

Image Restoration Using Joint Statistical Modelling In Space-Transform Domain

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Abstract: This paper presents a completely unique strategy for accurate image restoration by characterizing each native smoothness and nonlocal self-similarity of natural pictures during a unified statistical manner. the most contributions area unit three-fold. First, from the angle of image statistics, a joint statistical modeling (JSM) in an accommodative hybrid space-transform domain is established, that offers a strong mechanism of mixing native smoothness and nonlocal self-similarity at the same time to make sure a a lot of reliable and robust estimation. Second, a replacement variety of minimization purposeful for finding the image inverse drawback is developed using JSM underneath a regularization-based framework. Finally, so as to form JSM tractable and robust, a replacement Split Bregman-based algorithmic program is developed to expeditiously solve the on top of severely underdetermined inverse drawback associated with theoretical proof of convergence. intensive experiments on image inpainting, image deburring, and mixed mathematician and salt-and pepper noise removal applications verify the effectiveness of the proposed algorithmic program.

Keywords: inpainting ,JSM, Restoration ,Split Bregman.

I. INTRODUCTION

In recent years, perhaps the most significant nonlocal statistics in image processing is the nonlocal self-similarity exhibited by natural images. The main contributions are three-fold. First, from the perspective of image statistics, a joint statistical modeling (JSM) in an adaptive hybrid space-transform domain is established, which offers a powerful mechanism of combining local smoothness and nonlocal self-similarity simultaneously to ensure a more reliable and robust estimation. Second, a new form of minimization functional for solving the image inverse problem is formulated using JSM under a regularization-based framework The nonlocal self-similarity depicts the repetitiveness of higher level patterns (e.g., textures and structures) globally positioned in images, which is first utilized to synthesize textures and fill in holes in images nonlocal self-similarity of natural images in a unified statistical manner.. Finally, in order to make JSM tractable and robust, a new Split Bregman-based algorithm is developed to efficiently solve the above severely underdetermined inverse problem associated with theoretical proof of convergence.

Millions of digital documents are produced by a variety of devices and distributed by newspapers, magazines, websites and television. In all these information channels, images are a powerful tool for communication. Unfortunately, it is not difficult to use computer graphics and image processing techniques to manipulate images. Quoting Russell Frank, a Professor of Journalism Ethics at Penn State University, in 2003after a Los Angeles Times incident involving a doctored photo graph from the Iraqi

front: “Whoever said the camera never lies was a liar”. How we deal with photographic manipulation raises a host of legal and ethical questions that must be addressed [1]. However, before thinking of taking appropriate actions upon a questionable image, one must be able to detect that an image has been altered. Image composition (or splicing) is one of the most common image manipulation operations. One such example is shown in Fig. 1, in which the girl on the right is inserted. Although this image shows a harmless manipulation case, several more controversial cases have been reported, e.g., the 2011 Benetton Un Hate advertising campaign¹ or the diplomatically delicate case in which an Egyptian state-run newspaper published a manipulated photograph of Egypt’s former president, Hosni Mubarak, at the front, rather than the back, of a group of leaders meeting for peace talks². When assessing the authenticity of an image, forensic investigators use all available sources of tampering evidence. Among other telltale signs, illumination inconsistencies are potentially effective for splicing detection: from the viewpoint of a manipulator, proper adjustment of the illumination conditions is hard to achieve when creating a composite image [1]. In this spirit, Riess and Angelopoulou [2] proposed to analyze illuminant color estimates from local image regions. Unfortunately, the interpretation of their resulting so-called *illuminant maps* is left to human experts. As it turns out, this decision is, in practice, often challenging. Moreover, relying on visual assessment can be misleading, as the human visual system is quite inept at judging illumination environments in pictures [3], [4]. Thus, it is preferable to transfer the tampering decision to an objective algorithm.

II. LITERATURE SURVEY

As a fundamental problem in the field of image processing, image restoration has been extensively studied in the past two decades [1]–[12]. It aims to reconstruct the original high quality image \mathbf{x} from its degraded observed version \mathbf{y} , which is a typical ill-posed linear inverse problem and can be generally formulated as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \quad (1)$$

