Image Restoration Techniques in a Space Transform Domain - A Survey

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Abstract - Images are ubiquitous and indispensable in modern science and everyday life. Mirroring the abilities of our own human visual system, it is natural to display observations of the world in graphical form. Images are obtained in areas ranging from everyday photography to astronomy, remote sensing, medical imaging and microscopy. In each case, there is an underlying object or scene we wish to observe; the image is a visual representation of these observations. Yet imaging, just as any other observation process, is never perfect: uncertainty creeps into the measurements, occurring as blur, noise, and other degradations in the recorded images. The image is a projection of the real world onto the lower-dimensional imaging medium, a procedure that intrinsically discards information. Recent signal processing techniques can provide a means to overcome some of the problems of the imperfect observation process, by post-processing these blurred and noisy images. By representing the observation process mathematically, and applying prior knowledge of the types of images can be expect to see, there are numerous restoration methods such as Space-Transform Domain, joint statistical modeling(JSM) can be performed to recover detail and reduce image noise and in order to obtain images that can be visualized, raw images typically undergo some image processing such as denoising, color-filter array interpolation (demosaicking), enhancement (sharpening), color correction, and white balancing.

Keywords-Image Restoration, Image denoising, image deblurring, RGB-image denoising, Adaptive Image Restoration.

I. INTRODUCTION

In the past decade, there has been an exponential growth in the computing power of microprocessor chips. This combined with significant reduction in the cost of digital cameras have increased the amount of image data captured and processed on the computer. The advantage of digitizing an image is the access to several algorithms or image processing techniques that enhance the quality of the image. The term quality here and throughout the work refers to the perception of image quality to a human observer. A new field called computational photography is emerging that challenges the traditional boundaries of photography [1]. New kinds of imaging devices are being developed that obtain a customized image (of a scene) after processing the raw image using a computer [2][3]. In general, sophisticated algorithms are making novel and complex manipulations possible with imaging devices. One such topic where computer processing is useful is restoration of images degraded by blur.

With the advent of modern information processing systems (such as computers) which are capable of handling a vast amount of data, one special interest - combined with a certain sense of fascination - emerged: the processing of images. Although this might first look like a rather technical problem it is in fact an area which occupies a large number of disciplines. One major aspect is that our own cognitive system and also higher cognitive functions of our brain are based on visual information in the form of images.

The majority of applications can be divided into three main areas: image compression, image restoration and feature extraction. All of these can further be subdivided according to the methods used in the respective problem. Due to the boom in the telecommunication market, combined with the explosive growth of the Internet and the future perspectives for mobile communications and digital photography, the efficient transmission and storage of data, and in particular image data, has become one of the major challenges for scientists. To send still images and/or video uncompressed over the available channels or store them without any post-processing would be an enormous waste of capacities. For example a typical colour image with image dimensions of 1024x768 points would require more than 2 megabytes; however after compression with one of the standard methods this can be reduced to approximately 160 kilobytes of data. Hence a large community has devoted its research to the compression of images, which has resulted in several standard compression techniques, for example the well- known JPEG (Joined Photographic Experts Group, dealing with video data. Although the idea of a quantitative measure of information has been around for a while, the mathematical principles which are now called information theory were established by Claude E. Shannon in 1948[9].

Generally speaking, a statistical model comprises one or more probability distributions. Given a set of observed data, we are free to choose any valid probability distribution to establish a statistical model for the data. Assuming the observed data are realizations of a random variable, the probability distribution is a mathematical formula that gives the probability of each value of the variable (discrete case) or gives the probability that the variable falls in a particular interval.

