effects, and the like, it is also a mathematical artefact of the ill-posedness of the DE convolution

problem. In this method instead of estimating the PSFs directly and only once from the observed images, first generate a rough estimate of the PSFs using a robust multichannel DE convolution algorithm, and then "DE convolve the PSFs" to refine the outputs. The perfect recovery of the PSFs requires noise-free images and channel co-primness, i.e. a scalar constant is the only common factor of the blur PSFs.The strategy of post refinement on PSF estimation can efficiently reduce the PSF blur, mitigating the estimation sensitivity to noise and PSF size. But this approach is not suitable to blurred image that has got spatially variant blueness.

In [15] Peyman Milanfar presented a new algorithm for solving Multichannel blind DE convolution. The approach starts by defining an optimization problem with image and blur regularization terms. To force sparse image gradients, the image regularise is formulated using a standard isotropic TV. The PSF regularise consists of two terms: Multichannel constraint and scarcity–positivity. The MC constraint is improved by considering image Laplacian, which brings better noise robustness at little cost. Positivity helps the method to convergence to a correct solution, when the used PSF size is much larger than the true one. This method solves the optimization problem in an iterative way by alternating between minimization with respect to the image and with respect to the PSFs. Scarcity and positivity imply nonlinearity, but by using the variable splitting and ALM (or split-Bregman method), each step can be solved efficiently and the convergence of each step is guaranteed. But this method failed to DE blur image if the image is space-variant blurred image.

In[16]Haichao Zhang et.al proposes a robust algorithm for estimating a single latent sharp image given multiple blurry and/or noisy observations. The underlying multi-image blind DE convolution problem is solved by linking all of the observations together via a Bayesian-inspired penalty function which couples the unknown latent image, blur kernels, and noise levels together in a unique way. This coupled penalty function enjoys a number of desirable properties, including a mechanism whereby the relative-concavity or shape is adapted as a function of the intrinsic quality of each blurry observation. In this way, higher quality observations may automatically contribute more to the final estimate than heavily degraded ones. The resulting algorithm, which requires no essential tuning parameters, can recover a high quality image from a set of observations containing potentially both blurry and noisy examples, without knowing a priori the degradation type of each observation. It can handle a flexible number of degraded observations without requiring an extra 'cross-blurring' term, which generally limits the number of observations. The input can be a set of blurry or noisy observations without specifying the degradation type of each example; the algorithm will automatically estimate the blur kernel and the noise level for each one. In the case of a single observation, the method reduces to a robust single image blind DE blurring model. The penalty function couples the latent image, blur kernels, and noise levels in a principled way. This leads to a number of interesting properties, including an inherent mechanism for scoring the relative quality each observed image during the recovery process and using this score to adaptively adjust the scarcity of the image regularize. The algorithm is parameter-free thus requires minimal user involvement. But this method will not give good latent image for non-uniform blurred image inputs.

In [17] Shicheng Zheng et.al presented a framework for both uniform non-uniform motion DE blurring, leveraging an unnatural L0 sparse representation to greatly benefit kernel estimation and large-scale optimization. In latent image and the blurred image are expressed in their vector form first. Next, a sparse loss function is computed and it is incorporated to regularize optimization, which seeks an intermediate sparse representation which containing only necessary edges. It is not produced by local filtering, which thus guarantees to contain only necessary strong edges, regardless of blur kernels. It can be optimized using the half-quadratic L0 minimization. The computed optimized map is not the final latent natural image estimate due to lack of details. The natural image is restored by non-blind DE convolution given the final kernel estimate. A Hyper-Laplacian prior with norm regularization is used. Image restoration for both the uniform and non-uniform blur is accelerated by FFTs.