where \mathbf{x}, \mathbf{y} are lexicographically stacked representations of the original image and the degraded image, respectively, \mathbf{H} is a matrix representing a non-invertible linear degradation operator and \mathbf{n} is usually additive Gaussian white noise. When \mathbf{H} is identity, the problem becomes image denoising [4], [5], [11]; when \mathbf{H} is a blur operator, the problem becomes image deblurring [14], [21]; when \mathbf{H} is a mask, that is, \mathbf{H} is a diagonal matrix whose diagonal entries are either 1 or 0, keeping or killing the corresponding pixels, the problem becomes image inpainting [22], [35]; when \mathbf{H} is a set of random projections, the problem becomes compressive sensing [16], [17]. In this paper, we focus on image inpainting, image deblurring and image denoising. In order to cope with the ill-posed nature of image restoration, one type of scheme in literature employs image prior knowledge for regularizing the solution to the following minimization problem [14], [15]:

$$\operatorname{argmin}_{\mathbf{x}} \frac{1}{2} \|\mathbf{H}\mathbf{x} - \mathbf{y}\|_2^2 + \lambda \Psi(\mathbf{x}), \quad (2)$$

$\frac{1}{2} \|\mathbf{H}\mathbf{x} - \mathbf{y}\|_2^2$ is the ℓ_2 data-fidelity term, $\Psi(\mathbf{x})$ is called the regularization term denoting image prior and λ is the regularization parameter. In fact, the above regularization-based framework (2) can be strictly derived from Bayesian inference with some image prior possibility model.

Many Optimization approaches for regularization-based image inverse problems have been developed [13]–[15], [41], [42]. It has been widely recognized that image prior knowledge plays a critical role in the

performance of image restoration algorithms. Therefore, designing effective regularization terms to reflect the image priors is at the core of image restoration. Classical regularization terms utilize local structural patterns and are built on the assumption that images are locally smooth except at edges. Some representative works in the literature are total variation (TV) model [2], [14], half quadrature formulation [18] and Mumford-Shah (MS) model [20]. These regularization terms demonstrate high effectiveness in preserving edges and recovering smooth regions. However, they usually smear out image details and cannot deal well with fine structures, since they only exploit local statistics, neglecting nonlocal statistics of images.

In recent years, perhaps the most significant nonlocal statistics in image processing is nonlocal self-similarity exhibited by natural images. The nonlocal self-similarity depicts the repetitiveness of higher level patterns (e. g., textures and structures) globally positioned in images, which is first utilized to synthesize textures and fill in holes in images [19]. The basic idea behind texture synthesis is to determine the value of the hole using similar image patches, which also influences the image denoising task. Buades *et al.* [24] generalized this idea and proposed an efficient denoising model called nonlocal means (NLM), which takes advantage of this image property to conduct a type of weighted filtering for denoising tasks by means of the degree of similarity among surrounding pixels. This simple weighted approach is quite effective in generating sharper image edges and preserving more image details. Later, inspired by the success of nonlocal means (NLM) denoising filter, a series of nonlocal regularization terms for inverse problems exploiting nonlocal self-similarity property of natural images are emerging [25]–[29].

Note that the NLM-based regularizations in [25] and [28] are conducted at pixel level, i.e., from one pixel to another pixel. In [9] and [39], block-level NLM based regularization terms were introduced to address image deblurring and super-resolution problems. Gilboa and Osher defined a variational framework based on non-local operators and proposed nonlocal total variation (NL/TV) model in [25]. The connection between the filtering methods and spectral bases of the nonlocal graph Laplacian operator were discussed by Peyré in [27]. Recently, Jung *et al.* [29] extended traditional local MS regularizer and proposed a non-local version of the approximation of MS regularizer (NL/MS) for color image restoration, such as deblurring in the presence of Gaussian or impulse noise, inpainting, super-resolution, and image demosaicking

Due to the utilization of self-similarity prior by adaptive nonlocal graph, nonlocal regularization terms produce superior results over the local ones, with sharper image edges and more image details [27]. Nonetheless, there are still plenty of image details and structures that cannot be recovered accurately. The reason is that the above nonlocal regularization terms depend on the weighted graph, while it is inevitable that the weighted manner gives rise to disturbance and inaccuracy [28]. Accordingly, seeking a method which can characterize image self-similarity powerfully is one of the most significant challenges in the field of image processing.

Based on the studies of previous work, two shortcomings have been discovered. On one hand, only one image property used in regularization-based framework is not enough to obtain satisfying restoration results. On the other hand, the image property of nonlocal self-similarity should be characterized by a more powerful manner, rather than by the traditional weighted graph. In this paper, we propose a novel strategy for high-fidelity image restoration by characterizing both local smoothness and nonlocal self-similarity of natural images in a unified statistical manner. Part of our previous work has been published in [30]. Our main contributions are listed as follows. First, from the perspective of image statistics, we establish a joint statistical modeling (JSM) in an adaptive hybrid space and transform domain, which offers a powerful mechanism of combining local smoothness and nonlocal self-similarity

simultaneously to ensure a more reliable and robust estimation. Second, a new form of minimization functional for solving image inverse problems is formulated using JSM under regularization-based framework. The proposed method is a general model that includes many related models as special cases. Third, in order to make JSM tractable and robust, a new Split-Bregman based algorithm is developed to efficiently solve the above severely underdetermined inverse problem associated with theoretical proof of convergence.

