BLIND IMAGE DEBLURRING USING A SINGLE-IMAGE SOURCE: THE STATE OF THE ART

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ABSTRACT

The problem of accidental corruption and restoration of altered or damaged signals from intentional tampering was long-studied. Image deblurring is an example of signal restoration: the recovery of an approximate of the original image, which was convolved with a point spread function and altered by additive noise. This work is an introduction in the deblurring domain, is meant to offer some definitions and proposes an analysis of the existing methods for deducing the point spread function from a blurred image. One of the methods has a big importance for the second part of the paper: the cepstral domain, through which only close to rectilinear kernels can be recovered at the moment. We will point that cepstrum analysis is at least as powerful as other methods.

KEYWORDS: *blind deblurring, deblurring review, cepstrum analysis, image reconstruction.*

1. INTRODUCTION

The point spread function (PSF) is the system's response to an impulse. For example, a camera's PSF can be approximated by taking a photography of a single small light source, like a star. Affecting a single pixel by convolution will result in the convolution's PSF itself.

The image deblurring problem can be broken into two subproblems: first to recover the PSF and the initial estimate by using a known PSF. The methods of blind deconvolution concentrate on recovering the PSF while non-blind methods use a known PSF for performing robust deconvolution.

Even if blind deblurring is an ill-posed problem, the PSF can, in practice, be estimated from a single image, by imposing restrictions. These can be a prior knowledge about how edges should look like, at the local level [4], or how the gradients' histogram should be shaped like [5]. But as more images are included in the equation, the more accurate the

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results become. The information from multiple images can be used in generating good original estimates [2][3], or in the case of video deblurring, in tracing the moving object and considering the motion path as deblur kernel [1].

The non-blind deconvolution methods focus on minimizing the important impact additive noise has in deblurring with a known PSF [6] or the removal of artifacts originating from the estimations of approximate PSF [7][8][9] and data truncation in the altered image [10][11].

This paper is part of the work done during the 2 years of master studies at the faculty of Automatics and Computers from the "Politehnica" University of Bucharest by the author of the paper [36] and it includes research done by other researchers in the deblurring domain.

1.1. Convolution

The cause of the information alteration in blurred images is the mathematical operation of convolution. The convolution of two functions produces a third function that resembles the first, but which contains characteristics of the second on its entire domain. A delay is also introduced in the signal. Convolution is a typical case of alteration of the signal in the case of an electrical signal passing through a long wire.

Mathematically it can be defined by: [21]

$$(f \otimes g)(t) = \int_{-\infty}^{\infty} f(T)g(t-T)dT$$

Or more intuitively, it can be considered that the function which alters the signal is a function of weights which are used to generate a weighted sum of the neighbors. In the presented formula, the neighborhood is infinity.

Because it is intended to work on digital images, this is the definition for convolution in the 2D discrete space: [22]

$$(f \otimes g)(x, y) = \sum_{-\infty}^{\infty} f[i][j]g[x-i][y-j]$$

Figure 1. It is evident that the image's frequencies are multiplied by the bokeh kernel's frequencies because in spatial domain the kernel's characteristic is present in every pixel of the image.

The conclusion of this talk is that the result is similar with the input and contains characteristics of the kernel. As the kernel characteristics are present all over the image this implies that if in spatial (or pixel position domain) the kernel's pattern can be found in every pixel's neighborhood; in the frequency domain, every pixel of the image kernel's "fingerprint" is added to the image's frequencies. Meaning that in the frequency domain the image's frequencies are multiplied by the kernel's frequencies. (Fig. 1)

1.1.1. Another method of calculating convolution

Based on the observation that convolution is a multiplication of the images frequencies with the signal's frequencies, the same result can be obtained in logarithmic time just by multiplying the transforms of the images. [26]

$$(f \otimes g)(t) = Fourier^{-1}[F(v)G(v)](t)$$

Deconvolution is the inverse transformation that restores the signal in the space domain.

1.2. Deconvolution

Deconvolution is the name of the process that restores the initial signal from the convolved signal with a known convolution kernel. Blind deconvolution is another term used to describe an ill-posed mathematical problem that tries to recover both signals (image and kernel) from just the corrupted signal.

