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Normal Density and Variation based Blind Image Restoration

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Abstract— ***In mathematics, deconvolution is an algorithm-based process used to reverse the effects of convolution on recorded data. The concept of deconvolution is widely used in the techniques of signal processing and image processing. Because these techniques are in turn widely used in many scientific and engineering disciplines, deconvolution finds many applications. In general, the object of deconvolution is to find the solution of a convolution equation of the form:***

$$f * g = h$$

Usually, h is some recorded signal, and ƒ is some signal that we wish to recover, but has been convolved with some other signal g before we recorded it. The function g might represent the transfer function of an instrument or a driving force that was applied to a physical system. If we know g, or at least know the form of g, then we can perform deterministic deconvolution. However, if we do not know g in advance, then we need to estimate it. This is most often done using methods of statistical estimation.

Keywords— ***Blind Image Restoration, Deconvolution ,Multiframe Restoration, Multiframe Deconvolution Process, Majorization Minimization algorithm , Finite Normal Density Modeling***

I.INTRODUCTION

Image restoration is the process of reconstructing an approximation of an image from blurred and noisy measurements. In many applications such as medical imaging, remote sensing observed images are often degraded by distortion. The recovered original image from noisy image is shown in Fig1.1. Distortion may arise from much form, for example atmospheric turbulence, relative motion between object and camera.

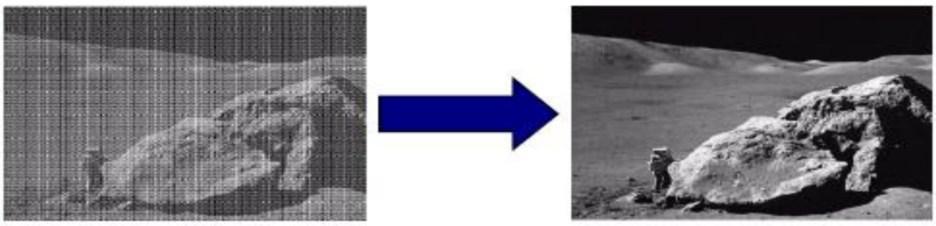

Fig1.1 Noisy image (left) and restored image

Image restoration remains an important research topic and one of the major applications driving the theory and practice of image processing since digital computers made processing large amounts of data possible. This section is not meant to provide a review of the extensive discussion on image restoration methods, but rather to provide some perspective on how modern multiframe blind image restoration algorithms grew out of the existing body of research and how these new multiframe methods define directions for future work.

Image restoration techniques may be very broadly categorized into two classes based on the number of observed frames. Specifically, the categorization is into the classes of single-input and multi-input restoration methods

Single Frame Restoration and Multiframe Restoration

The classical image restoration problem is concerned with restoration of a single output image from a single degraded observed image, also known as Single-Input Single-Output (SISO). The discussion on the restoration of a single input frame is extensive and spans several decades. A wide variety of techniques exist to tackle this problem and for a concise but representative review.

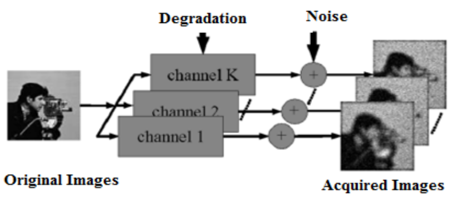

Fig 1.2 Single-input multiple-output model: The original scene is captured by K different channels which are subject to various degradations

Single input multiple output system is shown in Fig 1.2. More recently, with the growing interest in digital processing of image sequences, researchers have begun to address the problem of multiframe image restoration. The techniques developed for single frame restoration have often provided the theoretical basis for extending to the multiframe case.

While the field of single frame image restoration appears to have matured, digital images have provided many new restoration problems for image processing researchers. The Multi-Input Single-Output (MISO) methods in turn spurred the development of more general Multi-Input Multi-Output (MIMO) approaches.

What is Blind Image Restoration?

In many practical cases of interest point spread function (noise) is not known. For example when taking the photograph of a moving object, what is the shutter speed, and what is the speed of the object are unknowns. In this case a very difficult problem of "blind" image restoration is faced. In such cases prior knowledge of the process has to be utilized in order to recover the original image.

