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Literature Survey on Image Deblurring Techniques

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Abstract: ***This paper provides a quick overview of existing image de-blurring techniques that have been proposed by various researchers and have been cited by many published works. Reading this material can be helpful for amateur researchers who want to start off their research in this area of interest, as it would give them an insight of works that have already been done and give them an idea as in which direction their research should start on.***

Keywords: Motion Blur, Deblurring, Image Restoration, Enhancement, Sharpening

1. Introduction

Deblurring is essentially the elimination or the reduction of blur artifacts present in the blurry image. Blur artifacts can be applied to images resulting from, the movement of the camera while the image was being taken, longer exposure times, improper focus setting at the lens, or due to the actual movement of the object of interest while the camera was held stationary. While the presence of blurred artifacts is undesired in images, it may be interesting to note that some artists believe intentional addition of blur artifacts to images can sometimes improve the aesthetics of the image. For example, a background blur can be induced in the image to draw the attention of the viewer to the artifact in the image that we are most concerned about. It is purely the mindset of the viewer which flags a photograph, good or bad.

2. Blur Model

The blur is typically modeled as the convolution of a (sometimes space- or time-varying) point spread function with a hypothetical sharp input image, where both the sharp input image (which is to be recovered) and the point spread function are unknown. [6]Image deconvolution/deblurring is the process of recovering the unknown image from its blurred version, given a blurring kernel or the Point Spread Function (PSF). Two classes of deconvolution problems: a) Non-blind deconvolution-the PSF is known, b) Blind deconvolution-the PSF is unknown. Blind deconvolution is difficult because the blurring kernel is not known. In this literary survey, Deblurring techniques that have mostly been cited by a lot of researchers in their own work have been covered.

3. Image Restoration with Blurred/Noisy Image Pairs[1]

Photography under low light conditions can be a challenging task to amateur photographers. Trying to increase the exposure time to allow sufficient photons to reach the sensor surface can result in a blurry image due to camera movement during this interval. On the other hand, shorter exposure times can result in much darker and noisy image.Higher ISO settings can also make the image very noisy because the noise is also amplified as the camera's gain increases. This approach makes use of a blurred/noisy image pair to regenerate a plausible sharp image using the details present in the image pair, which cannot be easily obtained only from a single image (Blurred or Noisy).

This **patented** method was initially proposed by Lim and Silverstein [2006] and has later been optimised byL Yuan, J Sun, L Quan, HY Shum. [1] This method estimates a much more reliable blur kernel and generates a sharper image with almost no ringing artifacts.[1]**Note**: It is also required to note that this approachworks only if the noisy image has a high SNR and fine details. [1]

3.1 Process Overview[1]:

Step 1: Take a pair of images: A blurred image, B with a slow shutter speed and low ISO, and a noisy image N with a higher shutter speed and high ISO. The noisy image is usually underexposed and has a very low SNR since the camera noise is dependent on the image intensity level [9].

Step 2: Pre-multiply the noisy image by $ISO_B\Delta t_B/ISO_N\Delta t_N$ to compensate the exposure differences between the images, where Δt is the exposure time.

Step 3: Perform multiplication in the irradiance space then go back to the image space if the camera response curve is known. Otherwise a (γ=2.0) gamma curve is used as an approximation.

Step 4:Compute the denoised image N_D [8] and then compute the residual image ΔI (Wavelet based denoising Algorithm).

Step 5: Estimate the initial kernel by the constrained least squares optimisation.

Step 6: Perform iterative kernel estimation with the initialisation $I=N_D$. Use Tikhonov regularisation and hysteresis thresholding in scale space for better estimation of actual blurring kernel.

Step 7: Perform Residual Deconvolution using Gain controlled RL algorithm as described in[1]. Ringing artifacts are reduced by this step. The sharp image is thus obtained.

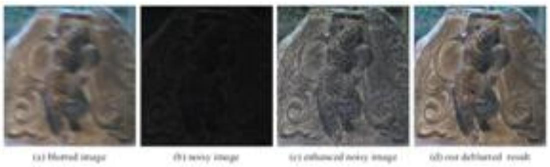

Figure 1: Photographs in a low light environment. (a) Blurred image (with shutter speed of 1 second, and ISO 100) due to camera shake. (b) Noisy image (with shutter speed of 1/100 second, and ISO 1600) due to insufficient light. (c) Noisy image enhanced by adjusting level and gamma. (d) Deblurred image.