1.2.1. Inverse Filtering

In conclusion, in the frequency domain, a blurred image, B, is the result of multiplying a clear original image C with a point spread function P: $B = C \cdot P$. Deconvolution is calculated the other way around: $C = \frac{B}{P}$

However, P contains many elements that are close to 0, making this operation unstable. (Fig. 2) Demonstrates the not (very) useful result obtained without adding a constraint or regularization.

Figure 2. Deconvolution without regularization on blurred image with additive noise

The observed noise is very strong in the naive method and has a high frequency. Strong frequency elements are obtained when P has a very small value, thus, in order to stabilize the solution is to remove the small elements from the division:

$$g[t] = \begin{cases} \frac{1}{P[t]}\gamma |P[t]|, |P[t]| < \gamma \\ \frac{1}{P[t]}, |P[t]| \geq \gamma \end{cases}$$ where g represents the 1/n factor.

This method is called Inverse Filtering [23]. The strong high-frequency noise is eliminated, but propagating waves generated by unknown boundaries or wrongly estimated PSF are still evident.

Figure 3. Inverse filtering on a naturally blurred image.

1.3. Regularization Techniques

Regularization techniques attenuate the impact factors that unknown borders, noise or non-optimal PSF estimation have, by introducing additional information in the system.

By artificially limiting small values in frequency domain a regularization was applied to the deconvolution. One other method is to introduce a constraint in the equations, so the total variance of the results have a small value. The total variation of the signals with excessive and possible fake detail is very high.

By using oriented wavelet packets, the three authors discovered a signal residing even in a highly noisy photo resulting from deconvolution, a useful signal which is powerful enough, separable and recoverable.

1.3.1. Richardson-Lucy deconvolution

The Richardson-Lucy method is an iterative spatial-domain approach that includes the regularization in the deconvolution. [22] The base idea is that the resultant image must be similar to the blurred image, but also that the blurred image must be the result of a convolution of the resultant image with a resultant kernel. The two estimates are iteratively refined.

$C_j^{(i+1)} = C_j^{(i)} \cdot \left(\frac{B}{C_j^{(i)} \otimes P} \otimes \hat{P} \right)$ where $\hat{P} = P(i-n)(j-m), 0 \leq n, m \leq i, j$ and the initial C_1 is any image.

1.3.2. Wiener Deconvolution

Wiener deconvolution works in the frequency domain. It was originally a noise filter aimed at correcting delayed signals from radar machines, by multiplying with a correction function $g(t)$: $r(t) = g(t) \cdot [C(t) + N(t)]$ where $C(t)$ is the original clear signal, $N(t)$ is noise and $r(t)$ is the function intended to equal $C(t+a)$ (the delayed signal because of the transmission distance).

Later, this filter was adapted to work for functions like:

$B(t) = C(t) * P(t) + N(T)$ where P = PSF. The solution to this convolution affected by additive noise is the Wiener Deconvolution [28]:

$g(t) = \frac{P(t) S_C(t)}{|P(t)^2| S_C(t) + S_N(t)}$ where S_C is the clear image spectrum and S_N the noise spectrum.

P with a greater power at the denominator makes the function act as a deconvolution. It has an extra filter for removing noise with a known spectrum (image signal / (image signal + noise signal)). The estimated clear image is:

$C = B \cdot g$.

Any of the deconvolution algorithms can be used with similar results on images containing small noise intensities.

2. PREVIOUS WORK

2.1. Blind deconvolution

The harder problem is the deduction of the kernel that generated the distorted image, using only the distorted image as input. This is a problem with origins in spatial domain research. Because stars are point-like elements, the solution is relatively simple. The telescope's PSF can by these methods be deduced only by taking a photograph of a distant star.

2.1.1. Using gradients

However, for a natural image, the first solution came just in 2006 with Fergus's work [5], where he observed that all natural clear photographs have a similar histogram of gradients. The shape of a histogram is changed by a blur transformation because motion blur inserts similarly oriented gradients over the whole surface of the image.

The PSV is estimated by going from small resolution to great resolution and tries to fit the resulting latent image into the mathematical gradient distribution by varying the PSF.

His work was refined in [6] by filtering the gradients used for estimation of the PSF. In opposition to all expectations, objects smaller than the kernel will degenerate the prediction, yet they should be ignored. The construction method was also changed by forcing the kernel to become a connected motion path.