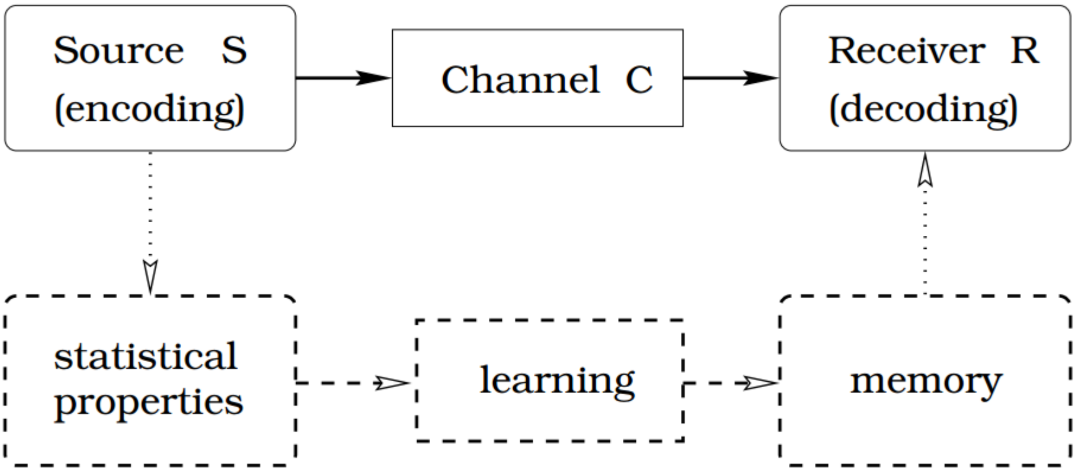

Figure 1.1 Shannon's model of an information transmitting system [9].

II. CLASSICAL RESTORATION TECHNIQUES

There are various types of distortion that an image may suffer. In some cases, the image degradations encountered in everyday photography are either considered not severe enough to merit correction, or the scene imaged is not considered important enough to have the distortions corrected. However there are many cases where this is not so. Photographs of scientific interest taken of rare phenomena can suffer from many distortions. It may be too expensive or impossible to duplicate the phenomena. Consider a space probe sent to take photographs of a distant planet. If the images have become blurred or degraded by noise during the transmission back to Earth, it may not be possible to instruct the spacecraft to take a second image of the planet. If a security camera photographs a crime in progress, a blurry picture may be the best hope for identifying the offender. In addition, some imaging technologies may have inherent problems. There will always be cases when the image is considered important enough to attempt to correct the distortion.

The act of attempting to obtain the original image given the degraded image and some knowledge of the degrading factors is known as "image restoration". The problem of restoring an original image, when given the degraded image, with or without knowledge of the degrading point spread function (PSF) or degree and type of noise present is an ill-posed problem

A. Transform Related Restoration Techniques

Transform related restoration techniques involve analysing the degraded image after an appropriate transform has been applied. By acting directly on the transformed image before applying an inverse transform, or using the transformed image information to develop an inverse filter, an image may be partially restored.

1. Inverse Filter

In the fourier domain the transfer function of this filter is the inverse of the transfer function of the distortion applied to the image. This produces a perfect restoration in the absence of noise, but the presence of noise has very bad effects. Some ad-hoc solutions modify the filter transfer function so that it approaches zero in regions where the noise power is greater than the signal power.

2. Wiener Filter

This filter is better than the inverse filter in the presence of noise because it uses a priori statistical knowledge of the noise field. The transfer function is chosen to minimise the mean square restoration error using statistical information on both the image and noise fields. Ozkan, et al. recently examined a method of accounting for spatial and temporal correlations when using multiframe Wiener filters to restore image sequences.

3. Parametric Estimation Filters

These filters are variations on the Wiener filter and are described by E.R. Cole [8]. Some examples are:

- Power spectrum filter: This filter matches the power spectrum of the reconstructed image to the original image. However, the power spectrum, unlike the fourier spectrum, is not unique to an image. Hence this filter may result in a large mean square error, unlike the traditional Wiener filter. A small variation in the transfer function of the power spectrum filter produces a very similar filter called the Geometrical mean filter.

- Constrained least-squares filter: This Wiener filter variation adds an extra term to the Wiener filter transfer function in the form of a design spectral variable. This variable may be used to minimise higher order derivatives of the estimate

4. Kalman Filter

The Kalman filter is a recursive filter for image restoration which has been examined a great deal recently. Wu and Kundu examined a faster simpler version of this filter and modified the filter to take account of non-gaussian noise.

5. Homomorphic Filter Restoration

Another class of filters which work on the principle of transforming the degraded image into another representation space. In theory, the new representation space may be such that the restoration operations are more easily performed.