By using a hard thresholding and gradient thresholding without extra ad-hoc operations, this method provide more appropriate edge reference maps within a well-established optimization framework. This method does not have the edge location problem inherent in shock filter when blur kernels are highly non-Gaussian or the saddle points used in shock filter do not correspond to latent image edges. The optimization framework can naturally produce a sparse representation faithful to the input, vastly benefiting motion deblurring. The method not only provides a principled understanding of effective motion DE blurring strategies, but also notably augments performance based on the new optimization process. But this method do not produce better result for non-uniform blurred images.

In [18] Atsushi Ito et.al proposes a methodology that recovers a sharp latent image from multiple blurry input images. An assumption is made that the input images are formed via a single latent image blurred with each different PSFs. An iterative estimation algorithm that recursively estimates both the unknown blur kernels and the latent was derived image. First,a single image DE blurring is done on each blurred image(a burst image).The blurred images typically require some registration before it is DE blurred. The need for registration stems from two factors. First, large displacements between the first and last image would require using an exceptionally large blur kernel; this would increase the computational burden of the recovery algorithm significantly.

Second, individual blurry images might have small camera rotations between them which would violate the single latent image with spatially invariant blur. For these reasons, a simple homographs-based registration step is introduced before multi-image deblurring. The blurred images are registered by, first DE blurring them using a DE blurring algorithm, then feature extraction using SIFT and matching with pre-selected reference image. The feature correspondences obtained from the matching algorithm are used to fit a tomography transformation using RANSAC.RANSAC makes the algorithm robust to mismatches due to outliers, poor DE blurring, or blurry features. The blurred images are registered using the estimated homographs parameters to give the registered blurred images. At this step, any image that has very poor registration with the reference image is rejected.

Initialization is done next. By using one of the best image from the burst images as latent image. This is a simple method to obtain the initial estimate. An alternate initialization strategy is to use the output of a single-image DE blurring algorithm. Then, the multi-image DE blurring algorithm is now applied on the registered blurred images starting with blur kernel estimation. The images that do not register well are discarded to avoid artifacts due to model mismatch. Finally, the convergence between the initial latent image and the estimated latend image is checked. Obtaining a few blurry images opportunistically provides blur profiles that are not aligned thereby making the DE blurring problem well-conditioned. Method has limitations that the assumptions of spatially invariant blur do not hold in all cases, including moving objects in the scene, defocus blur due to large apertures, and complex camera motion. Then, the assumption of a single latent image is violated when considering moving objects because background regions are selectively occluded and revealed in different images. If the initial registration is not properly done then the DE blurring is not effective.

In[19] Mauricio Delbracio et.al proposes 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 is because of the consequence of the random nature of hand tremor. The algorithm aggregates a burst of images taking what is less blurred of each frame to build an image that is sharper and less noisy than all the images in the burst. Fourier frequency of image will be differently affected on each frame of the burst. It takes as input a series of registered images and computes a weighted average of the Fourier coefficients of the images in the burst. An image is constructed by combining the least attenuated frequencies in each frame. The burst restoration algorithm is built on three main blocks: Burst Registration, Fourier Burst Accumulation, and Noise Aware Sharpening as a post processing. For burst registration, image correspondences is used to estimate the dominant homographic relating every image of the burst and a reference image (the first one in the burst).Image correspondences are found using SIFT features and then filtered out through the ORSA algorithm. Then, set of registered image is obtained. Next, the Fourier burst accumulation is done. The Fourier transform of the registered image is computed. Then it is low-pass filtered using Gaussian filter and weights are calculated. The weights are computed by arithmetically averaging the Fourier magnitude of the channels before the low pass filtering. Then, final Fourier burst accumulation is done. Next, a noise aware sharpening is done using NLBAYES algorithm, on the result of Fourier burst accumulation. Then, Gaussian sharpening is done on the denoised image.

This algorithm does not introduce typical ringing or overshooting artifacts present in most DE convolution algorithms. This is avoided by not formulating the DE blurring problem as an inverse problem of deconvolution. Since, shift feature extraction is used in the burst registration, the speed of registering the image is low. And this method uses only the RGB channels so efficiency of the DE blurred image is low. The method does not remove any Gaussian white noise.