Why Blind Image Restoration?

Images are ubiquitous and indispensable in science and everyday life. 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 has to be observed; the original or true image is the ideal representation of the observed scene.

Yet the observation process is never perfect, there is uncertainty in the measurements, occurring as blur, noise, and other degradations in the recorded images. Digital image restoration aims to recover an estimate of the original image from the degraded observations. The key to being able to solve this ill posed inverse problem is proper incorporation of prior knowledge about the original image into the restoration process.

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. In general, the degradation is nonlinear (including, for example, saturation and quantization) and spatially varying (non uniform motion, imperfect optics); however, for most of the work, it is assumed that the observed image is the output of a Linear Spatially Invariant (LSI) system to which noise is added. Therefore it becomes a blind deconvolution (BD) problem, with the unknown blur represented as a Point Spread Function (PSF).Many of the blind deconvloution algorithms have their roots in estimation theory, linear algebra, and numerical analysis.

An important question one may ask is why is blind deconvloution useful? Is there any better observation procedure in the first place? Perhaps, but there always exist physical limits, such as photonic noise, diffraction, or an observation channel outside of our control, and often images must be captured in suboptimal conditions. Also there are existing images of unique events that cannot be retaken, or that will be very difficult to recover (for instance with forensics or archive footage); furthermore in these cases it is often infeasible to measure properties of the imaging system directly. Another reason is that of cost. High-quality optics and sensing equipment are expensive. However, processing power is abundant today and opens the door to the application of increasingly sophisticated models. Thus blind deconvloution represents a valuable tool that can be used for improving image quality without requiring complicated calibrations of the real-time image acquisition and processing system (i.e., in medical imaging, video conferencing, space exploration, x-ray imaging, bio-imaging, and so on).

II.PROBLEM FORMULATION

The blind restoration of an image is investigated, when multiple degraded (blurred and noisy) acquisitions are available. Distorted frames are modeled as deconvolution process. Finite normal density mixture model is employed to find the intensity variation within its neighbor. Variation method is applied to find the first order intensity variation. Majorization Maximization is applied to minimize upper bound.

III.LITERATURE AND SURVEY

The amount of *a priori* information about the degradation, like the size or shape of blurring functions and the noise parameters, significantly influences the success of restoration. When the blur function is known, many conventional approaches have been developed to compensate for the distortion [1]. The problem is ill posed, and, to overcome this difficulty, it is common to use regularization. The modeling of blurring can be divided in two parts: blurring function (PSF) and noise modeling. Some ideal PSF models are Gaussian, out-of-focus and linear motion blur [3]. In astronomy, data extracted from clear stars in observed image is used to fit a synthetic PSF function by weighted nonlinear least squares method . The PSF measurement techniques are also discussed in [1].

The diversity of algorithms [3] developed nowadays reflects different ways of recovering a "best" estimate of the "true image". Wiener and regularized filters are better for known PSF and additive noise . Some iterative restoration techniques, i.e. Expectation Maximization (EM) algorithms, work better for known PSF and unknown additive noise. Blind image restoration algorithms [4] are more proper for unknown PSF and additive noise. Flow imaging experiments have a lot in common with astronomy observations. They are both low light level imaging. Both images are degraded by imaging optical system and suffer from signal related noise (Poisson noise), CCD camera read-out noise and quantization noise etc. These physical similarities suggest that a better starting point in applying image restoration techniques in flow scalar image restoration is to consider those successful ones in astronomy.

The process of restoring the original frame when the blur function is unknown is called as blind image restoration. A basic survey of different blind restoration techniques is given in [2]. Most of the methods are iterative or recursive. They involve regularization terms based on available prior information which assumes various statistical properties of the image and constrains the estimated image and/or restoration filter. As in the nonblind case, regularization is required to improve stability. For images with sharp changes of intensity, the appropriate regularization is based on variational integrals. A special case of the variational integral, total variation was first proposed in [1]. Minimization of the variational integrals preserves edges and fine details in the image and it was applied to image denoising and to blind restoration , as well. Since the blind case is strongly ill posed, all the methods suffer from convergence and stability problems.