B. Algebraic Restoration Techniques

Algebraic techniques involve attempting to find a direct solution to the distortion by matrix inversion techniques, or techniques involving an iterative method to minimise a degradation measure.

1. Pseudoinverse Spatial Image Restoration

This set of image restoration techniques attempt to restore an image by considering the vector space model of the image degradation and attempting to restore the image in this vector- space domain. This involves finding an approximation to the inverse of the matrix blurring operator which is multiplied with the column scanned image vector to produce the degraded observed image.

2. SVD Pseudoinverse Spatial Image Restoration

Using the technique of singular value decomposition (SVD), any matrix can be decomposed into a series of eigenmatrices. By applying this technique to decompose the blur matrix, the resultant eigenmatrices can be used to develop an estimation technique where successive estimations of the reconstructed image are based on the previous estimate.

3. Wiener Estimation

In this method the noise field is modelled again as a two-dimensional random process with a known mean and co-variance function. In addition, the ideal image is assumed to also be a sample of a two-dimensional random process with known first and second moments.

4. Constrained Image Restoration

Previous techniques considered images only as arrays of numbers, however a restored image is spatially smooth and strictly positive in amplitude. Often constrained restoration techniques are based on Wiener estimation and regressional techniques. Reeves and Mesereau have developed a method of assessing the validity of sets of constraints using cross-validation.

III. RELATED WORK

J. Zhang, D. Zhao, R. Xiong, S. Ma and W. Gao,[1] This research work presents 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. 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. 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. Extensive experiments on image inpainting, image deblurring, and mixed Gaussian plus salt-and-pepper noise removal applications verify the effectiveness of the proposed algorithm.

Y. Chen and K. J. R. Liu,[2] Based on the observation that every small window in a natural image has many similar windows in the same image, the nonlocal denoising methods perform denoising by weighted averaging all the pixels in a nonlocal window and have achieved very promising denoising results. However, the use of fixed parameters greatly limits the denoising performance. Therefore, an important issue in pixel-domain image denoising algorithms is how to adaptively choose optimal parameters. While the Stein's principle is shown to be able to estimate the true mean square error (MSE) for determining the optimal parameters, there exists a tradeoff between the accuracy of the estimate and the minimum of the true MSE. In this research work, we study the impact of such a tradeoff and formulate the image denoising problem as a coalition formation game. In this game, every pixel/block is treated as a player, who tries to seek partners to form a coalition to achieve better denoising results. By forming a coalition, every player in the coalition can obtain certain gains by improving the accuracy of the Stein's estimate, while incurring some costs by increasing the minimum of the true MSE. Moreover, we show that the traditional approaches using same parameters for the whole image are special cases of the proposed game theoretic framework by choosing the utility function without a cost term. Finally, experimental results demonstrate the efficiency and effectiveness of the proposed game theoretic method.

H. Xu, G. Zhai and X. Yang,[3] In this research work, we propose a single image super-resolution and enhancement algorithm using local fractal analysis. If we treat the pixels of a natural image as a fractal set, the image gradient can then be regarded as a measure of the fractal set. According to the scale invariance (a special case of bi-Lipschitz invariance) feature of fractal dimension, we will be able to estimate the gradient of a high-resolution image from that of a low-resolution one. Moreover, the high-resolution image can be further enhanced by preserving the local fractal length of gradient during the up-sampling process. We show that a regularization term based on the scale invariance of fractal dimension and length can be effective in recovering details of the high-resolution image. Analysis is provided on the relation and difference among the proposed approach and some other state of the art interpolation methods. Experimental results show that the proposed method has superior super-resolution and enhancement results as compared to other competitors.

J. Dai, O. C. Au, L. Fang, C. Pang, F. Zou and J. Li,[4] In this research work, we propose an advanced color image denoising scheme called multichannel nonlocal means fusion (MNLF), where noise reduction is formulated as the minimization of a penalty function. An inherent feature of color images is the strong interchannel correlation, which is introduced into the penalty function as additional prior constraints to expect a better performance. The optimal solution of the minimization problem is derived, consisting of constructing and fusing multiple nonlocal means (NLM) spanning all three channels. The weights in the fusion are optimized to minimize the overall mean squared denoising error, with the help of the extended and adapted Stein's unbiased risk estimator (SURE). Simulations on representative test images under various noise levels verify the improvement brought by the multichannel NLM, compared to the traditional single-channel NLM. In the meantime, MNLF provides competitive performance both in terms of the color peak signal-to-noise ratio and in perceptual quality when compared with other state-of-the-art benchmarks.

