

BLUR IDENTIFICATION AND CORRECTION FOR A GIVEN IMAGING SYSTEM

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Abstract - Estimating the blur function is the first step in all the image restoration techniques. A priori knowledge of the blur phenomenon helps improve the quality and certainty of image restoration. In this paper, a method of estimating the blur function for imaging setups that are not subject to change, for example surveillance cameras, is developed using the Wiener filter. A random noise image is used as a test image. Deconvolution is performed between the original test image and its observation taken from the given imaging system, to obtain the blur estimate for the system. Necessary preprocessing steps are implemented to compensate for the non-ideal nature of the imaging environment. Blur correction is then implemented on different observations taken from the same imaging system. The performance of the restoration is evaluated using Mean Square Error and Signal-to-Noise Ratio Improvement criteria.

1. DEGRADATION OF IMAGES

This paper deals with the identification of a blur function for an imaging system and blur correction by inverse filtering. The images obtained by various imaging systems are often degraded and are unsatisfactory to reveal all of the information present. Imperfections in the optical system, substandard imaging environment, and optical as well as electrical noise are the main causes of these degradations. Figure 1.1 shows a block diagram of a common electronic imaging system.

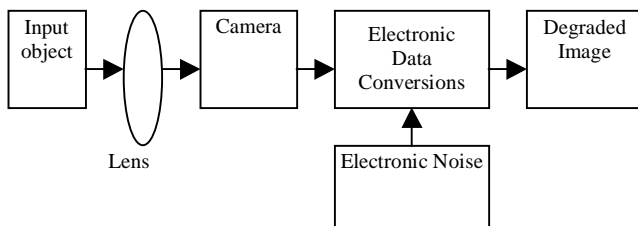


Figure 1.1: Image Degradation Model

The imaging system introduces distortions at different stages, starting from the optical components up to the electronic data conversions and recording of the images. The mathematical model for linear degradation caused by blurring and additive noise in a typical imaging system is given by (1.1) as stated below.

$$y(i, j) = \sum_{k=1}^M \sum_{l=1}^N h(i, j; k, l) f(k, l) + n(i, j) \quad (1.1)$$

where, $y(i, j)$ is the observed image, $f(i, j)$ is the original $M \times N$ image, $n(i, j)$ is the additive noise, and $h(i, j; k, l)$ is the two-dimensional point spread function (PSF) of the imaging system.

This PSF is generally spatially varying. In order to restore the images blurred with spatially varying PSF, one needs to know the directions and extent of change in the PSF with pixel position. This makes the image restoration problem more difficult and computationally complex. Therefore, a stationary model for a blur is typically used, as given below

$$y(i, j) = \sum_{k=1}^M \sum_{l=1}^N h(i-k, j-l) f(k, l) + n(i, j) \quad (1.2)$$

$$= h(i, j) ** f(i, j) + n(i, j)$$

where $**$ indicates two-dimensional convolution.

In most of the applications, an exact model of degradations is not available. It is seldom possible to model all of the distortions present in a system. The best one could do is model the degradations introduced by the imaging set-

up that is not subject to change. This paper demonstrates a method of deriving a model for a given imaging system using a Wiener filter. Standard test images are blurred using known degradation models and the estimates obtained by a Wiener filter are evaluated for accuracy against the original known blur models. The simulation helps to verify the performance of the Wiener filter algorithm when the exact PSF is known. Observations are taken for the test images through an imaging system and an attempt is made to obtain a blur estimate for the imaging system. The results from such an experiment will not be exact because not all of the possible degradations are being modeled, but significant improvement is still possible. The experimental set-up and required preprocessing steps to account for the nonideal nature of the imaging environment are described in Sections 4 and 5. The results are discussed in Section 6 and conclusions are summarized in Section 7.

2. THE DECONVOLUTION PROBLEM

The literal meaning of the word ‘deconvolution’ is ‘untangle’ or ‘unwind’. Mathematically, the word ‘deconvolution’ means separating the functions irreducibly from a convolution result. As can be seen from (1.2), the degraded image is a result of a two-dimensional convolution of the original image and the PSF of the imaging system. Hence, the problem of estimating the original image f , given the degraded image g and the PSF h , or the problem of estimating the blur PSF h , given the degraded image g and the original image f , becomes mathematically a deconvolution problem. The problem of estimating the original image f , given the other two functions g and h , is called the problem of image restoration, while the other problem is estimation of blur PSF for a given imaging system.

