An Adaptive Model for Blind Image Restoration using Bayesian Approach

S.K. Satpathy, S.K. Nayak, K. K. Nagwanshi, S. Panda, C. Ardil

Abstract—Image restoration involves elimination of noise. Filtering techniques were adopted so far to restore images since last five decades. In this paper, we consider the problem of image restoration degraded by a blur function and corrupted by random noise. A method for reducing additive noise in images by explicit analysis of local image statistics is introduced and compared to other noise reduction methods. The proposed method, which makes use of an a priori noise model, has been evaluated on various types of images. Bayesian based algorithms and technique of image processing have been described and substantiated with experimentation using MATLAB.

Keywords—Image Restoration, Probability Density Function (PDF), Neural Networks, Bayesian Classifier.

I. INTRODUCTION

THE ability of reducing noise in images is far from new. Noise reduction by linear low-pass filtering is as old as image processing itself. Far from new are also the rank based filters, including the well-known median filter [1]. Over the last fifteen years or so, numerous methods have been presented, incorporating methods and ideas from as well the engineering as from the mathematics communities. Many of the methods are closely related to each other, or even identical. With this background, the de-noising community does perhaps not need more methods, but rather a common framework within which the existing methods can be described. Within such a framework, new ideas on improvements are also more likely to appear. In this paper, we propose a non-linear noise reduction method based on the local statistics of the image. This does not qualify as a common framework for all de-noising methods, but it is shown how conventional low-pass filters as well as bilateral filters can be described as special cases of the proposed method.

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The various restoration techniques used currently can be broadly viewed under two categories, namely, the transform related techniques and the algebraic restoration techniques [2]. The transform related techniques involve analyzing the degraded image after an appropriate transform has been applied. The two popular transform related techniques are inverse filtering and Kalman filtering [3]. Inverse filtering [1, 4] produces a perfect restoration in the absence of noise, but the presence of noise has very bad effects. The Kalman filter approach can be applied to non stationary image but it is computationally very intensive.

Algebraic techniques attempt to find a direct solution to the distortion by matrix inversion techniques, or techniques involving an iterative method to minimize a degradation measure. The two popular algebraic techniques available are pseudo inverse filtering and constrained image restoration. The pseudo inverse spatial 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 technique does not take into account the effects of noise in the calculations of the pseudo inverse and so is sensitive to noise in the image. 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 image. Blur matrices are very large and it is not computationally feasible to invert them. Constrained restoration techniques are often based on Wiener estimation [5] and regression techniques. One of the major drawbacks in most of the image restoration algorithms is the computational complexity, so much so that many simplifying assumptions have been made to obtain computationally feasible algorithms.

A number of new restoration methodologies have been developed in recent years and has interest in new aspects of image restoration problems. Motivated by the biological neural network [6-9] in which the processing power lies in a large number of neurons linked with synaptic weights, artificial neural network models attempt to achieve a good performance via dense interconnection of simple computational elements. Neural network models have great potential in areas where high computation rates are required and the current best systems are far from equaling human performance. Restoration of a high quality image from a degraded recording is a good application area of neural nets. Joon K. Paik and Aggelos. K. Katsaggelos [10] proposed a Modified Hopfield neural network model for solving the restoration problem which improves upon the algorithm proposed by Zhou et al. [11].

A. The Imaging Model

The image degradation [12] process can be modeled by the following equation:

$$g = H \cdot f + w \qquad (1)$$

where, H represents a convolution matrix that models the blurring that many imaging systems introduce. For example, camera defocus, motion blur, imperfections of the lenses all can be modeled by H. The vectors g, f, and w represent the observed, the original and the noise images. More specifically, w is a random vector that models the random errors in the observed data. These errors can be due to the electronics used (thermal and shot noise) the recording medium (film grain) or the imaging process (photon noise). Obtaining f from Eq. (1) is not a straight forward task since in most cases of interest the matrix H is ill-posed. Mathematically this means that certain eigen-values of this matrix are close to zero, which makes the inversion process very unstable. For practical purposes this implies that the inverse or the pseudo-inverse solutions

$$f_1 = H^{-1}g \qquad (2)$$

$$f_2 = (H^T H)^{-1} H^T g \qquad (3)$$

amplify the noise and provide useless results. This fact is demonstrated in what follows.

