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A Literature Survey on Blind and Non Blind Approaches in Image Deblurring

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Abstract: Image restoration and recognition has high priority in fields like military, medicine, explorations etc. Image analysis in blurred and poorly illuminated images is difficult. The recognition and the restoration factors are of vital importance in this endeavour. Of the multiple methods proposed in this regard, few technologies and methods are surveyed and analysed.

Keywords: Blur Kernel, Point Spread Function (PSF), L1 norm, Blind Deblurring

I. INTRODUCTION

Every image seen through the lens is expected to be a time captured depiction of our visual reference. The quality of the image is always blurred, varying in intensity. Thus the quality of the image needs to be enhanced by deblurring methods.

Every image captured digitally is made of pixels (basic picture elements). The intensity of the pixel signified by the colour over rectangular segment characterizes the scene. A basic image is composed of anywhere around 2562 to 65536 pixels and HD image has 5 to 10 million pixels. In practical applications the intensity of the pixel spills over the adjoining pixels, this causes blurring of the image. This spilling can occur because of out of focussed lenses, motion of either the camera or the object, or both. In telescopic images the bending of light through atmospheric variations result in a blurred image.

The recovery of the true image is accomplished using a mathematical model,

$$y = k * x + n \qquad (1)$$

y ,x ,n represent degraded image, original image and additive noise respectively.

k denotes the point spread function (PSF) of the blurring operator.

' * ' indicates the convolution operator.

The equation denotes the blurring process, which is reversed to produce a deblurring effect. The knowledge of the PSF is used to switch effectively between the blind algorithm, for PSF unknown or arbitrary and non-blind algorithm for distinct PSF matrices.

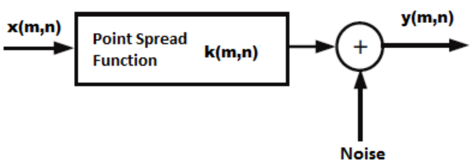

Fig. 1: Image Degradation Model

The figure shows the image degradation model for the eqn (1). Some information of the true image is lost during the blurring event. The understanding of the blurring assists in the recovery of the lost details. This blurring is unavoidable due to various errors in real time events. The fluctuations in the image capturing process and the digitization errors are the transgression factors for blurring. The recovery of the details in the reconstructed image is limited by noise influences and blurring elements. The understanding of the blurring elements and noise factors are used to device a simple effective method to enhance the deblurring efficiency.

II. LITERATURE SURVEY

[1] Kim Hui Yap and Ling Guan et. al have proposed an approach to recursive soft decision of blind image deconvolution, in which deconvolution is based on soft decision blur identification and hierarchical neural networks. This approach overcomes the difficulties of traditional hard-decision methods by providing a continual soft decision blur adaptation with respect to the best fit parametric structure throughout the deconvolution. The conjugate gradient optimization is applied to identify the blur and to minimize the cost function in the blur domain. The technique models the blur with the best fit parametric structure, evaluates the proximity measure and incorporates the weighted soft estimate into blur identification. The cost function consisting of the data fidelity measure, image, and blur domain regularization terms, and a soft estimation error is used. The cost function is lessened and optimized with respect to image and blur domains.

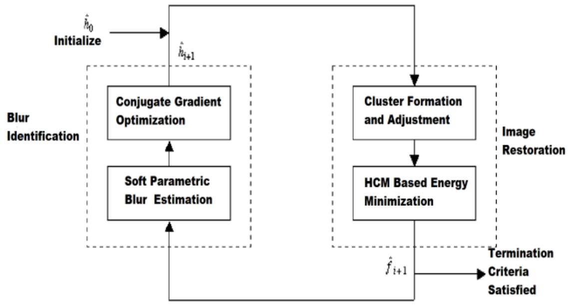

Fig. 2: Flowchart of Algorithm proposed by Kim-Hui Yap et. Al.

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Fig. 2 represents the flowchart outline of the algorithm proposed. The enhancement techniques are done two phases: Blur Identification and Image Restoration.

[2] Molina and Katsaggelos et. al. have proposed a variational Bayesian image restoration method. This method is based on the use of product of spatially weighted total variation image priors. The spatially weighted priors render better flexibility of capturing local image features. Also a fast iterative algorithm based on conjugate gradient is used to compute the diagonal elements of inverses of very large matrices, which are unable to find explicitly. The Bayesian prior can be used to overcome different image recovery problems like the super resolution, blind deconvolution and the tomographic reconstruction. It can be applied in the detection of the image watermarks and retrieval of images where it is necessary to have a statistical model for the image.

[3] The deblurring of noisy images are done with a method of non-parametric regression. The Local Polynomial Approximation (LPA) and the Intersecting Confidence Intervals (ICI) are applied to define the adaptive window sizes, of the LPA recovering as much information as possible from the given data. This paper provides a brief introduction to some of the existing image deblurring techniques and explains them briefly.

[4]Tony F, Chan et.al proposed blind deconvolution algorithm, which is based on total variational (TV) minimized method. The motivation for using TV regularization for PSF is to recover edges of images as well as motion blur and out-of-focus blur. Blur deconvolution problem can be stated below.

$$min\, f(p) = min \frac{1}{2} \|h * p - z\|2 + \alpha \int_{\Omega} |\nabla p|\, dx\, dy \qquad (2)$$

The eqn. (2) shows the cost function to be minimized. P is the image to be recovered, h is the PSF, * denotes convolution operation and α is the parameter.