III. PROPOSED WORK

In the method, mainly three phases are there: the burst registration, Fourier Burst accumulation, Noise Aware Sharpening. Each of the phases are explained in the next sections. The burst registration can be done by taking the image correspondence between the burst images and the referenced image. It is done by using SURF [20] algorithm. In the Fourier burst accumulation, the accumulation is done channel by channel using the same Fourier weights for all channels. The weights are computed by arithmetically averaging the Fourier magnitude of the channels before the low pass filtering. Noise aware sharpening is done in order to remove the noise in the final output, using NLMEANS Image Denoising and applying a Gaussian smoothening. Figure 3.1 shows the overview of the proposed methodology.

A. Burst Registration

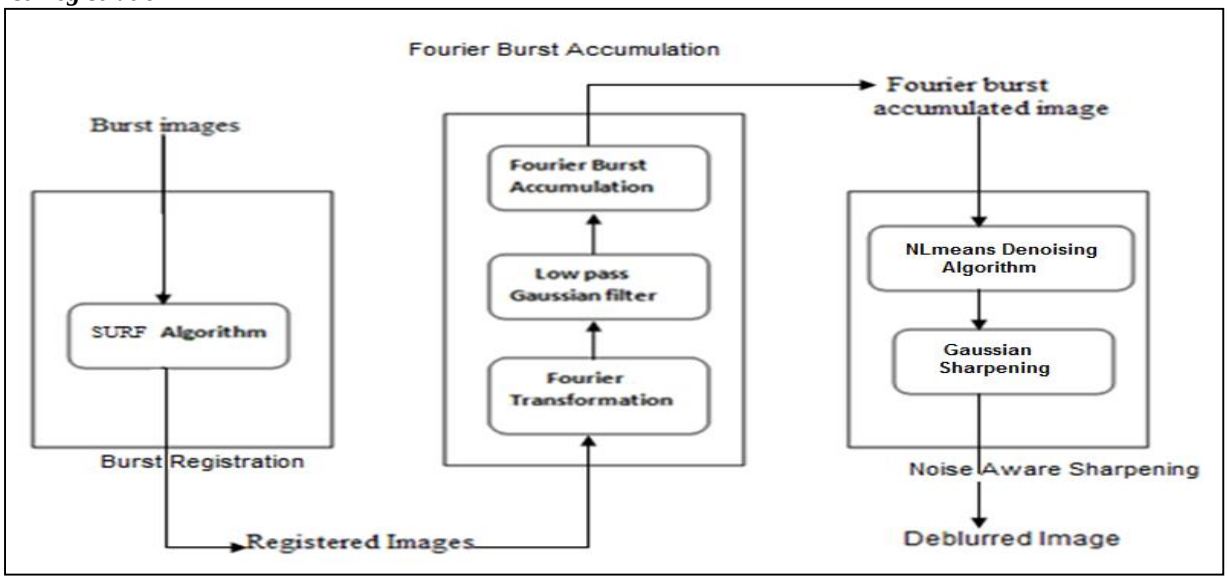

Fig. 3.1: The overview of the proposed methodology

Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors. It geometrically aligns two image-—the reference and sensed images. The present differences between images are introduced due to different imaging conditions. Image registration is a crucial step in all image analysis tasks in which the final information is gained from the combination of various data sources like in image fusion, change detection, and multichannel image restoration. The detected features in the reference and sensed images can be matched by means of the image intensity values in their close neighbourhoods, the feature spatial distribution, or the feature symbolic description.

Burst registration method uses the image correspondences to estimate the dominant homograph relating every image of the burst and a reference image (the first one in the burst).The holography 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 centre. Image correspondences are found using SURF features [25].

B. SURF Algorithm

The SURF (Speed up Robust Features) algorithm is based on the same principles and steps as SIFT; but details in each step are different. The algorithm has three main parts: interest point detection, local neighbourhood description and matching.

