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Survey on Blind Image Deblurring Using Row-Column Sparse Representations

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Abstract *– This paper presents different method for blind image deblurring. The method only makes weak assumptions about the blurring filter and is able to undo a wide variety of blurring degradations. The use of constrained blur models appropriate to the problem at hand, and/or of multiframe scenarios, generally improves the deblurring results. Tests performed on monochrome and color images, with various synthetic and real-life degradations, without and with noise, in single-frame and multiframe scenarios, showed good analysis, both in subjective terms and in terms of the increase of signal to noise ratio (ISNR) measure. In comparisons with other state of the art methods, our method yields better results, and shows to be applicable to a much wider range of blurs. To overcome the ill-posedness of the blind image deblurring problem, the method includes a learning technique which initially focuses on the main edges of the image and gradually takes details into account. A new image prior, which includes a new edge detector, is used.*

Keywords*: Deblurring, SNR, DWT*

I. Introduction

Image deblurring is an inverse problem whose aim is to recover an image from a version of that image which has suffered a linear degradation, with or without noise. This blurring degradation can be shift-variant or shift-invariant. Although there have been some proposed methods for recovering shift variant linear degradations [1]–[8], the majority of existing deblurring methods was developed for invariant degradations, and the blind recovery from shift-invariant degradations is still considered a rather challenging problem. This paper focuses on shift-invariant blurs, and, in the context of this paper, “blur” will refer to a linear, shift-invariant degradation, i.e., a convolution, with or without noise, unless stated otherwise.

Automatic image deblurring is an objective of great practical interest for the enhancement of images in photo and video cameras [9]–[11], in astronomy [12], in remote sensing [13], in tomography [14], [15], in other biomedical imaging techniques [16], etc.

Image deblurring methods can be divided into two classes: non blind, in which we assume the blurring operator to be known, and blind, in which we assume that the blurring operator is unknown. The method that we describe here belongs to the latter class. The application range of non blind methods is much narrower than the one of blind methods: in most situations of practical interest the blurring filter’s impulse response, also called point spread function (PSF), is not known with good accuracy. Since non blind deblurring methods are very sensitive to mismatches between the PSF used by the method and the true blurring PSF, a poor knowledge of the blurring PSF normally leads to poor deblurring results. Despite its narrower applicability, non blind deblurring already is a difficult problem. The main difficulty faced by non blind deblurring methods has to do with the presence of noise in the blurred image. Since the blurring operator typically is very ill- conditioned, this noise, even if very weak, can strongly contaminate the deblurred image. The problem is serious in situations in which the blurring PSF is exactly known, and gets worse if there is even a slight mismatch between the PSF used for deblurring and the one that caused the blur. Most non blind deblurring methods [1] overcome this difficulty through the use of prior information about the image to be recovered, often doing this within a Bayesian or maximum a posteriori framework.

In blind image deblurring (BID), not only the degradation operator is ill-conditioned, but the problem also is, inherently, severely ill-posed: there is an infinite number of solutions (original image + blurring filter) that are compatible with the degraded image. For an overview of BID methods. Most previously published blind deblurring methods are very limited, since they do not allow the use of a generic PSF. Most of them are based, instead, on PSF models with a small number of parameters. For example, to model an out-of-focus blur, they normally use a circle with uniform intensity, having as single parameter the circle’s radius. Similarly, to model a motion blur, they normally use a straight-line segment with uniform intensity, the only parameters being length and slope.

II. Literature Survey

Mohammad Tofighi,et. al. [1] "Blind Image Deblurring Using Row-Column Sparse Representations" In this paper author propose Blind image deblurring is a particularly challenging inverse problem where the blur kernel is unknown and must be estimated en route to recover the deblurred image. Theproblem is of strong practical relevance since many imaging devices such as cellphone cameras, must rely on deblurring algorithms to yield satisfactory image quality. Despite significant research effort, handling large motions remains an open problem. In this paper, we develop a new method called Blind Image Deblurring using Row-Column Sparsity (BD-RCS) to address this issue. Specifically, we model the outer product of kernel and image coefficients in certain transformation domains as a rank-one matrix, and recover it by solving a rank minimization problem. Our central contribution then includes solving two new optimization problems involving row and column sparsity to automatically determine blur kernel and image support sequentially. The kernel and image can then be recovered through a singular value decomposition (SVD). Experimental results on linear motion deblurring demonstrate that BD-RCS can yield better results than state of the art, particularly when the blur is caused by large motion. This is confirmed both visually and through quantitative measures.