If the images are smooth and homogeneous, an autoregressive model can be used to describe the measuring process. The autoregressive model simplifies the blind problem by reducing the number of unknowns and several techniques were proposed for finding its solution .

Bayesian maximum a posterior (MAP) estimation has been shown to be effective in blind restoration. In particular, A F M Smith [4] has recently demonstrated the effectiveness of generalized Gauss Markov random fields (GGMRF) in blind restoration of extended objects. Here both the source and blur were modeled as GGMRF's which have a parametric form allowing a great variety of image representations, including hard edged fields typical of real images and smooth fields typical of blurring point spread functions. However, the GGMRF model is not well suited to point-like sparse images. A Markov random field model which favours sparse solutions is essential if high resolution restorations and accurate point localizations are to be achieved, particularly in the blind case.

The ability to exploit known structure in the problem and impose a sparse form on the solution is essential in overcoming convolutional ambiguity in the blind problem. Blind restoration is a highly ill-posed inverse problem, and algorithms which incorporate known image structure in solutions will invariably perform better.

F Sroubek & J Flusser , have presented an MRF model that exploits the sparse nature of point source input images in the context of MEG-based imaging. Their model involves a dual field representation: first, a binary activity process determines which pixels have non-zero amplitudes, and then a Gaussian amplitude process represents active point intensity levels.

There are many applications, where different blurred versions of the same original image are observed (MC) models: the single-input multiple-output (SIMO) model and the multiple-input multiple-output (MIMO) model. The SIMO model is typical for one-sensor imaging under varying environment conditions, where individual channels represent the conditions at time of acquisition. The MIMO model refers, for example, to multi sensor imaging, where the channels represent different spectral bands or resolution levels. Color images are the special case of the MIMO model. An advantage of MIMO is the ability to model cross-channel degradations which occur in the form of channel cross talks, leakages in detectors, and spectral blurs. Many techniques for solving the MIMO problem were proposed and could be found in [2].

Multichannel measuring processes are common, e.g., in remote sensing and astronomy, where the same scene is observed at different time instants through a time-varying inhomogeneous medium such as the atmosphere; in confocal microscopy, where images of the same sample are acquired at different focusing lengths; or in broadband imaging through a physically stable medium, but which has a different transfer function at different frequencies. Nonblind MC restoration is potentially free of the problems arising from the zeros of blurs. The lack of information from one blur in one frequency can be supplemented by the information at the same frequency from the others. Intuitively, one may expect that the blind restoration problem is also simplified by the availability of different channels.

Two classes of MC blind image restoration algorithms exist. Extensions of single-channel blind restoration approaches form the first class, but since they suffer from similar drawbacks as their single-channel counterparts, they are of not much interest. The other class consists of intrinsic MC approaches and will be considered here.

One of the earliest intrinsic multichannel blind deconvolution (MBD) methods [12] was designed particularly for images blurred by atmospheric turbulence. Harikumar*et al.* [6] proposed an indirect algorithm, which first estimates the blur functions and then recovers the original image by standard nonblind methods. The blur functions are equal to the minimum eigenvector of a special matrix constructed by the blurred images. Necessary assumptions for perfect recovery of the blur functions are noise-free environment and channel coprimeness, i.e., a scalar constant is the only common factor of the blurs. Harikumar*et al.* developed another indirect algorithm based on identity of coprime polynomials which finds restoration filters and by convolving the filters with the observed images recovers the original image. Both algorithms are vulnerable to noise and even for a moderate noise level restoration may break down. In the latter case, noise amplification can be attenuated to a certain extent by increasing the restoration filter order, which comes at the expense of deblurring. Pai *et al.* [10] suggested two MC restoration algorithms that, contrary to the previous two indirect algorithms, estimate directly the original image from the null space or from the range of a special matrix.