1) Interest Point Detection

SURF uses square-shaped filters as an approximation of Gaussian smoothing. (The SIFT approach uses cascaded filters to detect scale-invariant characteristic points[20], where the difference of Gaussians (DoG) is calculated on rescaled images progressively.) Filtering the image with a square is much faster if the integral image is used:

$$S(x,y)=\sum\sum I(i,j)$$

The sum of the original image within a rectangle can be evaluated quickly using the integral image, requiring evaluations at the rectangle's four corners. SURF is based on multi-scale space theory and the feature detector is based on Hessian matrix. Since Hessian matrix has good performance and accuracy.

2) Scale-Space Representation and Location of Points Of Interest

Interest points can be found at different scales, partly because the search for correspondences often requires comparison images where they are seen at different scales. In other feature detection algorithms, the scale space is usually realized as an image pyramid. Images are repeatedly smoothed with a Gaussian filter, then they are subsampled to get the next higher level of the pyramid.

3) Local Neighbourhood Descriptor

The goal of a descriptor is to provide a unique and robust description of an image feature, e.g., by describing the intensity distribution of the pixels within the neighbourhood of the point of interest. Most descriptors are thus computed in a local manner, hence a description is obtained for every point of interest identified previously.

The dimensionality of the descriptor has direct impact on both its computational complexity and point-matching robustness/accuracy. A short descriptor may be more robust against appearance variations, but may not offer sufficient discrimination and thus give too many false positives. The first step consists of fixing a reproducible orientation based on information from a circular region around the interest point. Then construct a square region aligned to the selected orientation, and extract the SURF descriptor from it.

4) Matching

By comparing the descriptors obtained from different images, matching pairs can be found.

C. Fourier Burst Accumulation

Burst mode is an option in cameras where the photographer is allowed to take a series of images, one right after the other. Let us assume that the photographer takes a sequence of M images of the same scene u,

$$v_i = u * k_i + n_i; \text{ for } i = 1..M;$$

The movement of the camera during any two images of the burst will be essentially independent. Thus, the blurring kernels ki will be mostly different for different images in the burst. Hence, each Fourier frequency of u 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 , 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. However, for small motion kernels, the phase distortion introduced is small.

Given the registered images $\{v_i\}_M^{i=0}$ directly compute the corresponding Fourier transforms $\{\hat{v}_i\}_M^{i=0}$ .Since camera shake motion kernels have a small spatial support, their Fourier spectrum magnitudes vary very smoothly. Thus $||\{\hat{v}_i\}||$ can be low pass filtered before computing the weights, that is, $||\{\hat{v}_i\}|| = G_\sigma|\overline{\hat{v}_i}|$, where G_σ is a Gaussian filter of standard deviation σ. The strength of the low pass filter (controlled by the parameterσ) should depend on the assumed motion kernel size (the smaller the kernel the more regular its Fourier spectrum magnitude).Equation 3.1 shows the calculation of Fourier transform

$$\hat{v}_i = \mathrm{FFT}(v_i) \quad (3.1)$$

1) Gaussian Smoothing

Gaussian smoothing filters are commonly used to reduce noise. The strength of the low pass filter (controlled by the parameter σ should depend on the assumed motion kernel size (the smaller the kernel the more regular its Fourier spectrum magnitude).Although this low pass filter is important, the results are not too sensitive to the exact value of σ , where σ is the standard deviation , (m_h, m_w) the pixel size of the input images and k_s is set to 50 pixels. Equation 3.2 shows the application of Gausssian smoothing to the weights.

$$\sigma = (m_h, m_w) / k_s \quad (3.2)$$

$$(w_i = G_\sigma * w_i) \quad (3.3)$$

D. 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. Apply a denoising algorithm: NLMEANS image denoising, then on the filtered image apply a Gaussian sharpening. To avoid removing fine details, finally add back a percentage of what has been removed during the denoising step.

