

Image Noise Reduction System Using a Wiener Variant Filter in a Pyramid Image Representation

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Abstract

A DCT based method and system for reducing noise from an image is described. First, we perform noise modeling and estimation of the imaging source using flat fields to obtain a set of masks and LUTs that characterize the source of noise. Second, the image is represented in a pyramid structure by recursively using the DCT as a filter bank on the original image and then on the low frequency band. This representation is complete, reversible and allows us to process the image at different resolutions. Third, a Wiener variant filter using the estimated masks and LUTs is used to perform noise reduction on the image in the pyramid representation. Finally, the image is reconstructed by recursively using the IDCT as a filter bank in the inverse direction starting at the highest level of the pyramid.

We present examples for processing noisy images that are obtained from an electronic still camera and by adding colored noise, that show both quantitative and subjective improvement in image quality.

1. Introduction

An important area in signal and image processing is image restoration. In image restoration, an ideal image has been degraded in some manner and the goal is to reduce or eliminate the degradation and make the resulting processed image resemble the original image as much as possible. In addition, in some applications it is desirable to improve the visual appearance of the restored images to human viewers. In such instances, some type of an image enhancement technique is typically coupled with the image restoration method to provide for final images with great improvement in image quality.

The noise estimation step is performed once for a particular system while the filtering steps are repeated for every image in the system. There are three major steps that are involved in performing the proposed pyramid noise rcduction method. We will discuss each of them in detail. Figure I shows a block diagram of the method and the steps involved:
• Image decomposition (DCT with overlap)
• Wiener filtering
• Image reconstruction (IDCT with save)

2. Noise Estimation

The first step in our method is to obtain an estimated set of noise masks and LUTs (Look-Up-Tables) that characterize the noise in our system. An image of an object of constant brightness is called a flat-field. Let us first assume that the flat-field has only one component: the luminance. By taking the DCT of the flat-field on a block basis (8×8 pixels), we obtain an array of coefficients, which can bc used to characterize the noise in the frequency domain. For each block, we compute the DCT power spectrum. All the power spectra are averaged to give an estimate of the DCT power spectrum of the noise in the flat-field. Because noise content in many imaging systems depends upon the brightness level of the object or the mean value of the flat-field, we have different masks for flat-fields with different mean values. It turns out that for our particular system the noise masks have almost the same shape and that the masks differ only by a scale factor which is determined by the mean value of the flat-field. Based on this observation, we express the masks for a specific flat-field as follows:

$$M_u = L\,(u) \times\; M \qquad (1)$$

where M_u *is* the desired mask for the flat-field whose mean value is u, M *is* the normalized mask, and $L(u)$ is a scale factor that is function of u. We compute $L(u)$ for a finite number of values for u and obtain a look-up-table for all possible values of u by means of interpolation. Similar steps are performed to obtain the noise masks and LUTs for the chrominance component. The LUTs for the chrominance components, however, are indexed by the mean value of the luminance component rather than the chrominance components. In the pyramid representation, these estimation steps are repeated for every level of the pyramid in order to obtain estimated values of masks and LUTs at different resolutions.

3. Image Decomposition in the Pyramid Representation

The Laplacian pyramid which was introduced by Burt and Adelson is one example of a pyramid representation that has been used for compact image coding system where an image is represented at different levels of resolutions[1] The original image is referred to as the base level (level= 1) and the successive lower resolution levels are obtained in this case by blurring and downsampling the image at the previous level using a Gaussian blurring function.

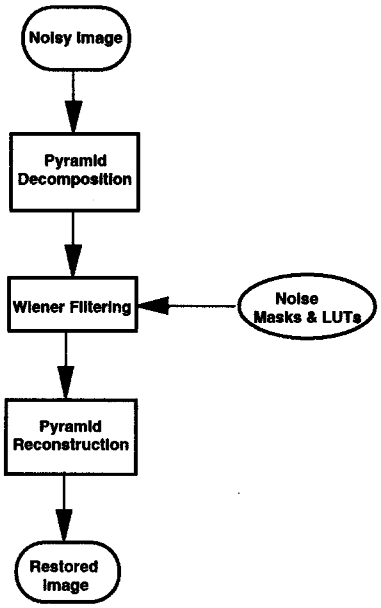

Figure 1. Block diagram of the noise reduction system.