J. Zhang, S. Liu, R. Xiong, S. Ma and D. Zhao,[5] Recently, total variation (TV) based minimization algorithms have achieved great success in compressive sensing (CS) recovery for natural images due to its virtue of preserving edges. However, the use of TV is not able to recover the fine details and textures, and often suffers from undesirable staircase artifact. To reduce these effects, this research work presents an improved TV based image CS recovery algorithm by introducing a new nonlocal regularization constraint into CS optimization problem. The nonlocal regularization is built on the well known nonlocal means (NLM) filtering and takes advantage of self-similarity in images, which helps to suppress the staircase effect and restore the fine details. Furthermore, an efficient augmented Lagrangian based algorithm is developed to solve the above combined TV and nonlocal regularization constrained problem. Experimental results demonstrate that the proposed algorithm achieves significant performance improvements over the state-of-the-art TV based algorithm in both PSNR and visual perception.

J. Zhang, D. Zhao, F. Jiang and W. Gao,[6] Compressive Sensing (CS) theory shows that a signal can be decoded from many fewer measurements than suggested by the Nyquist sampling theory, when the signal is sparse in some domain. Most of conventional CS recovery approaches, however, exploited a set of fixed bases (e.g. DCT, wavelet, contour let and gradient domain) for the entirety of a signal, which are irrespective of the nonstationarity of natural signals and cannot achieve high enough degree of sparsity, thus resulting in poor rate-distortion performance. In this research work, we propose a new framework for image compressive sensing recovery via structural group sparse representation (SGSR) modeling, which enforces image sparsity and self-similarity simultaneously under a unified framework in an adaptive group domain, thus greatly confining the CS solution space. In addition, an efficient iterative shrinkage/thresholding algorithm based technique is developed to solve the above optimization problem. Experimental results demonstrate that the novel CS recovery strategy achieves significant performance improvements over the current state-of-the-art schemes and exhibits nice convergence.

IV. PROBLEM STATEMENT

So far the investigated properties were that of the prior source data. However, for the transmission model it is also necessary to understand the nature of the channel noise. This requires suitable models for the noisy channel. This noise can originate from several sources: electronic noise during a transmission, atmospheric disturbance in long range transmissions, interference between different parts in circuits or biological noise due to fluctuations in action potentials and thermal movements, but also optical blurring or out- of-focus imaging. All of these can be subdivided in two classes: stochastic uncorrelated noise, and deterministic filters. Although one might expect that a deterministic mapping (like a linear filter) is mathematically exactly invertible and hence does not contribute to information loss, this is in fact not the case. Additionally, all source models rely on an accurate estimation of the underlying probabilities. However the number of data samples is limited to the size of the image and the sampled frequencies only approximate the exact probabilities. From a more technical point of view, image processing plays a major role in modern telecommunication, research and entertainment. Many developments in todays medical science would be impossible without sufficient image acquisition techniques. Today it is almost taken for granted to import a photo into one of the common image processing programs, enhance or manipulate it in various ways and finally send a digital copy of it to a relative or friend at the other side of the world.

V. CONCLUSION

This research work introduced various algorithms of image processing and image restoration noise in images always a big challenge in image processing image restoration. This work reviewed the three main steps of statistical image processing in early vision: modelization, optimization and parameter estimation. The field of digital image restoration is a signal processing discipline that attempts to restore the blurred and noisy observed image to give a better representation of the original scene. In doing so, the uncertainties in the observation process that have been described must be taken into account. Classical image restoration seeks an estimate of the true image assuming the blur is known. In contrast, blind image restoration tackles the much more difficult, but realistic, problem where the degradation is unknown. It is more difficult because there is a larger space of possible solutions. There are many blurred and image combinations which could have resulted in something close to the observed image. The problem is to find reasonable ones that make sense according to some criteria.

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