3.2 Discussions and Conclusions [1]

This approach generates a high quality estimate of the sharp image using details from both the blurred version as well as the noisy version of the image. This approach does not require special hardware and can use hand held cameras. The limitation of this approach is that it assumes a spatially invariant blurring kernel. In such cases, there is a need to locally estimate the blurring kernels and blend the convolution results.Also there is a need for an additional noisy image data, which may not be available at all times i.e. this approach cannot be used to deblur images after we have left the scene.

4. Image Restoration using Fast Single Image Blind Deconvolution[2]

It is common for blind deconvolution methods to be in the form an iterative process where the initial blur kernel is obtained from the estimated latent image and the given blurred image, which is used to estimate the latent image by non-blind deconvolution as the blurring kernel is now known. This latent image is now used to compute the blurring kernel for the next iteration. This makes the computation intensive, complex and time consuming, which is practically a poor method for images that are moderate or large in size. These methods give excellent results, but as the iteration count increases, ringing is one serious problem that is encountered.

Fast Single Image Blind Deconvolution approach is essentially, an extension to the single-image blind deconvolution method. It is particularly useful for deblurring images that are of moderate size. The execution time is about a few seconds. This high speed is achieved by accelerating latent image estimation and blurring kernel estimation.For accelerating latent image estimation, we assume that the latent image has enough strong edges, and explicitly pursue sharp edge restoration and noise suppression using image filters, instead of taking a computationally expensive non-linear prior. For kernel estimation, the numerical optimization process is acceleratedby excluding pixel values in the formulation.

4.1 Process Overview[2]

Step 1: Take the blurred image B and blurring kernel K. Remove the blur to obtain an estimate of latent image using simple and fast deconvolution using Gaussian prior. Due to the characteristics of Gaussian prior, the estimated latent image, L will now have smooth edges and noise in smooth regions.

Step 2: This step is the prediction step.Now obtain a refined estimate of latent image, L' by restoring sharp edges and removing noise from L with efficient image filtering techniques. This gives a high quality latent image estimation needed for accurate kernel estimation.

Step 3: Now use conjugate gradient method for kernel estimation. For gradient calculations, that involves multiplications of huge matrices and vectors, use Fast Fourier Transforms (FFTs).

Step 4: Now use the estimated kernel to perform deconvolution operation with the estimated latent image to compute the sharp image. If the result is unsatisfactory, iterate the process, till you arrive at a plausible sharp image.

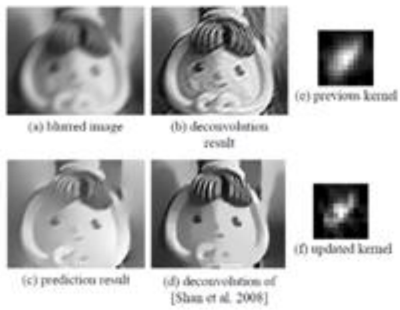

Figure 2: Effect of prediction. Our simple deconvolution with (a) and (e) produces a poor result (b). However, the prediction result (c) from (b) has only sharp edges while ringing artifacts have been removed. The kernel (f) estimated using (c) shows a refinement toward the real kernel, shown in Fig. 4. Comparison of (c) with (d) obtained directly from (a) and (e) shows that combination of simple deconvolution with prediction can produce a similar result to sophisticated deconvolution, for the purpose of the input for kernel estimation. For visualization, the image in (c) has been restored from the predicted gradient maps by Poisson reconstruction.

4.2 Discussion and Conclusions [2]

This deblurring method consists of simpler steps than previous methods which may lead to reduction of deblurring quality. However, it does prove to be comparable to sophisticated methods. The kernel estimation uses the Tikhonov regularization term, which is simpler than a sparsity prior used in [7].The prediction depends on local features rather than global structures of the image. If an image has strong local features inconsistent with other regions, this method may fail. This method may also tend to fail predicting sharp edges for large blurs, which results in poor estimation of latent image in Step 2.The results are also relatively sensitive to parameters, and improving the robustness to the parameters will be the future work. This method also shares common limitations with other uniform motion deblurring methods. Due to limitation of the blur model based on deconvolution, saturated pixels from strong lights, severe noise, and spatially varying blur would not be properly handled. Extending this method to resolve these limitations would be an interesting future work.

