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Multi-Channel Color Image Restoration using Zonal Filter

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Abstract_ Images may be degraded for many reasons for example, out-of-focus optics produce blurred images, and variations in electronic imaging components introduce noise. Reducing blur or noise or both in images is known as image restoration. Multi-channel blind image restoration recovers an original image from several blurred versions without any knowledge of the blur function. In many applications the image to be processed has a multi-channel nature; i.e., there are several image planes available, called channels with redundant as well as complementary information. Here we propose a multichannel blind restoration technique for linearly degraded images without the explicit knowledge of either the Point Spread Function (PSF) or the original image. The blurred noisy image is compressed using 8 by 8 blocks DCT and filtered using zonal filter.

1. INTRODUCTION:

IN many applications, multiple blurred renditions of a single image become available which the original image and the blurs remain unknown. Some of these applications such as electron microscopy and imaging through the atmosphere require image restoration to remove the effects of blur. With the prior knowledge of the blurs or the input and output (cross) power spectra, there exits many multichannel image restoration techniques based on different constraints such as minimum mean-squares. All these techniques are based on monochrome images, which remove blur or noise. So there is sophisticated need of multichannel blind image restoration technique which removes both blur and noise in color images.

We have shown that when at least three blurred noisy images are available it is possible to exploit the properties Multi-Input Single-Output (MISO) image data.

2. PROBLEM STATEMENT OF MULTI-CHANNEL IMAGES

Consider the Single-Input Multi-Output (SIMO) discrete-time Linear Shift Invariant system depicted in fig 1. Such an imaging system could result from multiple cameras; multiple focuses of a single camera, or acquisition of images from a single camera through a changing medium. The input to this system is a set of unknown images; the images are distorted by finite impulse response blurs h (n1, n2) and zero mean Additive White Gaussian Noise (AWGN) n (n1, n2). The 2-D convolution of the true image f(n1,n2) and the ith blur hi(n1,n2) is degraded with AWGN field ni(n1,n2) to produce ith output image gi(n1,n2).

It is assumed that the noise and the blur in each channel are uncorrelated with the noise from the other channels. The resulting images are a set of blurred noisy images.

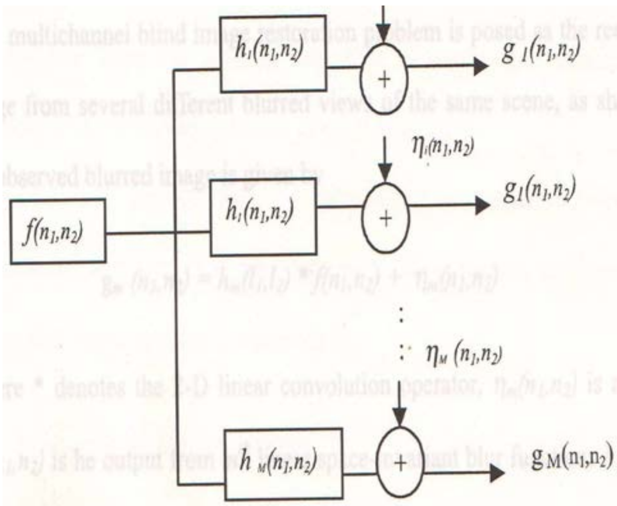

Fig1: Single Input Multi-output (SIMO) Model.

In general, a blurred image g (n1, n2) can be modeled as

$$g(n_1,n_2) = \mathrm{T}\Big(\sum_{l1}\sum_{l2} h(n_1,n_2,l_1,l_2)\, f(n_1,n_2)\Big) \odot \eta(n_1,n_2) \qquad \ldots\ldots\ldots\ldots\ldots (1)$$

Where Θ is a point wise (memory less) operation, f (n1, n2) is the original image h (n1, n2, l1, l2) is the 2-D impulse response of the blurred system, n (n1, n2) is the noise, and T (.) generally denotes a point wise operation. In remote sensing, astronomical imaging, and other image acquisition systems, the function T (.) models the response of an image sensor and may be nonlinear. In many practical situations, and perhaps most of the work in the image restoration area, a blurred image is modeled as the convolution of the original image and a linear space-invariant blur function to which signal-independent noise may be added.