2.1 Difficulties in Solving the Deconvolution Problem

The Fourier domain techniques used to solve the deconvolution problem involve the computation of an inverse, which is an ill-posed and ill-conditioned problem. Problems for which the inverse transform does not exist are said to be *singular*. The singularity problem generally signifies that the data from the original image is lost. In addition to being a singular problem, image restoration is ill-conditioned because a trivial perturbation in the observation can produce nontrivial perturbations in the restored image [1]. The deconvolution problem has more than one solution due to the possibility of having a spurious component satisfying the pseudo-inverse.

2.2 The Wiener Filter

The Wiener filter is applied in the frequency domain. It is a technique based on the principle of least squares [2]. The filter is defined in such a way that it minimizes the mean square error between the actual output of the filter and

the desired output. The use of the Wiener filter assumes that in addition to the degradation model, the second order statistic of noise and the undegraded image is known. Let $S_r(n,m)$ and $S_f(n,m)$ be the power spectrum of noise and the original undegraded image, respectively. The Wiener filter is then defined as given in (2.1) [2]

$$F(n, m) = \frac{H^C(n, m)}{|H(n, m)|^2 + \gamma \frac{S_n(n, m)}{S_f(n, m)}} G(n, m) \quad (2.1)$$

where, $H^C(n,m)$ is the complex conjugate of $H(n,m)$ and the parameter γ selects the type of the Wiener filter that is implemented. For γ not equal to one, the Wiener filter is referred to as the parametric Wiener filter. The second term in the denominator controls the amplification of noise from the degraded image. This term has a small value at low frequencies, and the filter acts almost like a simple inverse filter. However at high frequencies the second term in the denominator becomes significant and reduces the amplification of noise.

Usually, the power spectral densities (PSD) of the noise and the original undegraded image are not known and the right hand term of the denominator of (2.1) is replaced with a constant K

$$F(n, m) = \frac{H^C(n, m)}{|H(n, m)|^2 + K} G(n, m). \quad (2.2)$$

The parameter K is adjusted until the best restored image is obtained. For $K=0$ the Wiener filter becomes the simple inverse filter. The restored image for $K=0$ is the sharpest image, but the noise is greatly enhanced. As the value of K is increased, the Wiener filter performs less restoration but does not enhance the noise present in the degraded image as much. So, choosing the Wiener filter parameter K is a trade off between sharpness of restoration and noise elimination.

The optimum Wiener filter parameter, K , can be found by varying K in steps and comparing the Mean Square Error (MSE) between the restored and original image. The Mean Square Error is defined as,

$$MSE = \sum_{i=1}^M \sum_{j=1}^N |y(i, j) - f(i, j)|^2 \quad (2.3)$$

where E is the average or expected value operator.

2.3 Use Of Wiener Filter For Estimation Of Blur In A Given Imaging System

This paper uses the Wiener filter for the estimation of blur in a given imaging system. The commutative property of convolution makes it possible to perform deconvolution between the degraded observation g and the original undegraded image f , to obtain the blur PSF h . The idea is to take the observations of known test images from a given imaging system so that the degraded images as well as the original undegraded image are known. Consider (1.2) again for a noise free case for simplicity as follows

$$y(i, j) = h(i, j) * f(i, j) \tag{2.4}$$

Here, y is the observation taken from the imaging system and f is the undegraded original test image, which is also now a known function. The Wiener inverse filter can be defined with the original test image f and applied to the observation g to obtain the PSF h . Precautions need to be taken while choosing the test image, so that the difficulty of the deconvolution resulting in a nonunique solution is conquered.

It is assumed that the imaging system is linear. Simple nonlinear effects are dealt with using preprocessing steps as described in Section 5. In this case, the Wiener filter will be defined as,

$$H(n, m) = \frac{F^C(n, m)}{|F(n, m)|^2 + K} G(n, m) \tag{2.5}$$

where $F^C(n, m)$ is the complex conjugate of the Fourier transform $F(n, m)$. This formulation of the Wiener filter is used to obtain the blur estimate as shown in Section 3.

3. CHOICE OF TEST IMAGE

The simulation described in this section demonstrates that the choice of test image is very important while implementing the (2.5). Six different test images are used in this simulation. A simulated blurred observation is obtained from each test image using the same known out of focus blur function. The Wiener filter is defined in each case using the corresponding known test image. The blur estimates derived are visually compared with the original known blur function. Also, mean square error is calculated between each estimated blur function and the original known blur function. The test image, which gives the minimum mean square error, would be selected as the best test image for estimating the blur function of a given imaging system.

The original blur function is displayed in Figure 3.1. Figure 3.2a shows the Test Image 0, which is a black square on a white background and the estimated blur function is shown in Figure 3.2b. Similarly, the following figures show

the estimated blur function with the corresponding test image for a few cases. The mean square error between the estimated blur function and the known blur function for each case is listed in Table 3.1.