1) NLMEANS Denoising Algorithm

In any digital image, the measurement of the three observed colour values at each pixel is subject to some perturbations. These perturbations are due to the random nature of the photon counting process in each sensor. The noise can be amplified by digital corrections of the camera or by any image processing software. For example, tools removing blur from images or increasing the contrast enhance the noise.

The principle of the earlier denoising methods was quite simple: Replacing the color of a pixel with an average of the colours of nearby pixels. The variance law in probability theory ensures that if nine pixels are averaged, the noise standard deviation of the average is divided by three. Thus, if one can find for each pixel nine other pixels in the image with the same color (up to the fluctuations due to noise) one can divide the noise by three (and by four with 16 similar pixels, and so on). The most similar pixels to a given pixel have no reason to be close at all. Think of the periodic patterns, or the elongated edges which appear in most images. It is therefore licit to scan a vast portion of the image in search of all the pixels that really resemble the pixel one wants to denoised. Denoising is then done by computing the average colour of these most resembling pixels. The resemblance is evaluated by comparing a whole window around each pixel, and not just the colour. This new filter is called non-local means and it writes

$$\mathrm{NLu(p)} = \frac{1}{\mathrm{C(p)}} \int \mathrm{f(d\big(B(p), B(q)\big)u(q)\ dq} \quad (3.4)$$

Each pixel p of the non-local means denoised image is computed with the following formula:

$$\mathrm{NL(V)(p)} = \sum \mathrm{w(p,q)V(q)} \quad (3.5)$$

Where V is the noisy image, and weights w(p,q) meet the following conditions $0 \leq w(p,q) \leq 1$ and $\sum w(p,q) = 1$.Each pixel is a weighted average of all the pixels in the image. The weights are based on the similarity between the neighbourhoods of pixels p and to compute the similarity between two neighbourhoods take the weighted sum of squares difference between the two neighbourhoods. Pixel based processing is easy to perform as well as it will give accurate results in comparison to other methods. Two images have been taken in which one is available on system and the other which is taken from the digital media and then downloaded to the computer. Difference is occurred in the processing of two images i.e. the image which is already available has got aligned pixels than the image that is downloaded from the digital media.

The algorithm is briefly explained in the figure below:

Algorithm: Aggregation of blurred images

INPUT: A series of images $v_1, v_2, \ldots\ldots, v_n$, of size m x n x c .

An integer value p

OUTPUT: An aggregated image u_p

1 $w = \text{zeros}(m,n)$; $\hat{u}_p = \text{zeros}(m, n, c)$;

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

Burst Registration

3. $M_i = \text{SURF}(v_i, v_1)$

Fourier Burst Accumulation

4. $\hat{v}_i = \text{FFT}(v_i)$;
5. $w_i = \frac{1}{c}\sum_{j=1}^{c} |\hat{v}_i^j|$; *Mean over color channels*
6. $w_i = G_\sigma\, w_i$; *Gaussian smoothing*
7. $\hat{u}_p = \hat{u}_p + w_i \,.\, \hat{v}_i$; *Weighted Fourier accumulation*
8. $w = w + w_i$;

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

Noise Aware Sharpening

10. $\bar{u}_p = \text{DENOISE}(u_p)$;
11. $\bar{u}_p^s = 2\bar{u}_p - G_\rho \bar{u}_p$; *Gaussian sharpening,* $\rho \in [1, 3]$
12. $u_p = \bar{u}_p^s + \delta(u_p - \bar{u}_p)$; *Add a fraction of removed noise,* $\delta = 0.4$