Regularization is one way to avoid the problems due to the ill-posed nature of H. According to regularization instead of minimizing $\| g - Hf \|^2$ in order to find f one minimizes:

$$\| g - Hf \|^2 + \lambda \| Qf \|^2 \qquad (4)$$

the additional term $\| Qf \|^2$ is called regularization term and can be viewed as capturing the properties of the desired solution. In other words, the first term in Eq. (4) stirs the solution f to be "close" to the observed data g while the second term enforces "prior knowledge" to the solution. The prior knowledge that is used is that the image is locally smooth. In most cases Q represents the convolution with a high-pass filter. Thus the term $\| Qf \|^2$ can be viewed as the high-pass energy of the restored image. The parameter λ is called *regularization parameter* and controls the closeness to the data vs. the prior knowledge of the solution. Finding f based on Eq. (4) gives

$$f_3 = (H^T H + \lambda Q^T Q)^{-1} H^T g \qquad (5)$$

Finding the proper value for the parameter λ is an important problem. In the demo that follows one can choose different values of λ and observe the effect to the restored image. A large value of λ results in a smoother image and is necessary if the noise variance is high or H is highly ill-conditioned. On the other hand a large λ blurs out the image details. So one has to decide between smoothness and detail in the solution.

In many practical cases of interest H is not known. For example when taking the photograph of a moving object when the shutter speed and the speed of the object are unknowns. In this case we are faced with the very difficult problem of "blind" image restoration. In such cases we have to utilize prior knowledge in order to somehow recover simultaneously both f and H. There are many different ways to incorporate prior knowledge about the image f and the degradation H in the problem. One of them is using deterministic constraints in the form of Convex Sets [9]. Another approach is using stochastic constraints in the form of prior distributions in a Bayesian framework [13].

The paper has been organized in the following manner; section II proposes Bayesian interface , section III describes Bayes estimator, section IV gives problem formulation and solution methodology of proposed system followed by section V describes Result and discussion, section VI gives the concluding remarks, and finally section VII incorporates all the references been made for completion of this work.

II. BAYESIAN INFERENCE

Over the years, Bayesian inference has evolved as one of the popular tools to be used in image processing. Below, it is discussed briefly how Bayesian approach is different from the classical frequentist approach, based on a reinterpretation of the following simple yet most important formula.
Bayes' Formula:

$$P(x \mid y) = \frac{P(y \cap x)}{P(y)} = \frac{P(y \mid z)P(x)}{P(y)} \qquad (6)$$

where $P(x \mid y)$ denotes the conditional probability distribution of x given y. In Bayesian analysis, an image is a realization of a random matrix whose probability distribution is known a priori. There could be several ways to specify the prior probability distribution of an entry in a matrix or a spot in an image which is a discrete function defined over the set of pixel values, i.e., {0,1,2, ...,253,254,255}. For complete specification, the prior distribution of a spot could have value 1 at a certain pixel value and 0 at the rest of the pixel values. Or, for complete ignorance, the distribution could be uniform, i.e., having the constant value 1/255 at every pixel value. Or, there could be assumptions and observations which might suggest us other prior distributions. For example, a spot that is likely to be dark could have, as a prior; a binomial distribution peaked near 0. The choice of the prior is one of the main problems in Bayesian image analysis [14]and present paper will not be dealing with designing priors in this report, rather, it takes the prior distribution for an image data as given, usually, as a Gaussian distribution.