Yi Zhang et. al. [2] "Combining Inertial Measurements with Blind Image Deblurring Using Distance Transform" In this paper author propose an image deblurring method that infers the blur kernel by combining the inertial measurement unit (IMU) data that track camera motion with techniques that seek blur cues from the image sensor data. Specifically, we introduce the notion of IMU fidelity cost designed to penalize blur kernels that are unlikely to have yielded the observed IMU measurements. When combined with the image data-based fidelity and regularization terms used by the conventional blind image deblurring techniques, the overall energy function is nonconvex. Proposed method replaced the non-convex IMU fidelity term by its convex approximation using a distance transform that can be pre-computed. Thus the energy minimization can be solved with the existing solvers. Our approach was shown theoretically and experimentally to tolerate moderate levels of synchronization errors.

Anat Levin et. al. [3] "Image and Depth from a Conventional Camera with a Coded Aperture" In this work authors propose a simple modification to a conventional camera that allows for the simultaneous recovery of both (a) high resolution image information and (b) depth information adequate for semi-automatic extraction of a layered depth representation of the image. Our modification is to insert a patterned occlude within the aperture of the camera lens, creating a coded aperture. Authors introduce a criterion for depth discriminability which we use to design the preferred aperture pattern. Using a statistical model of images, we can recover both depth information and an all-focus image from single photographs taken with the modified camera. A layered depth map is then extracted, requiring user-drawn strokes to clarify layer assignments in some cases. In this work author have shown how a simple modification of a conventional lens – the insertion of a patterned disc of cardboard into the aperture – permits the recovery of both an all-focus image and depth from a single image. The pattern produces a characteristic distribution of image frequencies that is very sensitive to the exact scale of defocus blur.

Stefan Harmeling et. al. [4] "Space-Variant Single-Image Blind Deconvolution for Removing Camera Shake" Blind deconvolution of images degraded by space-variant blur is a much harder problem than simply assuming space-invariant blurs. Our experiments show that even state-of-the-art algorithms such as Cho and Lee's are not able to recover image details for such blurs without unpleasant artifacts. Authors proposed an algorithm that is able to tackle space-variant blurs with encouraging results. Presently, the main limitation of our approach is that it can fail if the blurs are too large or if they vary too quickly across the image. Author believes there are two main reasons for this: (i) on the one hand, if the blurs are large, the patches need to be large as well to obtain enough statistics for estimating the blur. On the other hand, if at the same time the PSF is varying too quickly, the patches need to be small enough. Our method only works if we can find a patch size and overlap setting that is a good trade-off for both requirements. Modeling camera shake as a space-invariant convolution simplifies the problem of removing camera shake, but often insufficiently models actual motion blur such as those due to camera rotation and movements outside the sensor plane or when objects in the scene have different distances to the camera.

Neel Joshi et. al. [5] "Image Deblurring using Inertial Measurement Sensors" Authors present a deblurring algorithm that uses a hardware attachment coupled with a natural image prior to deblur images from consumer cameras. Authors approach uses a combination of inexpensive gyroscopes and accelerometers in an energy optimization framework to estimate a blur function from the camera's acceleration and angular velocity during an exposure. We solve for the camera motion at a high sampling rate during an exposure and infer the latent image using a joint optimization. In this method is completely automatic, handles per-pixel, spatially-varying blur, and out-performs the current leading image-based methods. In this work, we presented an aided blind deconvolution algorithm that uses a hardware attachment in conjunction with a corresponding blurry input image and a natural image prior to compute per pixel, spatially-varying blur and that deconvolves an image to produce a sharp result.