Another direct method based on the greatest common divisor was proposed by in [2]. In noisy cases, the direct algorithms are more stable than the indirect ones. Interesting approaches based on the ARMA model are given in [3]. MC blind deconvolution based on the Bussgang algorithm was proposed in [12], which performs well on spatially uncorrelated data, such as binary text images and spiky images. Most of the algorithms lack the necessary robustness since they do not include any noise assumptions (except ARMA and Bussgang) in their derivation and miss regularization terms.

Formulation of the Multiframe Deconvolution Process

Let us consider y_1, $y_{2\ldots}y_M$ be the set of M degraded images (observed frames) of a scene, obtained in a noisy multi-frame environment. Each frame, of (M *X* N) pixels in dimension, is considered to be subject to different version of blurring and different kind of noise. In other words, these set of images consists of different distorted versions of either the same original scene, or slightly different scenes, whose information, however, can be efficiently exploited as follows.

A linear space invariant (LSI) model has been assumed for modeling the blurring process given by

$$y_m = h_m * x_m + n_m \qquad (2.1.1)$$

where y_m is the degraded image corresponding to particular sensor m, x_m is the original noiseless or undistorted image, h_m is the blurring function also known as the point-spread function (PSF) and n_m is additive zero mean white noise. It should be noted that it has been assumed that $x_1=x_2=\ldots x_M$ such image model approximations, as discussed earlier, are frequently encountered in medical imaging applications, e.g., in phased-array beam forming for Ultrasound imaging or brain/cardiac MRI and CT scans. The ultimate goal of the proposed algorithm is to reconstruct a single an enhanced representation of the original scene, based upon the set of distorted observations

The multiframe blind image restoration problem has recently considerable attractable attentions. The first blind deconvolution attempts were based on single-channel formulations. The problem is extremely ill-posed in the single-channel framework and cannot be resolved in the fully blind form. These kinds of methods do not exploit the potential of the multichannel framework, because in the single-channel case missing information about the original image in one channel is not supplemented by information in the other channels.

IV.IMPLEMENTATION

First step of the project is acquiring the original image. Simulate blurry image and blurred noisy image. Formulate these images as multiframe images for blind deconvolution. Finite normal density modeling is performed and then variation method is applied. Finally, Majorization Minimization algorithm is applied to minimize the maximizer thus amount of solving the linear equations of the system. Complete design of the project is shown in Fig 4.1, and its implementation steps are as follows