In this paper, two assumptions are made:

- All blur functions are linear and space-invariant with finite support.
- The noise is additive.

The multichannel blind image restoration problem is posed as the recovery of an ordinal image from several different blurred views of the same scene, as shown in fig 1. The Mth observed blurred image is given by

gm(n1,n2)= hm (l1,l2) * f(n1,n2)+ nm(n1,n2) ………. (2)

Where * denotes the 2-D linear convolution operator, nm(n1,n2) is a noise process, and gm(n1,n2) is he output from mth linear space-invariant blur functions hm(l1,l2). The extent of the original image is f(n1,n2) is N1XN2. The extent of the mth blurred image hm (l1,l2) is L1XL2. There are M blurred images. Therefore nj=0,1…Nj – 1j= 0,1…Lj – 1, j=1,2 and m=1,2…M.

3 Noise:

The principle sources of noise in digital images arise during image acquisition and/or transmission. The performance of imaging sensors is affected by a variety of factors, such as environmental conditions during image acquisition, and by quality of the sensing elements themselves. For instance, in acquiring images with a CCD camera, light levels and sensor temperature are major factors affecting the amounts of noise in the resulting image. Images are corrupted during transmission principally due to interference in the

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channel used for transmission. For example, an image transmitted using a wireless network might be corrupted as a result of lightning or other atmospheric disturbance [7].

3.1. Spatial and Frequency Properties of Noise

Frequency properties refer to the frequency content of noise in the Fourier sense (i.e., as opposed to the electromagnetic spectrum). For example, when the Fourier spectrum of noise is constant, the noise usually is called white noise. This terminology is a carryover from the physical properties of white light, which contains nearly all frequencies in the visible spectrum in equal proportions.

Spatially periodic noise is independent of spatial coordinates, and that it is uncorrelated with respect to the image itself that is there is no correlation between pixel values and values of noise components [1].

4 Noise Reduction Filters

Median filters are quite popular because, for certain types of random noise, they provide excellent noise-reduction capabilities. Median filters are particularly effective in the presence of impulse noise, also called salt-and-pepper noise because of its appearance as white and black dots superimposed on an image. The median filter is normally used to reduce noise in an image [14].

4.1 Median Filter

The median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used). For example, suppose that a 3x3 neighborhood was values (10, 20, 20, 20, 15, 20, 20, 25,100). These values are sorted as (10, 15, 20, 20, 20, 20, 20, 25,100), which results in a median of 20. Thus, the principal function of median filters is to force points with distinct gray levels to be more like their neighbors. In fact isolated clusters of pixels that are light or dark with respect to their neighbors and whose area is less than n2/2 (one-half the filter area) are eliminated by an n x n median filter [1].

Impulse noise randomly and sparsely corrupts pixels to two intensity levels-relatively high or relatively low, when compared with neighboring pixels. Recently standard Median filters were initially introduced to eliminate impulse noise and shown to achieve reasonably good performance. They exploit the rank order information i.e. order statistics of the input data to effectively remove impulse noise by substituting the pixel position with the median of the re-ordered input data. Intuitively and ideally, the filtering should be applied only to the corrupted pixels while leaving those uncorrupted ones intact. Applying median filter unconditionally across the entire image as practiced in the conventional schemes would inevitably alter the intensities and remove signal details of those uncorrupted pixels.

In this project a new noise removal technique called as zonal filter or zonal coding is proposed i.e. by applying zonal mask to low frequency components and discarding the high frequency components in DCT domain, the noise, which is present in the image, is filtered.

4.2 Zonal Filter or Zonal Coding

Zonal Filter are based on transform coding, in case of Transform coding a given image is divided into a small rectangular blocks, and each block is transform coded independently. For an N X M image divided into NM/PQ blocks, each of size p x q. Frequency and shape characteristics of image become distinct in transform domain. Transform domain features can be extracted by zonal filtering or zonal coding.