5. Blind Image Restoration using Image Statistics[3]

Traditional blind deconvolution techniques try to extract a single blurring kernel for the complete image. However, in case of varying motions, where the objects in the image are moving in different directions, independent of the camera movement, the blur cannot be modelled with a single blurring kernel. Using such kernel for deconvolution over the entire image can induce serious artifacts. This necessitates the segmentation of image into regions with different blurs. [3]

Various approaches have been put forward for deblurring images with spatially variant blur kernels. While most of them handling different motions, rely on multiple frames, this method, instead, relies on the observation of statistics of derivative filters in a single frame that are significantly changed by the blur. The expected derivatives distributions are modelled as a function of width of the blurring kernel. These distributions aid in discriminating regions with different blurs.[3]

This approach is completely automatic, provided two key assumptions. First assumption is that the image is comprised of small number of blurring patches, with the same blurring kernel within each patch. The second assumption is that the motion velocity of the camera/objects within each patch is constant. This results in the blurring kernel, in each patch, to be a simple one dimensional box filter. The only unknown variables here are the blur direction and the width of the blurring kernel.[3]

5.1 Process Overview[3]

Step 1: Take the blurred image.
Step 2: Apply Gaussian Derivative filters to the blurred image.
Step 3: Analyse the variation in derivatives. Direction of motion blur is selected as the direction with minimal derivatives variation.
Step 4: Compute the histogram of derivatives in the image in the direction of motion blur estimated in previous step to determine the size of the blurring kernel. Refer [3] for more detailed information about this step.
Step 5: Analyse the histogram and segment the image into patches or windows which have different blurring kernels. The data log-likelihood can be measured by associating each window with the maximum likelihood kernel. Refer [3] for more detailed information about this step.
Step 6: Search for blurring model for each window such that when combined with derivatives of the unblurred image, will maximise the log-likelihood of the observed derivatives.
Step 7: Perform deconvolution in each segment with the respective blur kernel using the MATLAB implementation (deconvlucy) of the Richardson-Lucy algorithm.
The deblurred image is thus obtained.

Figure 3: Deblurring Results. (a) Input image. (b)Deblurred result.

5.2 Discussions and Conclusions[3]

In defining the likelihoods, especially in uniform areas, or areas with pure edges in the direction of the blur don't contain any information about the blur. On the other hand, uniform areas receive the highest likelihoods from wide blur kernels since the derivatives distribution for wide kernels is more concentrated around zero [3]. The algorithm might fail to produce convincing results for blurs that cannot be modelled as a box filter or can even fail to identify the exact blur direction. Sometimes it might also fail to estimate the correct blur size and may infer incorrect segmentation. [3]

Future research works could be to develop stronger statistical models in conjunction to simple first order derivatives, forming a larger class of blurring kernels rather than just box type filters. Newer strategies could look to identify the exact blur direction and stronger vertical edge detection methods.

In future work, it will also be interesting to try to detect different blurs without assuming a small number of blurring layers. This will require estimating the blurs in the image in a continues way, and might also provide a depth from focus algorithm that will work on a single image.[3]

6. Robust Flash Deblurring [4]

Single image deblurring techniques exhibit ringing effects. This can be avoided by seeking to make use of correlation among multiple images of the same scene for image deblurring. Some methods like [1], use blurred/noisy image pair as inputs. Such image duos can compensate each other and generate an accurate kernel estimation and deblurring results. However, some of the high frequency details are lost in the blur process, which cannot be recovered by any of those methods. In this approach, a pair of blurred/flash image is used. Blurred image is taken with longer exposure times and the flash image is taken with short exposure time. The flash image is sharp and retains the high frequency details of the scene. The key contribution of this approach is that by using flash photography, ringing artifacts are significantly reduced while retaining fine image details, generating high quality deconvolution results. The problem formulation can be decomposed into two sections.

Firstly, we find the correlation between the image pairs and propose a flash gradient [6]. The flash gradient aligns well with the gradient of the reconstructed sharp image. Secondly, by integrating the flash gradient with maximum-a-posteriori (MAP) framework, the optimisation of kernel estimation and sharp image estimation can be solved iteratively. This method relates to the flash/no-flash technique proposed by [6].

6.1 Process Overview[4]

Step 1: Take the blurred/flash image pair.

Step 2: Compute the flash gradient, ∇Fn the flash image as discussed in [6]. This will be used later for optimisation of kernel and sharp image estimation.