2.1.2. Using iterative methods

Iterative methods use the result from a previous step in order to compute the following image.

In [3] two input images are used as starting point: a noisy and a blurred image. A denoised image has clear edges, in precise positions. The filtered image is the latent image in the iterative kernel estimation algorithm. According to the result, the deblurred image can be used to remove the noise from the sharp image. The sharp image is used to clear the waves from the deblurred image.

The more images are introduced in the deblurring equations, the smaller the ratio of unknowns to knowns becomes and more accurate results can be obtained, as you can notice in the example [2].

2.1.3. Cepstral analysis

An observation was made that taking the Fourier transform of the logarithm amplitude of the Fourier transform reveals shapes similar to the motion blur kernel. Unfortunately, this method is limited to linear movements because the recovered PSF is somehow over-imposed with different orientations. An approach interprets the cepstrum geometrically, imagining that the same shape is over imposed, and manages to find curves with small curvature. [24] (Fig. 4)

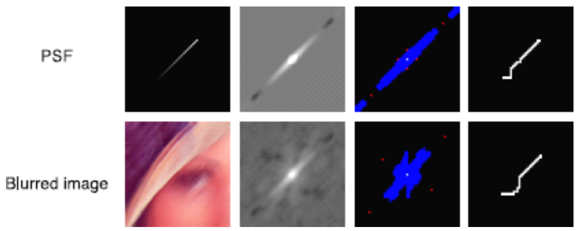

Figure 4. Estimation using geometrical cepstrum analysis. Image from [24]

2.2. Non-uniform motion blur

The majority of the deblurring approaches consider a shift-invariant linear blur model, meaning that the image is blurred the same way everywhere. True, but only if the photographed objects are situated at the same distance, or at considerable distances from the camera, in order to avoid introducing perspective blur, and the camera follows only a translational movement in a plane which is parallel to the objects. As the description shows, very few images fall in this class of alterations. The simplest example to point that the blur kernel suffers changes at every pixel of the image is the rotational motion blur. Blur occurred by individual moving objects is even more difficult to describe.

Some approaches try to deblur moving objects from static backgrounds. One approach is to segment the image based on blur direction [13][15] (Fig. 5). They are cut by means of spectral mating [14], thus maintaining the transparent shading induced by the blur. Another method is to deduce the movement by reducing the local kernel to a line but in multiple zones of the image. [4]

Figure 5. Splitting of a blurred image using the blur information. Image from [15].

Instead of splitting the image, another possibility is to change the kernel over the surface of the image during the deblurring process (only an iterative spatial-domain blurring is available for the researcher in this situation) [25]. The idea is to generate a 3D kernel based on the real camera movement deduced from the photograph and project it over the image.

2.3. Artifact Minimization

2.3.1. Deringing

There are some approaches for estimating the PSF and removing a large amount of the amplified noise. A different artifact that is generated during the deblurring process is ringing. The difference between the estimate and the exact information is being propagated by adding and subtracting the residual values, generating a periodic ripple near the aberrances.

A method similar to the one presented in noisy/blurry image pair is to use only the blurred image as a base in order to estimate the ringing artifacts. [9] The initial estimate is a deblurred image. By utilizing the unclear photo, the ring remover deduces uniform patches that may suffer from long range ringing, resulting from far away strong edges. Then, small regions are identified around edges in the clarified image, which might suffer from short range ringing. Afterward, the waves are cleared by a filter that is dependent on the size of the wave and the distance from the edge.

Similarly, more estimates can be built from different scales or frequencies. In [8] intra-scale refers to fine-tuning inside the respective resolution and inter-scale to using the result from precedent resolutions. The method begins with a small resolution representing the base clarified image for the next bigger resolution. Then it estimates the greater resolution by an iterative Joint Bilateral Richardson-Lucy deconvolution. The edge detections resulted from the coarser resolution image is the base for better accurate edge detection in the finer resolution image. A regularization approach removes undesired artifacts in uniform zones. More than this, using the smaller resolution as a guide and a residual deconvolution algorithm, an important amount of details can be recovered. This method entirely eliminates ringing and, moreover, it generates a sharp image with unimportant texture loss.