III. BAYES ESTIMATOR

The Bayes principle supposes that images f are realizations of a random matrix F, say of size $M×N$, with a known prior distribution π. Image data are usually supposed to contain additive white Gaussian noise W, a vector of length MN whose components identically and independently follow the normal distribution with mean 0 and standard deviation σ^2, written $W \sim N(0, \sigma^2 I_{MN})$. Thus, the noisy data is

$$X[n_1, n_2] = F[n_1, n_2] + W[n_1, n_2] \qquad (7)$$

The noise $W[k_1, k_2]$ and the image $F[n_1, n_2]$ are supposed to be independent for any $0 \le k_1$, $n_1 < M$ and $0 \le k_2$, $n_2 < N$. By Bayes' formula, the conditional distribution of F given the observed data X, called the posterior distribution, is specified by the joint distribution of F and W which is the product of the distributions of F and W. Bayesian inference is to estimate F from the posterior distribution which is the updated distribution in light of the data X. This denote the estimate of $F \times \hat{F}$. The error of the estimation is quantized as the loss function which can be the square Euclidean norm of the difference, i.e., $\| F - \hat{F} \|$. Since $\hat{F}$ is an estimate of F from X, one can construct a so-called decision operator D on X specifying the estimator as $\hat{F} = DX$. Then the risk of the estimator is the expected loss with respect to the probability distribution of the noise W denoted by:

$$r(D, F) = E_w\{\| F - DX \|^2\} \qquad (8)$$

The Bayes risk is the expected risk with respect to the prior probability distribution π of the image and is given by

$$
\begin{aligned}
r(D, F) &= E_\pi\{r(D, F)\} \\
&= E_{w, \pi}\{\| F - \hat{F} \|^2\} \\
&= \sum_{n_1=0}^{M-1} \sum_{n_2=0}^{N-1} E_{w, \pi}\{\| F(n_1, n_2) - \hat{F}(n_1, n_2) \|^2\}
\end{aligned}
\qquad (9)
$$

IV. PROBLEM FORMULATION AND SOLUTION METHODOLOGY

Image restoration is an old problem in image processing, but it continues to attract the attention of researchers and practitioners alike. A number of real-world problems from astronomy to consumer imaging find applications for image restoration algorithms. Plus, image restoration is an easily visualized example of a larger class of inverse problems that arise in all kinds of scientific, medical, industrial and theoretical problems. Besides that, it's just fun to apply an algorithm to a blurry image and then see immediately how well you did.

Suppose X is the sum of two stochastic and independent variables:

$$X = S + N \qquad (10)$$

Using a Bayesian approach, the *a posteriori* distribution $f_{S|X}=x$ is found as:

$$f_{S|X=x}(s) = \frac{f_{S|X=x}(x) . f_S(s)}{f_X(x)} \qquad (11)$$

To find an apriori probability, note that f_X equals the convolution of f_S and f_N :

$$f_X(x) = f_S(x) * f_N(x) \qquad (12)$$

If it is known that $S = s_0$, we can write $f_S(s) = \delta(s_0)$, which gives:

$$f_{S|X=x}(x) = \delta(s) * f_N(x) = f_N(x - s) \qquad (13)$$

So the Eq. (11) can be written as:

$$f_{S|X=x}(s) = \frac{f_N(x - s) . f_s(s)}{f_x(x)} \qquad (14)$$

For a given $X = x$, thus it has an expression for the probability density of S. It will use this density to find the most suitable estimate of S. In doing so, this will only consider the relative probabilities and therefore define a function $g(s)$ to be:

$$G(s) = f_N(x - s) \cdot f_s(s) \qquad (15)$$

The purpose of image restoration is to enhance or correct a degraded image. Image degradation occurs for many reasons including noise, quantization through digitization, or blurring. The correction process depends on the type of degradation that occurred. This paper focuses on restoring images that were degraded by blurring due to motion, and this section describes the process through which the motion blur occurs. Blurring can be caused by many factors, including lens misfocus, atmospheric distortion, or movement during the image capture [15]. Blurring smoothes high frequency components, reducing detail. This blurring is essentially a low-pass filter effect, and so some details may be unrecoverable.

Motion blur is captured in a given frame due to the finite exposure time necessary for the light to travel to the film or photo sensors. This phenomenon is a consequence of the physics involved in taking a picture, regardless of whether the camera is film or digital . For simplicity, the concepts will be discussed in terms of digital cameras (pixels versus film grains), although the concepts apply to film cameras as well. A lens focuses light to the photo sensors, which are activated by the light photons. The amount of light received at each sensor determines the degree of that sensor's contribution to the final image. The longer the sensor is exposed to light, the greater the degree of its activation. A large sensor can capture more light over the same time period than a small sensor can. However, the resolution of the final image will be lower, because there are fewer independent pixels. Motion during the exposure time causes the incoming photons to shift relative to the receiving photo-sensors. Therefore, neighboring sensors can receive similar visual information, and involvement of multiple pixels causes the blurring effect in the resulting image.