Step 3: Select a good patch from the blurred and flash images. Optimise the below equation iteratively to estimate blur kernel, K and sharp image, I.

$$\arg\min_{I,K} \|I \otimes K - B\|^2 + \lambda_f \rho(\nabla I - \nabla F) + \lambda_k |K|^\alpha$$

Step 4: Fix K and now optimise the below equation iteratively by the re-weighted least squares method to solve for I.

$$\arg\min_{I} \|I \otimes K - B\|^2 + \lambda_f \rho(\nabla I - \nabla F)$$

Step 5: Now fix I and estimate K by solving

$$\arg\min_{K} \|I \otimes K - B\|^2 + \lambda_k |K|^\alpha$$

Step 6: With the estimated kernel, reconstruct sharp image using equation in step 4. Weight the differences in gradients less in regions where ringing effects are not suppressed. Sharp image is thus obtained.

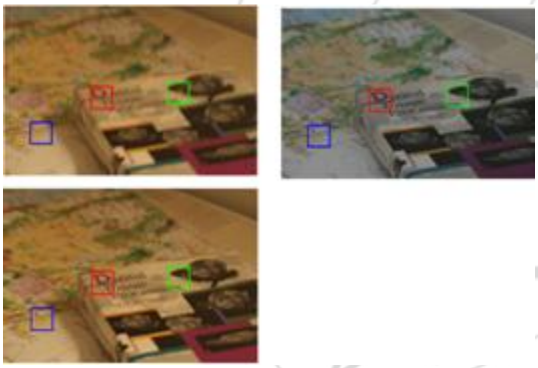

Figure 4: Deblurring Results. (a) Blurred image. (b)Flash Image. c) Deblurred Result

6.2 Discussions and Conclusions[4]

This method provides high quality reconstructed image without loss of fine details. Ringing artifacts are reduced significantly. This method can also handle large blurs. It outperforms existing single image deblurring methods by making use of image pairs.

Comparing the estimations of blurring kernels in this method and with Yuan et al's [1] method, it is observed that the latter's is affected by noise and detail is lost in the denoised image.However, this approach is not devoid of drawbacks. Like single image blind deconvolution methods, this method does not take into account of spatially variant blurring kernels.Future work would be to incorporate strategies to take into account spatially variant blurring kernels.

7. Robust Dual motion Deblurring [5]

This approach makes use of a pair of blurred images to compute the blur kernel and reconstruct the sharp image. This approach makes use of "Burst Shot" capabilities of both compact and DSLR cameras, to capture multiple blurred versions of the scene in a very less time. It makes use of a robust cost function in kernel estimation. The estimation of blur kernel is significantly improved by applying a continuity prior together with sparseness prior. Once the kernel is estimated, a novel deblurring algorithm, which uses two blurred images, is applied to generate sharp image. This algorithm is robust to both kernel noise and image noise. This is due to the addition of a feedback loop. It also suppresses ringing artifacts greatly while retaining image details.

7.1 Process Overview[5]

Step 1: Take a pair of blurred images, taken using a burst shot.
Step 2: Use method prescribed in [10] for dual image kernel estimation.
Step 3: Generate the robust cost function best suitable for this pair [5]. This improves data energy in kernel estimation.
Step 4: Calculate the sparseness and continuity priors to further refine kernel estimation.[7][11]
Step 5: Obtain the clear image by using estimated kernels together with two blurred images.
Step 6: Define feedback energy function[5]. Combine with original data energy and kernel priors and feedback to the kernel estimation step. [5] Iterate the process till clear image is obtained.

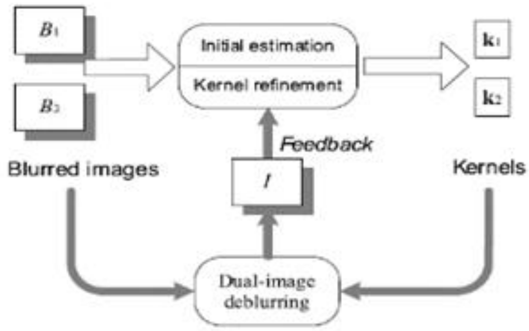

Figure 5: Flowchat showing the algorithm

Figure 6: (a) Blurred image 1. (b)Blurred image 2. c) Deblurred Result

7.3 Discussions and Conclusions [5]

This method gives better results even when the estimated kernels are not perfectly accurate. Ringing effects are removed. The run time of the algorithm is linear with the image size, kernel size and the no. of iterations. It usually requires 5-10 feedback iterations to converge depending on the difficulty of the input image data. It outperforms similar methods explained in[1] and [4].

Future work may include accelerating the method and investigating automatic alignment algorithms combined with deblurring so that this method could also be applied to multiple images and videos.

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