IV. DEBLURRING

One of the most common artifacts in digital photography is motion blur caused by camera shake. In many situations there simply is not enough light to avoid using a long shutter speed, and the inevitable result is that many of our snapshots come out blurry and disappointing. Recovering an un-blurred image from a single, motion-blurred photograph has long been a fundamental research problem in digital imaging. If one assumes that the blur kernel – or point spread function (PSF) – is shift-invariant, the problem reduces to that of image deconvolution. Image deconvolution can be further separated into the blind and non-blind cases. In non-blind deconvolution, the motion blur kernel is assumed to be known or computed elsewhere; the only task remaining is to estimate the unblurred latent image. Traditional methods such as Wiener filtering [Wiener 1964] and Richardson-Lucy (RL) deconvolution [Lucy 1974] were proposed decades ago, but are still widely used in many image restoration tasks nowadays because they are simple and efficient. However, these methods tend to suffer from unpleasant ringing artifacts that appear near strong edges. In the case of blind deconvolution [Fergus et al. 2006; Jia 2007], the problem is even more ill-posed, since both the blur kernel and latent image are assumed unknown. The complexity of natural image structures and diversity of blur kernel shapes make it easy to over- or under-fit probabilistic priors [Fergus et al. 2006]

Image blur is difficult to avoid in many situations and can often ruin a photograph. Deblurring an image is an inherently ill-posed problem. The observed blurred image only provides a partial constraint on the solution $i_c^{1/2}$ with no additional constraints, there are infinitely many blur kernels and images that can be convolved together to match the observed blurred image. Even if the blur kernel is known, there still could be many $i_c^{1/2}$ sharp $i_c^{1/2}$ images that when convolved with the blur kernel can match the observed blurred and noisy image. One of the central challenges in image deblurring is to develop methods that can disambiguate between potential multiple solutions and bias a deblurring process toward more likely results given some prior information. We are investigating new image priors that are more constraining than those that are typically used. We are investigating both PSF/blur kernel estimation and non-blind deconvolution. Our work in this area has resulted in methods to create sharper, higher-quality images from a blurry input image.

In this paper, we begin our investigation of the blind deconvolution problem by exploring the major causes of visual artifacts such as ringing. Our study shows that current deconvolution methods can perform sufficiently well if both the blurry image contains no noise and the blur kernel contains no error. We therefore observe that a better model of inherent image noise and a more explicit handling of visual artifacts caused by blur kernel estimate errors should substantially improve results. Based on these ideas, we propose a unified probabilistic model of both blind and non-blind deconvolution and solve the corresponding Maximum a Posteriori (MAP) problem by an advanced iterative optimization that alternates between blur kernel refinement and image restoration until convergence. Our algorithm can be initialized with a rough kernel estimate (e.g., a straight line), and our optimization is able to converge to a result that preserves complex image structures and fine edge details, while avoiding ringing artifacts.

V. INPAINTING

Inpainting is the process of reconstructing lost or deteriorated parts of images and videos. For instance, in the museum world, in the case of a valuable painting, this task would be carried out by a skilled art conservator or art restorer. In the digital world, inpainting (also known as image interpolation or video interpolation) refers to the application of sophisticated algorithms to replace lost or corrupted parts of the image data (mainly small regions or to remove small defects). Inpainting, the technique of modifying an image in an undetectable form, is as ancient as art itself. The goals and applications of inpainting are numerous, from the restoration of damaged paintings and photographs to the removal/replacement of selected objects. In this paper, we introduce a novel algorithm for digital inpainting of still images that attempts to replicate the basic techniques used by professional restorers. After the user selects the regions to be restored, the algorithm automatically fills-in these regions with information surrounding them.