The amount of motion captured, due to the spread of light across the pixels, depends on the length of the exposure time of the image and the velocity of relative motion between the camera and the image being captured. Exposure times are constrained by the light available as well as the mechanical limits of the shutter. The exposure time cannot be shorter than the speed at which the shutter can operate. The required exposure time is a factor of the sensitivity and size of the imaging sensors, as well as the external light conditions. Low light conditions require a

longer exposure time in order to achieve acceptable contrast in the image.

The motion blur is a relative effect, and therefore can be caused by movement in either the subject or the camera. When the camera is the source of movement, the blur field is generally consistent throughout the image [15]. However, motion in front of the camera may also contribute to the blurring effect. When the motion lies in the field of view of the camera, the motion contributing to the blurring may vary at points across the image, making this situation more difficult to analyze. Many cameras come with stabilization hardware to reduce handling motion on the part of the photographer. Hardware solutions have also been developed to track camera motion during the image capture and provide a motion estimate [8]. Sensors on the subject of the image can be used to track motion in front of the lens as well, but this sensor tracking requires cooperation from the subject, as well as foreknowledge of the moving objects to be photographed. This paper assumes that there is no prior knowledge of the direction of motion from either the camera or the subject. In many cases the motion is undesirable from both a visual and practical standpoint. In addition to being more visually appealing, unblurred images are important for the future processing the image may undergo. Images with sharper edges and more distinct features and textures improve the ability of many. Furthermore, identification processes such as iris recognition require clear, high-resolution images to perform the identification. Acquiring adequately detailed images without post-processing involves cooperative interaction between the subject and the imager which can be difficult in many cases. Estimating the motion blur is critical for accurately restoring the image to remove the motion.

A. Probability distribution of image data

It is a two-dimensional integer- valued discrete function, or more explicitly, a function of the form $f : \{1,2, ...,M-2,M-1,M\} \times \{1,2, ...,N-2,N-1,N\} \rightarrow \{0,1,2, ...,253 ,254, 255\}$. It should be noted, however, that if f is a color image, it is a tensor product of three such functions f_1, f_2 and f_3 corresponding to red, green and blue components of the image, or, in the matrix form, a tensor product of three corresponding matrices. It can be, for convenience, visualize this as three matrices stacked one on top of the other in the order red, green and blue from bottom to top. This idea is further generalized with multi-spectral images which can capture more than just RGB components, for example, it could have a fourth matrix at the top of the stack corresponding to the infrared component of the image. Since a color image, or a multi-spectral image, for that matter, is handled by handling each monochromatic image one at a time and repeating the process to all such images in the tensor product, it can, without loss of generality, talk of monochromatic images only whose corresponding matrices are two-dimensional.

A matrix of size $M \times N$ has $M \times N$ entries that directly correspond in the image to the array of spots of possibly different brightness level called pixel values. Each entry x thus has a probability density function (PDF) or a probability distribution which, in turn, is a discrete function $Px : \{0,1,2,$

$...,253,254,255\} \rightarrow [0,1]$ such that $\sum_{i=0}^{255} Px(i) = 1$. Then, the probability distribution of an image f will consist of probability distributions of all the entries of its corresponding matrix, namely, $\{Px\}x \in f$. In the case of an image f having number of distinct classes, say, $\omega j, j = 1,2, ...,W$, for example, of landmass, sky, water, snow, objects, scenery, etc., the probability distribution of f will be a collection of conditional probability density functions $\{Pj(x|\omega j)\}, j = 1,2, ...,W$ and class probabilities $P(\omega j), j = 1,2, ...,W$ which, if it has been omitted, is understood as being $P(\omega j) = 1/W$ for each j, i.e., each class occurring equally likely in the image.

