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A Survey on Camera Shake Removal Techniques

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Abstract

Camera Shake is caused by not holding the camera still. Because of hand tremors, the shake can be too much. This will result in a blurred, or sometimes an image over image. Camera shake is more when there is no adequate light source and when using long lenses which exaggerate movement, and also when taking images of moving objects. Camera Shake is caused by not holding the camera still. Because of hand tremors, the shake can be too much. This will result in a blurred, or sometimes an image over image. Camera shake is more when there is no adequate light source and when using long lenses which exaggerate movement, and also when taking images of moving objects. Image blur can be observed when the camera focus is not properly set, when there are different objects at different depths, or in the presence of is a motion blur. In order to remove camera shake, many algorithms have been proposed. In this paper we will examine different methods and techniques of camera shake removal. In order to remove camera shake, many algorithms have been proposed. In this paper we will examine different methods and techniques of camera shake removal.
Keywords- Deblurring, SURF algorithm, Burst registration

I. INTRODUCTION

Many of the favorite 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 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. 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.

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).The camera shake can be modeled mathematically as a convolution $= u * k + n$, 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.

II. IMAGE DEBLURRING ALGORITHMS

There are so many methodologies that integrate different biometrics and developed a multi-biometric system. In [1] David C. M Wong et al. new approach for the personal identification using hand images that attempts to improve the performance of palm print based verification system by integrating hand geometry features. In [2] Guiyu Feng1 et.al a novel fusion strategy for personal identification using face and palm print biometrics. First, the facial features from a face image is extracted using both Principle Component Analysis(PCA) and Independent Component Analysis (ICA) methods. The extracted features of palm print and face are then integrated to form a combined feature vector. Based on this extracted features classification is done using Nearest Neighbor classifier.

A. Multi-Image Denoising

T.Buades[2] 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.

B. Multi-Image Blind Deblurring
The author, H.Zhang [3] 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 deconvolution. 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 deblurring. $y_l = k_l * x + n_l$, k_l is a Point Spread Function (PSF) , $*$ is the operator for convolution , and n_l is a Gaussian noise term with covariance $\lambda_l I$ .The premature convergence is avoided by the penalty function, which is highly desirable and course structure can be accurately identified.

C. Blind Motion Deblurring
Motion blurring, is complex to remove by using the technique called blind deblurring. The clear image with high quality is recovered by Multi frame approach. The author, Boracchi[4] analyzed 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 deconvolution and blind convolution are the two different types of image deconvolution problem. Non blind deconvolution mainly focuses 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 deconvolution such as blur kernel and clear image is unknown and can be resolved by infinite solution, one can be under constrained.

D. Image Restoration from Motion Blur
J.Flusser [5] 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 analyzed by the deblurring algorithm such as point spread function and monte-carlo approach. The restoration performance is based on the three relevant deconvolution algorithms: the Anisotropic LPA-ICI Deblurring, Sparse Natural Image Priors deconvolution, and the Richardson-Lucy Deconvolution [6]. The motion is measured the hybrid imaging system by using the first algorithm. The inversion of blur is done by Richardson-Lucy Deconvolution; the motion information is used compute the blur PSF. The noise parameters are estimated by Anisotropic LPA-ICI and the Lucy Richardson Deconvolution and the noise model can implicitly addressed by Sparse Natural Image Priors deconvolution. The three deconvolution is used for increasing the quality of the image restored during exposure time.

During 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 deconvolution 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 deblurring the blurred image alone.

III. CAMERA SHAKE REMOVAL TECHNIQUES

In [7] 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 deblurring for the images that has the motion blur degradation is always in the same direction, example the images taken from a moving car.

In [8] 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 deconvolution algorithm is applied to estimate the latent or unblurred image.

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 gray scale blurred patch P. The method approximates the full posterior distribution and then computes 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 reduces the robustness.