2.3.2. Outliers handling

The mathematical model presented in the regularization techniques takes into account only Gaussian additive noise but there are also present other aberrations that can unsettle the convolved image. Bright spots with intensities greater than what the image format can hold, yet they are clipped. Clipping, along with dead pixels or hot pixels, is not taken into consideration in the original theoretical model. Color curves represent other influences implemented by software in order to capture an image more similar to what the eye can see. The first step is to clear the color curve by applying a gamma correction, this way the colors vary linearly. The characteristics of the camera can be measured photographing printed targets [33] or read the camera manual if available, otherwise, the common PC 2.2 decoding gamma is used. Then, the algorithm of the outliers' elimination is able to separate pixels that respect the model from those that may be possible errors (the saturated and the dark pixels). An approach of Expectation Maximization fills then the areas where pixels have been removed. [10]

This model has the ability to clear the repetitive and wave-like artifacts that derive from software truncations and hardware errors. Also, it generates fewer rings caused by non-linear color transformations.

2.3.3. Noise reduction

A situation when simple regularization techniques fail is when blurred images have a significant amount of noise (the signal source of space telescopes is very far away, medical imaging uses a small amount of radiation in order to minimize the impact on the patient). This means that noise can be compared to the signal power.

Wohlberg and Rodrigues developed a model which deals only with impulse noise. [16] The solution of this mathematical model is a modified Total Variance (TV) regularization (this generates an image with the smallest variations between the pixels that still follow the original shape of the signal). The variance is defined as follows:

$\frac{\lambda}{q}\left\|\sqrt{(D_x u)^2 + (D_y u)^2}\right\|_p^p$ where D is the derivative and λ represents the power of the filter. The measure how generated signal approximates the original one is the p norm of:

$\frac{1}{q}\|Ku - B\|_p^p$ where K is a linear operator of the forward problem and B represents the altered signal.

These functions are modified for the purpose to accommodate pixels that fall over or below a threshold. The result is locating and clearing salt and pepper noise.

In [6] a similar but faster technique for impulse noise and Gaussian noise is used.

In [17] the authors use the idea that most natural images has most derivatives around 0, and use a sparse before that opts to concentrate the derivatives at a small number of pixels, leaving the rest almost untouched in the deconvolution process. [17] In this manner, the image has sharp edges, less noise, smaller ringing artifacts, yet fine texture details are lost in the process of convolution.

Instead of trying to generate a deconvolution model that includes noise, in [12] the clear image is reconstructed from the very noisy deblurred image. This implies very powerful filtration by means of 26 orientate complex wavelet packets.

3. RECENT ADVANCES CONCLUSIONS

During the past few years, this domain evolved to the point of actually constructing useful everyday applications, like introducing special camera aperture [20] or coded camera exposures [19].

These results can help in other connected domains, like super resolution (by removing the blur that inherently is generated during the combination of multiple images [32][18], or by achieving more information from the larger space that has been occupied by the moving object on the image [19]).

The recent advances are presented in other papers addressing just these issues: [35][37].

3.1. Non-blind deconvolution method conclusions

The inverse filtering method will be used as non-blind deconvolution, as it offers similar results to other regularized methods and is easy to implement.

3.2. Point Spread Function estimation conclusions

Present blind deconvolution methods rely on assumptions regarding the image type in order to work. The three main directions include:

- Iterative deconvolution based upon Fergus's work, that goes through image scales and estimates the kernel in order to obtain an as close as possible gradient distribution to a reference considered an ideal natural image.
- Iterative deconvolution based on the Richardson-Lucy method with the minimization of total variation. The assumption here is that the resultant image should have small energy and variation because the high energy part is given by the noise induced.
- Cepstrum geometrical analysis methods that try to find as much as possible from the kernel from a heavy distorted signal similar to it observed in the Fourier of the logarithm of the amplitude of the Fourier of the signal. The assumption here is that the kernel has a simple filiform shape.

In the second part of the paper, we start developing a technique for recovering the blurring kernel in the cepstral domain. Unlike the presented cepstral domain method, we aim at recovering any shape for the kernel and unlike other methods that rely on presumptions, the only presumption we make is the natural one, that the kernel is the most repetitive structure on the image. PSF filtering methods will be introduced and results for artificial and natural images will be offered.

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