B. Proposed Algorithm

To deblur the image, it desires a mathematical description of how it was blurred. (If that's not available, there are algorithms to estimate the blur. But that's for another day.) This will usually start with a shift-invariant model, meaning that every point in the original image spreads out the same way in forming the blurry image. One can model this with convolution:

$$g(m,n) = h(m,n) * f(m,n) + u(m,n) \qquad (16)$$

where $*$ is 2-D convolution, $h(m,n)$ is the point-spread function (PSF), $f(m,n)$ is the original image, and $u(m,n)$ is noise (usually considered independent identically distributed Gaussian). This equation originates in continuous space but is shown already discretized for convenience.

Actually, a blurred image is usually a windowed version of the output $g(m,n)$ above, since the original image $f(m,n)$ isn't ordinarily zero outside of a rectangular array. Let's go ahead and synthesize a blurred image so one must have something to work with. If it has been assumed, $f(m,n)$ is periodic, the convolution becomes circular convolution, which can be implemented with FFTs via the convolution theorem. If this model out-of-focus blurring using geometric optics, one can obtain a PSF using fspecial and then implement circular convolution.

To assess the performance of the proposed filters for removal of impulse noise and to evaluate their comparative performance, different standard performance indices have been used in the paper. These are defined as follows:

Peak Signal to Noise Ratio (PSNR): It is measured in decibel (dB) and for gray scale image it is defined as:

$$PSNR \ (dB) = 10 \log_{10} \left[\frac{\sum_i \sum_j 255^2}{\sum_i \sum_j \left(S_{i,j} - \hat{S}_{i,j} \right)^2} \right] \qquad (17)$$

Where $S_{i,j}$ and $\hat{S}_{i,j}$ are the original and restored image pixels respectively. The higher the PSNR in the restored image, the better is its quality.

Signal to Noise Ratio Improvement (SNRI): SNRI in dB is defined as the difference between the Signal to Noise Ratio

(SNR) of the restored image in dB and SNR of restored image in dB i.e.

SNRI (dB) =
    [SNR of restored image in dB- SNR of noisy image in dB] (18)

Where,

SNR of restored image dB =

$$10 \log_{10} \left[\frac{\sum_i \sum_j S_{i,j}^2}{\sum_i \sum_j \left(S_{i,j} - \hat{S}_{i,j} \right)^2} \right] \quad (19)$$

SNR of Noisy image in dB =

$$10 \log_{10} \left[\frac{\sum_i \sum_j S_{i,j}^2}{\sum_i \sum_j \left(S_{i,j} - X_{i,j} \right)^2} \right] \quad (20)$$

Where, $X_{i,j}$ is Noisy image pixel

This result is obviously far better than the first attempt. It still contains noise but at a much lower level. It's not dramatic and satisfying, but it's a step in the right direction. It can see some distortion due to the fact that some of the frequencies have not been restored. In general, some of the higher frequencies have been eliminated, which causes some blurring in the result as well as ringing. The ringing is due to the Gibbs phenomenon - an effect in which a step like transition becomes wavy due to missing frequencies. A similar but slightly improved result can be obtained with a different form of the pseudo-inverse filter. By adding a small number δ^2 to the number being divided, it gives nearly the same number unless the number is in the same range or smaller than δ^2. That is, let

$$H_I = \frac{H^*}{|H|^2 + \delta^2} \quad (21)$$

Then, $H_I \approx \dfrac{1}{H}$ if $|\delta| << |H|$ (22)

And, $H_I \approx 0$ if $|\delta| >> |H|$ (23)

V. RESULT AND DISCUSSION

The most important advantage of the Bayesian approach in the image restoration was the possibility to handle the situation where some of the prior knowledge is lacking or vague, so that one is not forced to guess values for attributes that are unknown. The best Bayesian models were mostly those with least restrictive hierarchical priors, so that even though the Bayesian approach is based on inherently subjective selection of prior probabilities, the final Bayesian models were much less subjective than the corresponding classical (error minimization) methods. From Fig. 3 and Fig. 8 it has been observed right away that the magnitude response of the blur has some very low values. When it will divide by this point wise, this is also dividing the additive noise term by these same low values, resulting in a huge amplification of the noise enough to completely swamp the image itself.