Similarly, we decompose the image into different resolutions but we use the Discrete Cosine Transform (DCT) on overlapped blocks of the image to perform filtering. Also, we perform downsampling by grouping the DC coefficients from each of the DCT block to form the lower resolution image. The process of applying DCT and regrouping the DC coefficients is repeated to obtain different levels of the pyramid that represent the low frequency part of the image. The DCT is widely used in many image processing applications such as still image coding (JPEG) and moving image coding (MPEG) and fast and efficient hardware and software that implement the DCT are widely available.[2]

Figure 2 shows an example of this transformation where the original image is transformed from the spatial domain into the frequency domain using the DCT with a block size of 8 × 8 with 50% overlap. The process is repeated to obtain three levels of the pyramid. Other block sizes, different amounts of overlap, and number of pyramid levels are also possible. In Figure 2, x_1 (n_1, n_2), represents the original noisy image in the spatial domain and it is considered to be the first level of the pyramid, x_2 (n_1, n_2) and x_3 (n_1, n_2), represent the second and third level of the pyramid in the spatial domain representation. X_1 (k_1, k_2), X_2 (k_1, k_2), and X_3 (k_1, k_2), represent the image in the overlapped frequency domain at three different levels where in this case, X_1 (k_1, k_2) represents the highest resolution and X_3 (k_1, k_2) represents the lowest resolution in the trequency domain.

The image decomposition starts by taking the DCT of the original image, x_1 (n_1, n_2), using block size of 8 × 8 with 50% overlap. The resulting image in the frequency domain, X_1 (k_1, k_2), has twice the size of the original image in each dimension because of the overlap. The image in the second level of the pyramid, x_2 (n_1, n_2), is obtained by grouping the DC coefficients (Pick-DC) from each DCT block in X_1 (k_1, k_2). The resulting image after scaling looks like a blurred and downsampled version of the original image. This image, x_2 (n_1, n_2), which is similar to the original image but a quarter the size in each dimension, forms the second level of the pyramid in the spatial domain. This process is repeated to form the different levels of the pyramid. Figure 2 shows the image decomposition for a pyramid with three levels where we have three images, x_1 (n_1, n_2), x_2 (n_1, n_2), and x_3 (n_1, n_2), that represent the image in the spatial domain at different resolutions. X_1 (k_1, k_2), X_2 (k_1, k_2), and X_3 (k_1, k_2) are their corresponding representations in the frequency domain using the overlapped DCT.

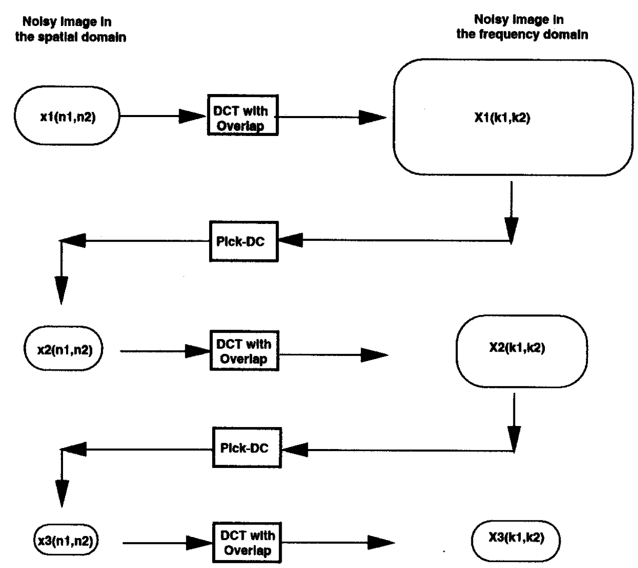

Figure 2. Image decomposition.