A small zone of transformed image is transmitted. Let N1 be the number of transmitted samples. We define a zonal mask as the array.

$$m(k, l) = \begin{cases} 1 & k, l \in I_t \\ 0 & otherwise \end{cases} \quad \ldots\ldots\ldots (3)$$

This takes the unity value in the zone of largest N1 variances of transformed samples

Transform, domain compression works by only sending part of the transform, i.e. if we apply a zonal mask (simplest, just transmit top left corner of the transform) to transformed blocks and encode only nonzero elements, then the method is called zonal coding or zonal filter. Various zonal masks that are considered in our paper are shown below [2].

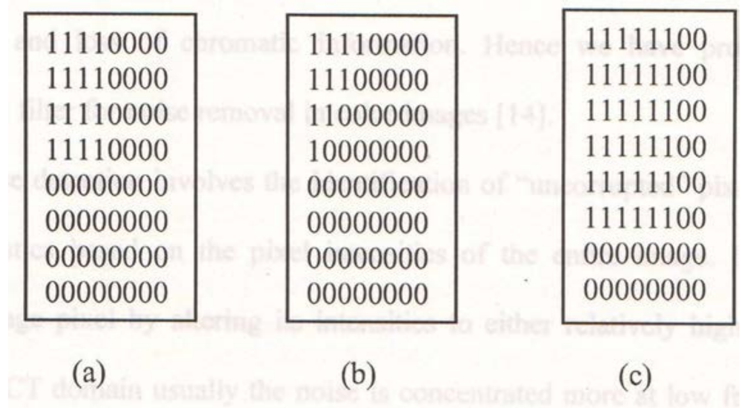

Fig 2: Different zonal masks

(I) (II)

(II) A classical 256-level colored Lena Test image

(II) A classical 256-level colored Barbara Test image Fig 3: Test images

5 Noise Removal in Color Images

Most of noise removal methods were originally devised for monochromatic images. In the majority of cases it is possible to operate on color channels separately and in this way the gray scale image algorithms can be applied directly for the color images working independently on separate channels. Unfortunately, these methods introduce shifts in color and loss of chromatic information. Hence we have proposed a new technique, zonal filter for noise removal in color images [14].

The noise detection involves the identification of "uncorrupted" pixel by utilizing the global statistics based on the pixel intensities of the entire image. Impulse noise corrupts the image pixel by altering its intensities to either relatively high or relatively low value. In DCT domain usually the noise is concentrated more at low frequency than the high frequency components [3].

An estimation of the original image can be obtained by compressing the degraded or blurred noisy image into a JPEG format i.e. image is divided into 8 by 8 blocks, zonal mask (present in fig 3g) is applied to each block, the zonal filter filters the noise present in the image. This process is applied to all the blocks of the entire image. By applying zonal filter only low frequency components are retained while the high frequency components are discarded, as most of the information is concentrated at low frequencies in images. Thus the proposed technique has proven to provide optimum results for color images.

6 Restoration of Multiple Images with Motion Blur

Blurred images can be restored when the blur function is known. Restoration of a single motion-blurred image without prior knowledge of the blur functions is much harder. Early deblurring methods treated blurs that can be characterized by a regular pattern of zeros in frequency domain such as uniform motion blur. More recent methods deal with a wider range of blurs, but require strong assumptions on the image model. For example, assuming that the image is spatially isotropic, or can be modeled as an autoregressive process. In case that the image motion is constant for the entire imaging period, the motion blur can be inferred from motion analysis and used for restoration.

Unfortunately, the assumption of constant motion during the entire imaging process does not hold for many cases for motion blur. For example analysis of images takes with small digital cameras shows that consecutive images covering the same scene have different motion blur. In particular the direction of motion blur is different from one image to another due to trembling of hand. In image restoration algorithm include an estimation of PSF (Point Spread Function) from two images. However it assumes a pure translation between the images, and uses the location of singularities in the frequency domain, which are not stable [13].

In this paper we describe how different images, each degraded by motion blur in different directions can be used to generate a restored image. It is assumed that the motion blur can be described by a convolution with a one-dimensional kernel. No knowledge is necessary regarding the actual motion blur other than its direction, which is computed by Iterative Blind Deconvolution.

6.1 A model for Motion Blur

Let g denote the observed image, degraded by a motion blur with a one dimensional kernel m=(m1…mk) at an angle œ.Let f be the original image. We assume that f was degraded in the following way.