The fill-in is done in such a way that isophote lines arriving at the regions' boundaries are completed inside. In contrast with previous approaches, the technique here introduced does not require the user to specify where the novel information comes from. This is automatically done (and in a fast way), thereby allowing to simultaneously fill-in numerous regions containing completely different structures and surrounding backgrounds. In addition, no limitations are imposed on the topology of the region to be inpainted. Applications of this technique include the restoration of old photographs and damaged film; removal of superimposed text like dates, subtitles, or publicity; and the removal of entire objects from the image like microphones or wires in special effects. The modification of images in a way that is non-detectable for an observer who does not know the original image is a practice as old as artistic creation itself. Medieval artwork started to be restored as early as the Renaissance, the motives being often as much to bring medieval pictures "up to date" as to fill in any gaps [1, 2]. This practice is called retouching or inpainting. The object of inpainting is to reconstitute the missing or damaged portions of the work, in order to make it more legible and to restore its unity [2]. The need to retouch the image in an unobtrusive way extended naturally from paintings to photography and film. The purposes remain the same: to revert deterioration (e.g., cracks in photographs or scratches and dust spots in film), or to add or remove elements

In painting is rooted in the restoration of images. Traditionally, inpainting has been done by professional restorers. The underlying methodology of their work is as follows:

The global picture determines how to fill in the gap. The purpose of inpainting is to restore the unity of the work. The structure of the gap surroundings is supposed to be continued into the gap. Contour lines that arrive at the gap boundary are prolonged into the gap. The different regions inside a gap, as defined by the contour lines, are filled with colors matching for those of its boundary. The small details are painted, i.e. "texture" is added.

a) Structural inpainting

Structural inpainting uses geometric approaches for filling in the missing information in the region which should be inpainted. These algorithms focus on the consistency of the geometric structure.

b) Textural inpainting

Like everything else the structural inpainting methods have both advantages and disadvantages. The main problem is that all the structural inpainting methods are not able to restore texture. Texture has a repetitive pattern which means that a missing portion cannot be restored by continuing the level lines into the gap.

c) Combined Structural and Textural inpainting

Combined structural and textural inpainting approaches simultaneously try to perform texture and structure filling in regions of missing image information. Most parts of an image consist of texture and structure. The boundaries between image regions accumulate structural information which is a complex phenomenon. This is the result when blending different textures together. That is why, the state of the art inpainting method attempts to combine structural and textural inpainting.

4.3 NOISE REMOVAL

Imagine an image with noise. For example, the image on the left below is a corrupted binary (black and white) image of some letters; 60% of the pixels are thrown away and replaced by random gray values ranging from black to white.

One goal in image restoration is to remove the noise from the image in such a way that the "original" image is discernible. Of course, "noise" is in the eye of the beholder; removing the "noise" from a Jackson Pollack painting would considerably reduce its value. Nonetheless, one approach is to decide that features that exist on a very small scale in the image are noise, and that removing these while maintaining larger features might help "clean things up".

One well-traveled approach is to smooth the image. The simplest such version is replace each pixel it by the average of the neighboring pixel values. If we do this a few times we get the image in the middle above; if we do it many times, we get the image on the right.

On the plus side, much of the spotty noise has been muted out. On the downside, the sharp boundaries that make up the letters have been smeared due to the averaging. While many more sophisticated approaches exist, the goal is the same: to remove the noise, and keep the real image sharp. The trick is to not do too much, and to "know when to stop".

Many scientific datasets are contaminated with noise, either because of the data acquisition process, or because of naturally occurring phenomena. Preprocessing is the first step in analyzing such datasets. There are several different approaches to denoise images. The main problem faced during diagnosis is the noise introduced due to the consequence of the coherent nature of the image capture. In image processing applications, linear filters tend to blur the edges and do not remove Gaussian and mixed Gaussian impulse noise effectively [7], [8]. Inherently noise removal from image introduces blurring in many cases. These noises corrupt the image and often lead to incorrect diagnosis.

Many methods have been available for noise reduction [13], [14], [9]. The existing filters used for mixed noise reduction techniques includes median filter, center weighted median filter and wavelet filters. Nowadays, the uses of wavelet based denoising techniques have gained more attention by researchers [10]. In this work a fusion technique is proposed to find the best possible solution, so that after denoising PSNR, MSE, UQI and ET values of the image are optimal.