In [9] 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 deconvolute the deblurred image, which unfortunately will have significant artifacts, e.g, ringing effects. Instead of recovering deblurred image direct. The residual image can be reconstructed from a residual deconvolution 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 deconvolution 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 deblurring problem using two images, developed an iterative deconvolution algorithm which can estimate a very good initial kernel and significantly reduce deconvolution 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 deconvolution results.

In [10] Aseem Agarwala et.al proposes a method that computes a deblurred image using a unified probabilistic model of both blur kernel estimation and deblurred 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 unperceivable amount of loss.

The method unifies blind and non-blind deconvolution into a single MAP formulation. Then an algorithm for motion deblurring 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 deblurring algorithm continues until a convergence is occured. This method builds a unified model that solves non-blind and blind deconvolution problems. The optimization scheme re-weights the relative strength of priors and likelihoods over the course of the optimization. This method also emphasis on the local prior in orders 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 [11] Sunghyun Cho .et.al. presents a fast deblurring method that produces a deblurring result from a single image of moderate size in a few seconds. It incorporates both latent image estimation and kernel estimation in an iterative deblurring 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 deconvolution to estimate the latent image, as small deconvolution artifacts can be suppressed in the prediction. For kernel estimation, the optimization functions 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 deblurring 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 rong local features inconsistent with other image regions, method may fail to find a globally optimal solution.

In [12] Filip Sroubek et.al proposes a new algorithm for motion deblurring 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 sparsity 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 sparsity and positivity properties is then carried out to deconvolve the estimated PSFs. Finally the output image is computed through a standard non-blind multichannel deconvolution 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 artifact of the ill-posedness of the deconvolution 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 deconvolution algorithm, and then “deconvolve the PSFs” to refine the outputs. The perfect recovery of the PSFs requires noise-free images and channel co-primeness, 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 blurness.

In [13] Peyman Milanfar presented a new algorithm for solving Multichannel blind deconvolution. The approach starts by defining an optimization problem with image and blur regularization terms. To force sparse image gradients, the image regularizer is formulated using a standard isotropic TV. The PSF regularizer consists of two terms: Multichannel constraint and sparsity–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. Sparsity 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 deblur image if the image is space-variant blurred image.

In[14] 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 deconvolution 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 deblurring 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 sparsity of the image regularizer. 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 [15] Shicheng Zheng et.al presented a framework for both uniform non-uniform motion deblurring, 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 deconvolution given the final kernel estimate. A Hyper-Laplacian prior with 0.5 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 deblurring strategies, but also notably augments performance based on the new optimization process. But this method does not produce better result for non-uniform blurred images.

In [16] 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 were derived image. First, a single image deblurring is done on each blurred image(a burst image).The blurred images typically require some registration before it is deblurred. 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 homography-based registration step is introduced before multi-image deblurring. The blurred images are registered by, first deblurring them using a deblurring 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 homography transformation using RANSAC.RANSAC makes the algorithm robust to mismatches due to outliers, poor deblurring, or blurry features. The blurred images are registered using the estimated homography 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 images 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 deblurring algorithm. Then, the multi-image deblurring 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 deblurring 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 deblurring is not effective.

In[17] 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 are used to estimate the dominant homography 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 sharpen in is done on the denoised image. This algorithm does not introduce typical ringing or overshooting artifacts present in most deconvolution algorithms. This is avoided by not formulating the deblurring 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 deblurred image is low. The method does not remove any Gaussian white noise.

IV. CONCLUSION

In this paper, different deblurring techniques and camera shake removal methods are discussed. In most of the algorithms the image registration was carried out as the preliminary step and later the processing was done. To estimate the burst registration the algorithm may consider the key points mapping as one of the steps. This helps in mapping the images with same features. The camera shake was removed by using both single and pair of images. The algorithms for the removal of blurriness using burst of images was less compared to that of other. The camera shake removal using Fourier Burst Accumulation is the better technique and in that if the image registration is done using SURF algorithm then it will give better result.

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