4. Wiener Filtering

The pioneering work of Norbert Wiener was an important cornerstone for many of the current and past successful image restoration methods. Even though his work on finding the best filter, using the mean square error as criteria, was done in 1942, it was not until the mid 1960s that his ideas were applied to digital image processing at JPL in the early Ranger and Mariner missions.[3] Since then various image restoration methods have been developed by modifying the fundamental ideas that were presented by Wiener, in order to improve the performance and make the restoration methods more practical for the specific applications.

The frequency response of a wiener variant filter is shown below:

$$H(k_1,k_2)=\left(\frac{P_s(k_1,k_2)}{P_s(k_1,k_2)+\alpha P_v(k_1,k_2)}\right)^{\beta} \quad (2)$$

where (k_1, k_2) is the frequency response of the desired filter, $P_s(k_1, k_2)$ and $P_v(k_1, k_2)$ are the power spectrum of the input image and the estimated noise respectively. This filter is known in the literature as the generalized wiener filter because it is similar to the wiener filter but with two extra parameters α and β.

The wiener filter affects the spectral magnitude of the processed signal in the following manner: for high signal-to-noise ration (SNR) i.e. $P_s(k_1, k_2) >> P_v(k_1, k_2)$ the signal is preserved while for low SNR the signal is attenuated. Because the characteristics of both the image and the noise might change considerably over different regions of the image (non-stationary noise) we compute different filters for each DCT blocks. After the wiener filter is determined in the frequency domain, each of the DCT blocks is point-by-point multiplied by the frequency domain wiener filter. For instance in our example, shown in Figure 3, the filtering step is repeated for each DCT block in the base level of the pyramid, $X_1(k_1, k_2)$ and the filtered image in the frequency domain is denoted by $X_1F(k_1, k_2)$. The same process is repeated for the second and third levels of the pyramid, $X_2(k_1, k_2)$ and $X_3(k_1, k_2)$ to obtain $X_2F(k_1, k_2)$ and $X_3F(k_1, k_2)$. For some systems, it is desirable to sharpen the image to enhance its appearance for human viewers. In our flexible system, this can be easily done because the image is represented in the overlapped frequency domain.

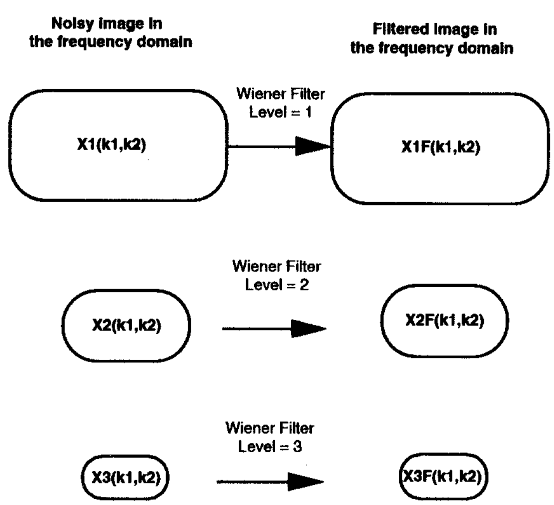

Figure 3. Wiener filtering stage.

5. Image Reconstruction in the Pyramid Representation

In this stage, the processing starts at the highest level of the pyramid, which is the third level in our discussion. Figure 4 shows a block diagram of the image reconstruction for a three level pyramid. The filtered image at the third level, $X_3F(k_1, k_2)$, is taken as an input and an 8×8 inverse DCT (IDCT) is performed on each block. Because of the overlap in the DCT stage, the middle 4×4 region of each filtered and inveresed block is saved (IDCT with save) to form the filtered image in the spatial domain of the third level in the pyramid, Each pixel value of the filtered image in the third level of the pyramid, $x_3f(n_1, n_2)$, represents a modified DC coefficients from the DCT image of the second level of the pyramid, $X_2F(k_1, k_2)$. Therefore, every pixel of the filtered image at the third level is inserted back into its corresponding DCT block in the second level of the pyramid. The process of taking 8×8 IDCT and saving the middle 4×4 region is repeated in the second level of the pyramid. The pixel values of the resulting filtered image of the second level, $x_2f(n_1, n_2)$. is inserted back into the DCT blocks of the first level of the pyramid, $X_1F(k_1, k_2)$. Finally, the 8×8 IDCT is performed on each block of the image in the first level, $X_1F(k_1, k_2)$ and the middle 4×4 of every block is saved to form the spatial filtered image in the first level, $x_1f(n_1, n_2)$. This resulting spatial image is considered as our best estimate of the uncorrupted image.