III. Independent Component Analysis (ICA)

ICA is another technique based on the independency concepts of Blind Signal Separation (BSS), which provides a framework for deconvolution. Assuming the source and blurring signal to be independent and non-Gaussian, it tries to estimate the source signal as the most independent one. According to the CLT, this is the most non-Gaussian signal. ICA as a multivariate data analysis method has gained wide spread use in the image processing community [3, 10-14]. ICA has successfully been applied as the solution to the BSS problem [10]. But its application is not limited to BSS only, and many signal and image processing fields like image denoising, image segmentation and recognition and others have also benefited from this [18].

Independent Component Analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlying sets of random variables, measurements, or signals. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear or nonlinear mixtures of some unknown latent variables, and the mixing system is also unknown. The variables are assumed to be non-Gaussian and mutually independent and they are called the independent components of the observed data. These independent components (also called sources or factors) can be estimated by ICA. ICA can be seen as an extension to PCA and factor analysis [10].

ICA is one of the increasingly important tools in signal processing. It has gained its novelty in the successful solution of BSS problems [2, 3, 10]. It was initially proposed to provide a solution to the BSS problem [4] which aims at recovering a set of unobserved sources mixed in an unknown manner from a set of observations. Since its inception, numerous algorithms based on the ICA concept have been employed successfully in various fields of multivariate data processing, from biomedical signal applications and communications to financial data modeling and text retrieval. While linear mixtures of unknown sources have been examined thoroughly in the literature, the case of nonlinear ones remains an active field of research.

IV. Blind image quality assessment

Image quality assessment (IQA) is a practical scientific research and has been attracting increasing attentions throughout the past decades because of the dramatic development of visual equipment, such as TVs, digital cameras, and mobile phones. The quality of those equipments and also the images we obtained by using these equipment affects the data perception of human beings. However, we cannot get the undistorted version of these pictures in most cases. Therefore, it is necessary to develop blind IQA (BIQA) algorithms to estimate the visual quality of those images to help us select a better equipment or image.

Due to the limited exploration of human visual system (HVS) and also the mechanism of subjective quality assessment, it is a challenging task either to extract quality-aware options or build the connection between the image options and also the visual quality. It is therefore of great difficulty to develop effective BIQA metrics, especially universal BIQA (UBIQA) metrics which can work for various types of distortions.

Until now, most BIQA metrics available try to extract statistical options based on the natural scene statistics (NSS) and learn the mapping function from the options to the quality score using the supervised learning technique based on a large quantity of labeled pictures. Although many promising BIQA metrics have been planned based on this methodology, there are 2 drawbacks of these algorithms. First, only the labeled pictures are adopted for machine learning. However, it has been proved that using unlabeled data within the training stage will improve the learning performance (Yang et al. 2006). In addition, these metrics try to learn the direct mapping function from the image options to the quality score. However, subjective quality evaluation would rather be a fuzzy method than a particular one. Equally, human beings tend to evaluate the quality of a given image by first judging the extents it belongs to “excellent,” “good,” “fair,” “poor,” and “bad,” and estimating the quality score subsequently, rather than directly giving a particular subjective quality score. This is according to the subjective experiments conducted for constructing the IQA databases.

V. Conclusion

In The implementation of research for IQA aims to propose computational models to compute the image quality in a subjective-consistent manner. IQA problems can be classified as FR-IQA, RR-IQA, and NR-IQA problems according to the availability of the reference information. Quality scores predicted by the modern FR-IQA methods can be highly consistent with the subjective ratings. There is still a large room for development of NR-IQA methods. The both BIQA methods show that although opinion unaware methods have a good generalization ability but the prediction of quality of distorted images are not accurate than opinion aware methods. An approach which uses natural scene statistics model for feature extraction of distorted image without the need of any distorted sample images or subjective scores for training can be more précised if more features of an image can be used so that high correlation can be achieved.

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