1 and 2 are positive parameters which measure trade-offs between good fit and regularity of the solutions "u" and "h". Alternating minimization (AM) algorithm recover both the images and PSF's without any priori information on PSF existing numerical methods for solving the above non-linear type PDE's are time marching, lagged diffusivity field point(FP) and primal-dual methods. Due to the robustness and simplicity of implementation usually we choose FP algorithm. Reconstructing Arbitrarily Focused Images from Two Differently Focused Images Using Linear Filters

[5]Akira Kubota, kiyoharu aizawa had proposed novel filtering method for reconstructing all-in-focus image and an arbitrarily focused image against two images that are differently focused. This method can arbitrarily and directly manipulate the degree of blur objects using linear filters, because of that it does not need any segmentation. The filters are differently determined from a linear imaging model in the Fourier domain, and their characteristics are stable, without any amplifying noise. The effective and accurate blur estimation method has been proposed. Here the accuracy and computational time are improved compared with respect to previous iterative method, and the effects estimates. The LPA-ICI algorithm is spatially adaptive and non-linear with respect to the irregularities and smoothness of the images degraded with additive noise. The deblurring technique is based on the LPA applied for the design of LPF (Low Pass Filter) joined with regular inversion and Weiner inversion. The ICI transforms the original linear LPA and inversion filters into non-linear adaptive systems. The LPA allows the kernel filters to be optimized in order to enhance the algorithm performance. The differentiation filters also can be designed using the LPA. Edge detection, image improvements, recognition problems etc. are some of the areas where these algorithms can be used.

[6] Poor image quality in digital imaging is usually caused by motion blurring. In which the image captured by a digital camera represents the scene over a period of time. If objects in a scene are moving fast or the camera is moving over the period of *exposure* time, the objects or the whole scene will look blurry along the direction of relative motion.

Jian-Feng Cai, Hui Ji, Chaoqiang Liu, and Zuowei Shen proposed a new optimization approach to remove complex motion blurring from a single image by introducing new sparsity-based regularization terms on both images and motion-blur kernels. Based on the assumption that the motion-blur kernel can be approximated by a smooth function with the support close to a continuous "thin" curve, we proposed mixed regularization strategy for the blur kernel. The framelet system proposed by A.Ron and Z.Shen's analysis operator and I. Daubechies, B. Han, A. Ron, and Z. Shen, "Framelets: MRA-based constructions of wavelet frames," is used to represent both original images and motion-blur kernels for its implementation simplicity and computational efficiency to provide a powerful algorithm for uniform motion deblurring.

[7] Recovering a sharp image from a motion blurred image without the knowledge of its blur kernel is called blind motion deblurring. Chao Wang, Yong Yue, Feng Dong, Yubo Tao, Xiangyin Ma, Gordon Clapworthy, Hai Lin, and Xujiong Ye address the non-applicability of the blind motion deblurring methods existing. Most of the existing methods have been tested only on very small sets of natural images. In fact, some algorithms are able to produce satisfactory results only on a small number of selected images. The poor robustness has severely hindered the applicability of the deblurring techniques to real-world applications, especially in the face of highly diverse natural images.

Chao Wang and team iterate a non-edge specific to an edge specific scheme as it's not designed to carry out deblurring based on the detection or prediction of LSEDs, so it avoids the limitations. Marginalizing the sparse prior distribution proved that this approach leads to the true solution under the condition that the image size is much larger than the kernel size. A critical issue in current methods - their robustness to image diversity, which has been neglected for many years. Based on this principle, NEAS is proposed as a novel blind motion deblurring method. Experiments on a large set of images have shown that it produces high-quality results.

[8] Jinshan Pan and Zhixun Su present to regularize a blur kernel estimate. Each alternating direction methods (ADMs) internal problems have solutions with their closed forms. An adaptive structure map is adopted, therefore the delta kernel is simpler and no salient edge selection is required. Efficiency of the deblurring is high due to adaptive structure producing algorithms explicitly for the source codes of those problems. Hence the computational time required to map qualitative quantities is reduced. Experimental tests conclude Mr.Pan and Mr.Su's adaptive method is superior to the state of the art methods.

[9] Anat Levin, Yair Weiss, Fredo Durand, William Freeman propose the blind deconvolution using estimator to blind deconvolution using prior. The Gaussian prior is used to obtain a proper estimation rule. An understanding of the MAPx,k approach reveals explicit edge detection leaning towards delta kernel (no-blur) explanation. The variational Bayes approximation outperforms all existing alternatives in ground truth. The coarse to fine ideology provided optimizes the high noise variance; as such the frequencies below noise variance are set to zero, allowing for more and more bands of frequency to be nailed down.

[10] The central problem of imaging science is noise measurement. Mohammad Rostami, Oleg Michailovich and Zhou Wang provide a specific application focusing on reconstruction of short-exposure optical images measured through atmospheric turbulence.

TABLE I
SUMMARY OF LITERATURE SURVEY

Paper	Summary
1	Soft decision blur identification and neural network approach
2	Image prior based on Student's s-t PDF and new conjugate gradient based algorithm for very large matrices
3	New adaptive scale deblurring technique based on directional LPA
4	Use of TV norm instead of h1 norm
5	Reconstructing all-in-focus image from two differently focused images
6	analysis-based sparsity prior of images in the framelet domain and a mixed regularization on motion-blur kernels
7	conjunctive deblurring algorithm (CODA), which performs the deterministic filter and Bayesian estimation in conjunctive manner
8	develop an l^0-regularized method, develop an efficient ADM algorithm
9	Limitation of the simple MAPx;k approach
10	simplifying the structure of the SHI through reducing the number of its wave front lenslets - Bregman algorithm

III. CONCLUSION

A brief survey on many deblurring approaches has been made to understand different possibilities to performed enhanced deblurring through prior or estimated methods. Each paper signifies its pros and cons. Elimination of the cons and pooling of the pros is used to enhance the quality of the deblurred image. This method concludes the possibility of using multiple fields varying in functionality and applications to be channelled towards a different approach to relevant problems in various situations.

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BIOGRAPHIES

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