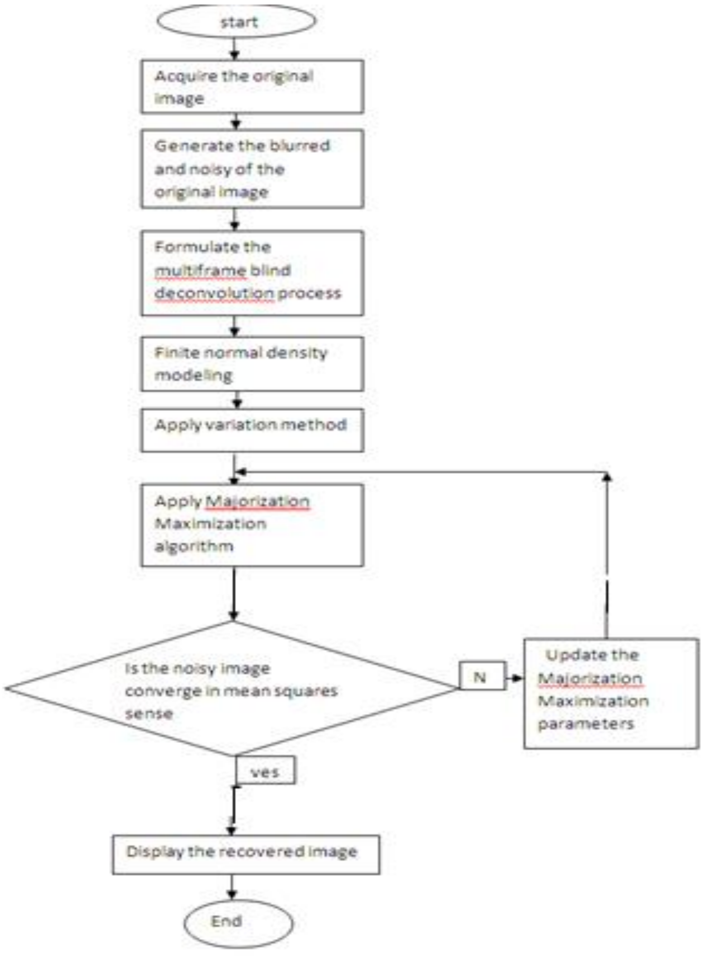

Fig 4.1 Flowchart of the project

V. EXPERIMENTAL RESULTS

Read the Image

Image can be read by the *imread* function which stores the input image intensity values in I. Image is cropped to resize it. Fig 5.3 shows the board image read by *imread* function.

```
I = imread('car.jpg');
I = I(50+[1:256],2+[1:256],:);
figure; imshow(I); title('Original Image');
```

Original Image

Fig 5.1 Input the original image for blind deconvolution process

Simulate a Blur and Noise

Simulate a real-life image that could be blurred (e.g., due to camera motion or lack of focus) and noisy (e.g., due to random disturbances). The example simulates the blur by convolving a Gaussian filter with the true image (using *imfilter*).

```
PSF = fspecial('gaussian',5,5);
Blurred = imfilter(I,PSF,'symmetric','conv');
figure;imshow(Blurred);title('Blurred');
```

Blurred Image

Fig 5.2 Input imaged blurred by Gaussian noise of mean 0 and variance 0.02

The example simulates the noise by adding a Gaussian noise of variance V to the blurred image (using *imnoise*). The noise variance V is used later to define a damping parameter of the algorithm. The blurred image due to Gaussian noise is shown in Fig 5.2 and blurred and noisy image is shown in Fig 5.3

```
V = .002;
BlurredNoisy = imnoise(Blurred,'gaussian',0,V);
figure;imshow(BlurredNoisy);title('Blurred & Noisy');
```

Blurred & Noisy image

Fig 5.3 Adding noise to blurred image to get noisy image

Finite Normal Density Modeling

Create a *gmdistribution* object defining a two-component mixture of bivariate Gaussian distributions:

```
MU = [1 2;-3 -5];
SIGMA = cat(3,[2 0;0 .5],[1 0;0 1]);
p = ones(1,2)/2;
obj = gmdistribution(MU,SIGMA,p);
```

y = pdf(obj,X) returns a vector y of length *n* containing the values of the probability density function (pdf) for the gmdistribution object obj, evaluated at the *n*-by-*d* data matrix X, where *n* is the number of observations and *d* is the dimension of the data. obj is an object created by gmdistribution or fit.

Applying Variation Method

```
mu = .05/max(sigma,1.e-12);
MU = [mu/5 mu mu*5];
gamma  = beta/mu;
Denom  = Denom1 + gamma*Denom2;
vartol1 = tol*(beta_max/beta)^2;
varmaxit = maxit/2;
```

Majorization Minimization Algorithm

Majorization Minimization is performed after initializing parameters so that parameter of image is updated at each iterations. Majorization Minimization algorithm steps are as follows

1. Start with Initial estimate $x^{(0)}$
2. Compute $y' = H^T y$; with t:= 0.
3. Till "Majorization Maximization stopping criterion" is not satisfied do 3 to 6
4. Compute $W^{(t)}$
5. $x^{(t+1)} := x^{(t)}$
6. Till $x^{(t+1)}$ does not satisfy "Conjugate Gradient stopping criterion" do 6
7. $x^{(t+1)}$:= Conjugate Gradient iteration for system $A(t)x = y'$, initialized at $x^{(t+1)}$
8. End

VI.Conclusion

A blind image multiframe restoration method was described in this paper,for improving the quality of an image scene when multiple degraded acquisition were available. The proposed method did not require knowledge of the PSF support size, nor eact alignment of the acquired frames. The set of distorted frames,potentially obtained through a multiframe environment, were individualy filtered. We conclude that the majorization /minimization algorithm is a robust and efficient method for solving the minimization problem. The case of highly ill-conditioned blurring operators such as Gaussian blur still requires more investigation to improve its rate of convergence

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