IV. EXPERIMENTAL RESULTS AND ANALYSIS

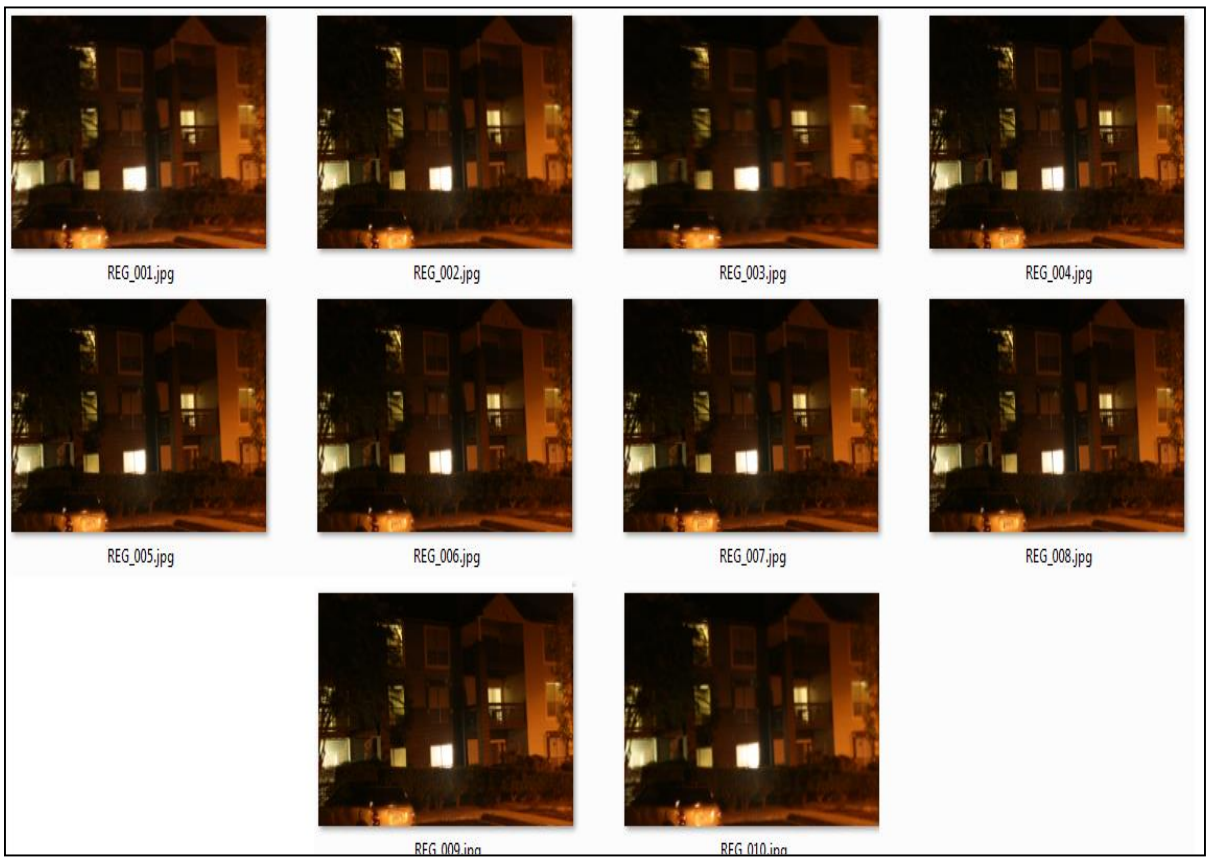

Fig. 4.1: Burst of Images

Fig. 4.2: Reference Image

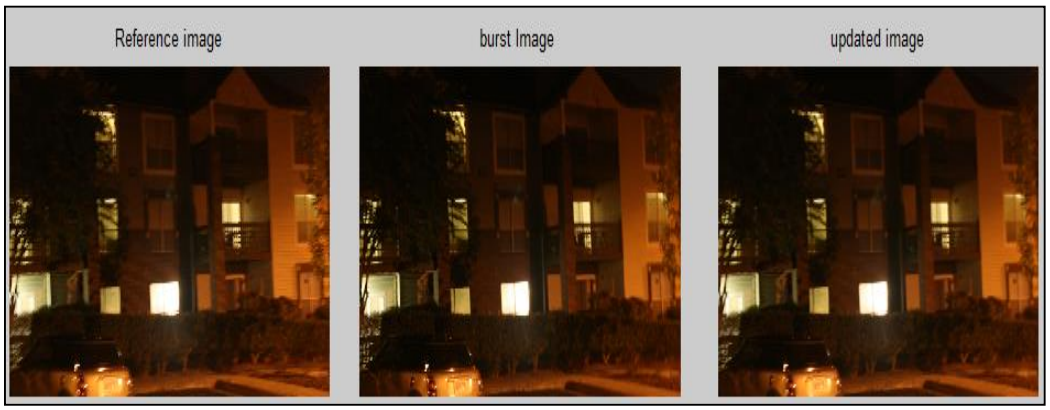

Fig. 4.3: Burst Registration

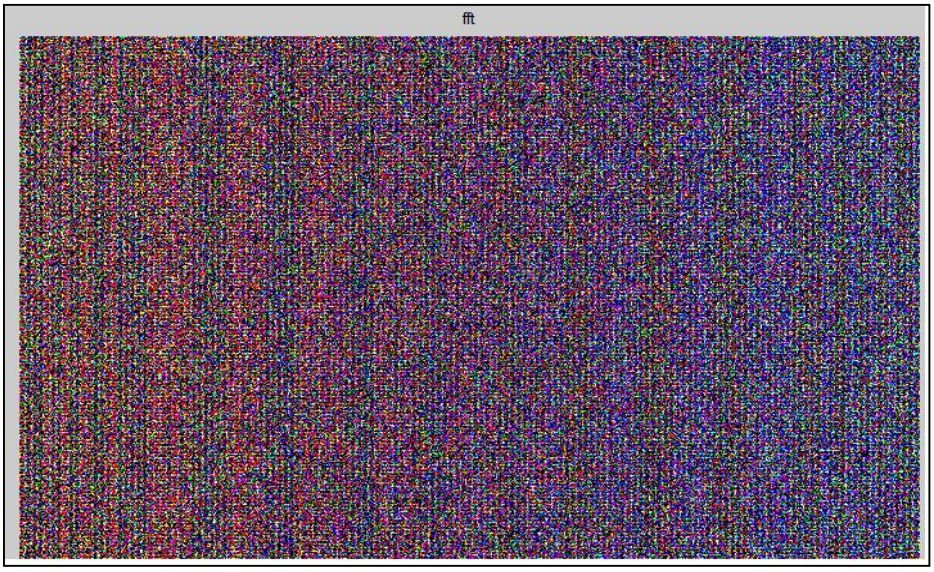

Fig. 4.4: FFT of the Registered Image

Fig. 4.5: Inverse FFT of the registered Image

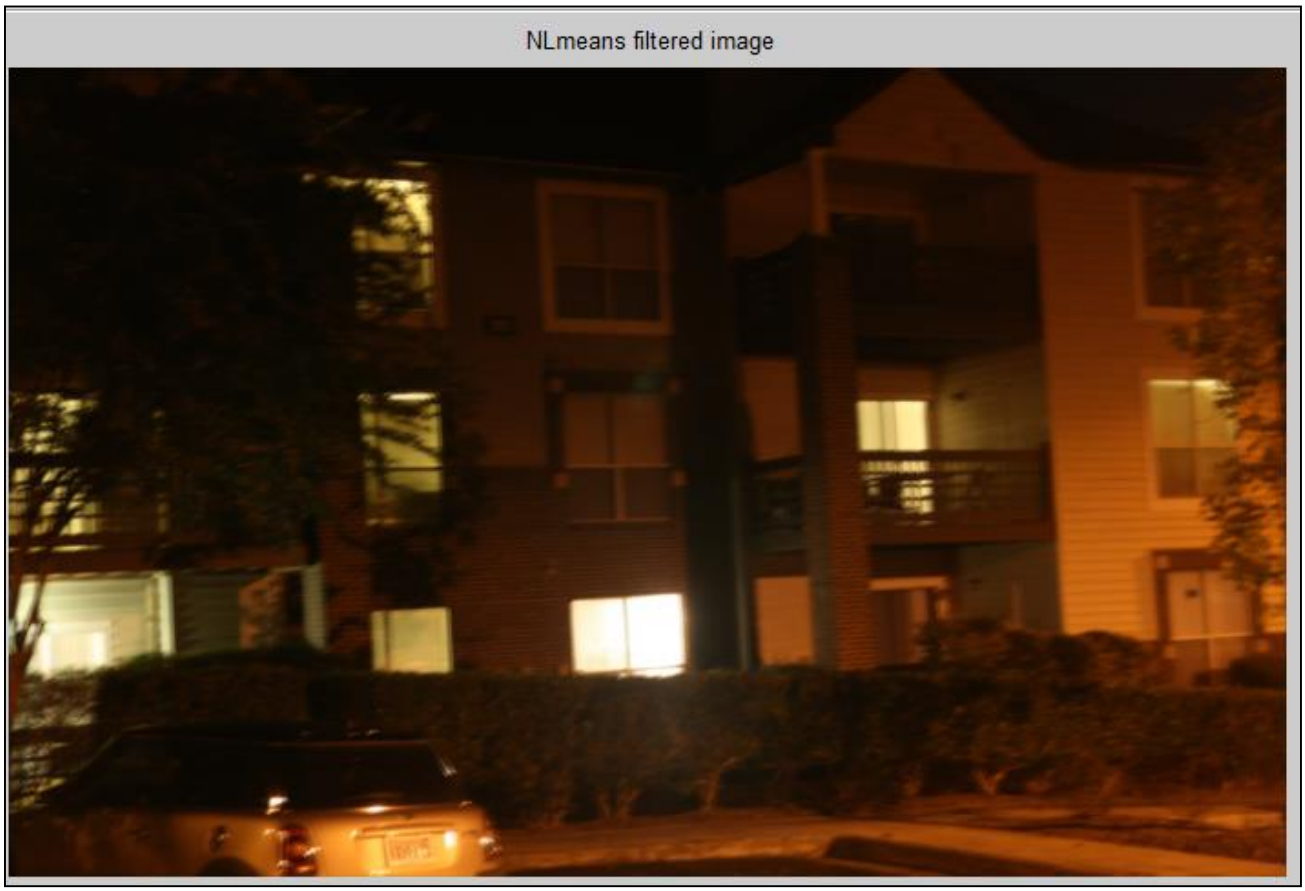

Fig. 4.6: Non Local Means Filtered Image

Fig. 4.7: DE noised Image, Gaussian corrected Image and Image after adding a small noise back

Fig. 4.8: The Final Shake Removed Image

The experimental result shows that the proposed method works efficiently for burst images containing more number of images. The method takes only few seconds to give the output. The method is developed in matlab2014.The Operating system is Windows7.

V. CONCLUSION

In this work an algorithm is described which removes the camera shake (blur) from a burst of images. The basic concept used here is though each image in a burst is differently blurred, the results are found without calculating the blurring kernels. It is done by doing a weighted average in the Fourier domain, the image is reconstructed by combining the least attenuated frequencies in each frame. The goal of the proposed system is to improve the time for deblurring an image from burst of images, by using SURF Algorithm for burst registration and doing a weighted Fourier burst accumulation and noise sharpening. Advantage is that it does not introduce typical ringing or overshooting artifacts present in most deconvolution algorithms. Experimental results showed that the reconstructed image is sharper and less noisy than the original ones. Video deblurring can also be done using this proposed method provided the input video should have at least one clear frame. Thus, the proposed method is a fast and efficient way of blur removal.

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