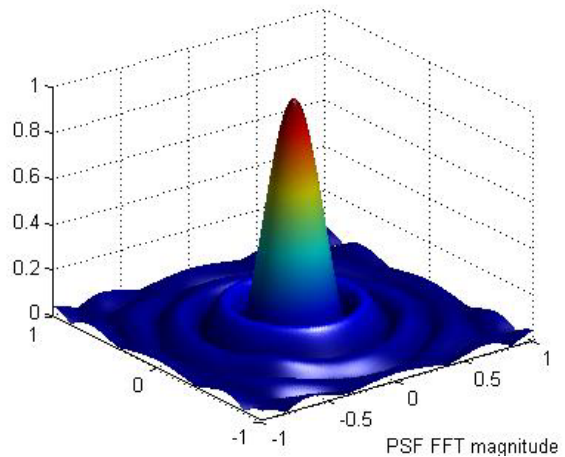Fig. 1 Original camman image

Fig. 2 Blurred image

Fig. 3 PSF FFT magnitude

Fig. 4 Pseudo-inverse restoration

Fig. 7 Blurred image with noise

Fig. 5 Final result of restoration by proposed methodology
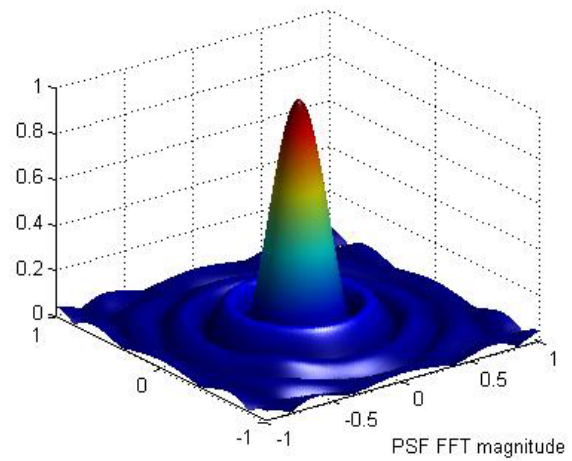

Fig. 8 PSF FFT magnitude

Fig. 6 Original text.tif image

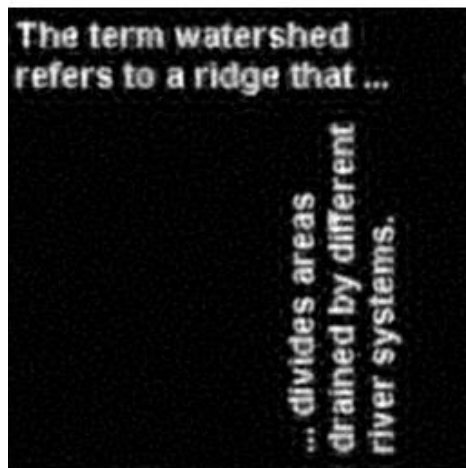Fig. 9 Pseudo-inverse restoration without noise

Fig. 10 Final result of restoration by proposed methodology

Fig. 1 and Fig. 6 are the original images of cameraman.tif and text.tif. Fig. 2 is the blurred image without noise of cameraman. while Fig. 7 is the blurred image with some additive noise. Figure 3 and 8 shows PSF FFT magnitudes. Fig. 4 and Fig. 9 will shows result after pseudo-inverse restoration and finally Fig. 5 and Fig. 10 depicts restoration in proposed Bayesian approach.

VI. CONCLUSION

This paper proposed Bayesian approach to remove the impulse noise from the images. To illustrate the efficiency of the proposed schemes, it has been simulated the new schemes along with the existing ones and various restored measures have been compared. Proposed techniques have been simulated in MATLAB 7.1 with Pentium-IV processor. The schemes are simulated using standard images TEXT and CAMMAN. The impure contaminations include Salt and Pepper noise. The proposed schemes is found to be superior, i.e. better restored results and other parameter for restoration compared to the existing schemes when Salt and Pepper impulse noise is considered. In this direction further work can be extended by utilizing other soft computing techniques, like fuzzy and ANN, so that the properties of images can be better retained in the restored images.

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