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$$g(x,y) = f \overset{\alpha}{*} m \overset{def}{=}$$

$$= \sum_{k=0}^{k-1} m_k . f(x + k\cos(\alpha), y + k\sin(\alpha), y + k\sin(\alpha)) \quad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

This assumption is valid when the motion blur is uniform for the entire image. Otherwise, the image can be divided into regions having approximately a constant motion blur. For a discrete image f, interpolation is used to estimate the gray levels at non-integer locations. [13]

7. The Proposed Multi-Input Single-Output Model (MISO)

In many applications the image to be processed has a multi-channel nature, with several image planes called channels with redundant as well as complementary information. The different channels may correspond, for instance to different frequencies, different sensors or different time frames. The goal of multi-channel image restoration is to obtain an estimate of the source multi-channel image from its blurred noisy observations, exploiting the known complementary of different channels. Restoring an unknown image form its known complementary of several image planes without the knowledge of the blur and the noise variance is called multi-channel blind image restoration [16].

The multi-channel blind image restoration technique, which is used here, is shown in fig (4) below, The Multi-Input Single-Output (MISO) model is shown which has three different blurred noisy images from different blurred noisy images. We get a single restored image, which fulfills the assumptions of the true image.

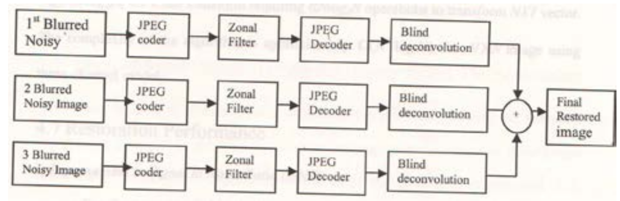

Fig 4: Proposed Multi-input Single-output Model (MISO) using zonal filter

In the proposed model classical Lena and Barbara colored images which are shown in fig (4a) were chosen as test images. Three different blurred and Noisy versions of the test image were considered which are corrupted by Additive White Gaussian Noise (AWGN) with SNR ~20 dB and motion blur at an angle of 20, 30, 40 degrees. Then they obtained images were compressed into a JPEG format. Zonal mask was applied to the blurred noisy versions in order to remove the noise contained in it. i.e. 8x8 block DCT was considered and the mask was applied only to the lower frequency components and the higher frequency components were discarded as most of the noise resides in high frequency components. The inverse DCT is applied, the obtained image is a noise free image. In order to remove the blur, the deblurring filter i.e. Blind deconvolution was applied to three different channels. Finally from the three multiple-channels a single output image is obtained which fulfills most of the assumptions made about the true image.

Thus the proposed restoration model involves a pre-processing DCT domain zonal filtering followed a post-processing step of time domain deconvolution. For an N X M image divided into MN/pq blocks, each of size p x q (i.e. for example a 256x256 image is divided into 8 by 8

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blocks) the main storage requirements for implementing the transform are reduced by a factor of NM/PQ. The computational load is reduced by a factor of log2mn/log2pg for a fast transform requiring a Nlog2N operations to transform NX1 vector. The complexity of the algorithm is approximately O (N2logN) for NXN image using three-channel model.

8 Restoration Performances

a) Improvement in Signal to Noise Ration (ISNR):

For the purpose of objectively testing the performance of the restored image the Improvement in Signal to Noise Ration (ISNR) is used which is defined by [3].

$$ISNR = 10\log_{10} \frac{\sum_{i,j}[f(i,j)-y(i,j)]^2}{\sum_{i,j}[f(i,j)-\hat{f}(i,j)]^2} \quad \ldots\ldots\ldots\ldots (5)$$

Where f (i, j) and y (i, j) are the original and degraded images and f(x, y) is the restored image.

b) Blurred Signal to Noise Ratio (BSNR):

In most image restoration studies, the degradation modeled by blurring and additive noise is referred in terms of a metric called BSNR.

$$BSNR = 10\log_{10}\left[\frac{\frac{1}{N^2}\sum_{i,j} g(i,j)^2}{\sigma^2}\right] \quad \ldots\ldots\ldots\ldots (6)$$

For an NXN image, where g (i, j) is the noise free blurred image and σ2 is the noise variance.

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