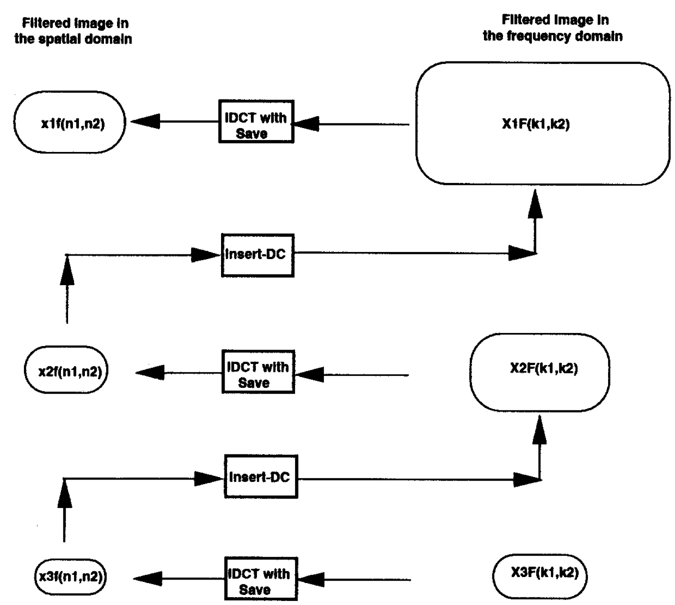

Figure 4. Image reconstruction.

6. Experimental Results

Figure 5 shows the effectiveness of the proposed noise reduction method. The top set shows a degraded image from an ESC camera with a small amount of noise in the red, green and blue channels on the upper-left corner, and the resulting image after performing noise reduction on the upper-right corner. Also demonstrated is the ability of the proposed method to reduce colored $(\bar{f})$ noise. The Lena image was degraded by adding $(\bar{f})$ noise. The degraded image is shown in the bottom-left corner and the noise reduced image is shown in the bottom-right corner of Figure 5. It is clear that not only has the high-frequency noise been reduced but the low-frequency noise has also been reduced using the low-resolution images in the pyramid representation.

Original Noisy Image

Noise Reduced Image

Original Noisy Image

Noise Reduced Image

Figure 5. Experimental results for an ESC picture and Lena

7. Concluding Remarks

Presented in this paper is a generic approach to performing noise reduction in a pyramid representation. Noise estimation and modeling are obtained for a given imaging system using flat-fields with different mean values. The image decomposition/reconstruction is performed using the block DCT which has fast implementation in software and hardware. The block DCT is recursively applied on the low frequency band to obtain images at different resolutions. This allows noise reduction in different resolutions inside of an imaging system. The actual filtering step is performed in the frequency domain using a variant wiener filter which can be coupled with a sharpening filter to further enhance the final image. From the theoretical and experimental results, it can be concluded that the proposed method allows noise reduction at different resolutions in the image for systems. that have frequency-dependent and non-stationary noise. Furthermore, the implementation is fast and efficient because it is based on the DCT, a tool that is widely used in image processing.

8. References

1. P. J. Burt and E. H. Adelson, "The Laplacian Pyramid as a Compact Image Code", *IEEE Trans. on COM*, Vol. **COM-31,** No. 4, April 1983.
2. W. B. Pennebaker and J. L. Mitchell, *JPEG Still Image Compression Standard.* Van Norstrand Rienhold, New York, 1993.
3. J. S. Lim *Two-dimensional Signal and Image Processing.* Englewood Ciiffs, N.J.: Prentice Hall, 1990.