SIMULATION RESULTS

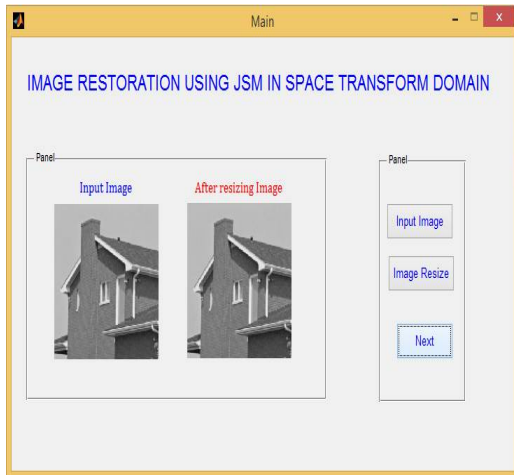


Fig1: Image restoration using jsm in a space transform domain

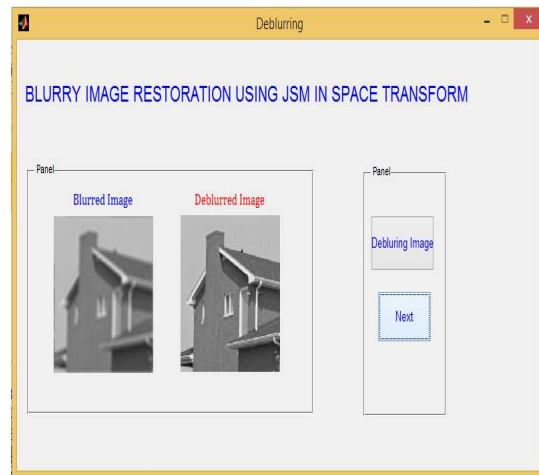


Fig2: Blurry image restoration using jsm in space transform

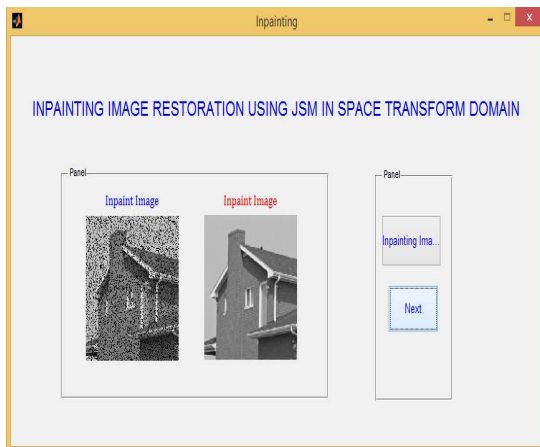


Fig3: Inpainting image restoration using jsm in space transform domain

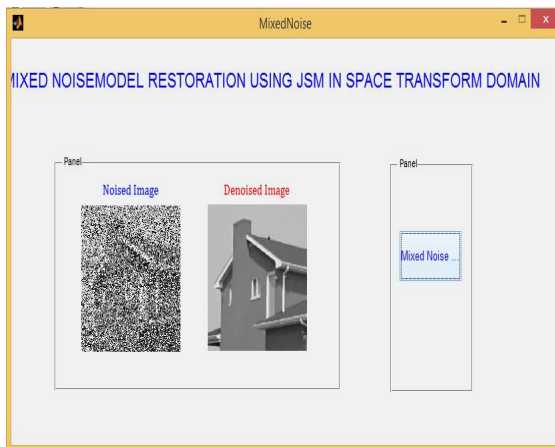


Fig4: Mixed noise model restoration using jsm in space transform

IV. Conclusions And Future Work

In this work, we presented a new method for detecting forged images of people using the illuminant color. We estimate the illuminant color using a statistical gray edge method and a physics-based method which exploits the inverse intensity- chromaticity color space. We treat these illuminant maps as texture maps. We also extract information on the distribution of edges on these maps. In order to describe the

edge information, we propose a new algorithm based on edge-points and the HOG descriptor, called HOGedge. We combine these complementary cues (texture- and edge-based) using machine learning late fusion. Our results are encouraging, yielding an AUC of over 86% correct classification. Good results are also achieved over internet images and under cross-database training/testing. Although the proposed method is custom-tailored to detect splicing on images containing faces, there is no principal hindrance in applying it to other, problem-specific materials in the scene. The proposed method requires only a minimum amount of human interaction and provides a crisp statement on the authenticity of the image. Additionally, it is a significant advancement in the exploitation of illuminant color as a forensic cue. Prior color-based work either assumes complex user interaction or imposes very limiting assumptions. Although promising as forensic evidence, methods that operate on illuminant color are inherently prone to estimation errors. Thus, we expect that further improvements can be achieved when more advanced illuminant color estimators become available. For instance, while we were developing this work, Bianco and Schettini [49] proposed a machine-learning based illuminant estimator particularly for faces. An incorporation of this method is subject of future work. Reasonably effective skin detection methods have been presented in the computer vision literature in the past years. Incorporating such techniques can further expand the applicability of our method. Such an improvement could be employed, for instance, in detecting pornography compositions which, according to forensic practitioners, have become increasingly common nowadays.

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