The random noise test images are generated using the ‘RANDN’ command in MATLAB, which generates a matrix with random entries with a normal distribution. This matrix is then converted to black and white binary levels using a threshold such that 50% of the pixels are black and 50% are white. The resulting matrix has a mean of 0.5 and a variance of 0.5. Simply scaling the size of the matrix can vary the pixel size.

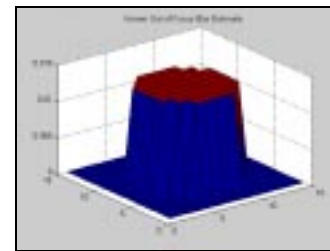


Figure 3.1 Known Out Of Focus Blur Function

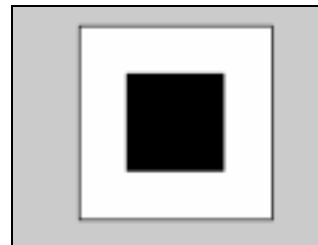


Figure 3.2a Test Image 0

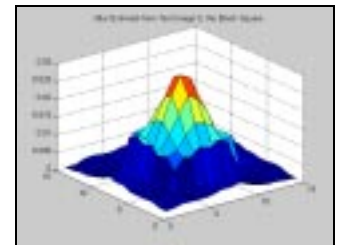


Figure 3.2b Estimated Blur Function for Case 0



Figure 3.3a Test Image 1

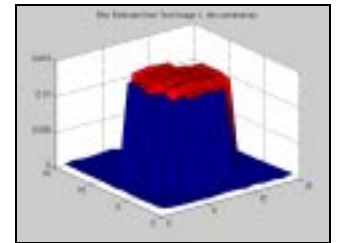


Figure 3.3b Estimated Blur Function for Case 1

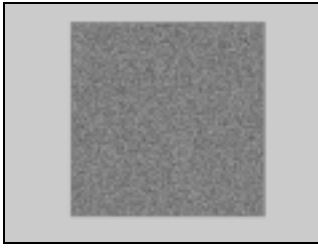


Figure 3.4a Test Image 2

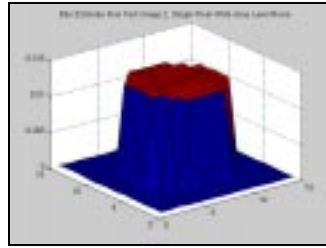


Figure 3.4b Estimated Blur Function for Case 2

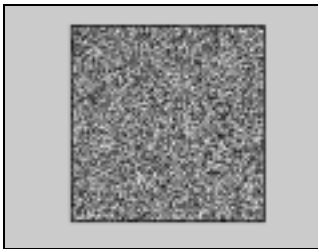


Figure 3.5a Test Image 3

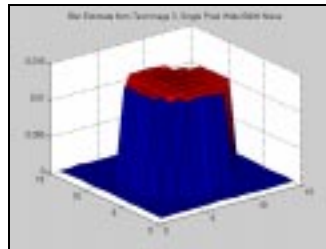


Figure 3.5b: Estimated Blur Function for Case 3

Table 3.1: Mean Square Error Comparison for Different Test Images

Test Image	Mean Square Error
Case 0: The Black Square on White Background	15.03
Case 1: The 'cameraman'	0.1426
Case 2: Single Pixel Wide Random Noise Gray Level Image	0.0092
Case 3: Single Pixel Wide Random Noise Black & White Image	0.0692
Case 4: Double Pixel Wide Random Noise Black & White Image	0.1392
Case 5: Four Pixel Wide Random Noise Black & White Image	1.3343

The simulation uses six different test images. The purpose of using these test images is to vary the frequency content of the test image and see the effect on the performance of the deconvolution algorithm. As can be seen from the Table 3.1, the Test Image 2, which is a single pixel

wide random noise gray level image, gives the least mean square error. If we look at the power spectrums of these test images, it can be seen that the Test Image 2 has the flattest spectrum. In other words, the Test Image 2, has the most uniform distribution of signal energy over all frequencies, and gives the most accurate blur estimate.

4. EXPERIMENTAL SETUP

A Panasonic VW SHM20, video camera was used throughout the experiments for this paper. The camera was mounted on a tripod, such that the axis of the camera is at 90 degrees to a vertical wall and approximately 4.5 feet away from the wall. Images were printed on a Lexmark Optra SC1275 printer and taped onto the wall to take an observation from the camera. All the automatic control features of the camera, such as the iris control, shutter control, and video gain were disabled and set to constant parameters. The aperture was kept at F2.4 and the shutter opening was fixed at 1/100. See Figure 4.1 for a graphic representation of the imaging setup used.

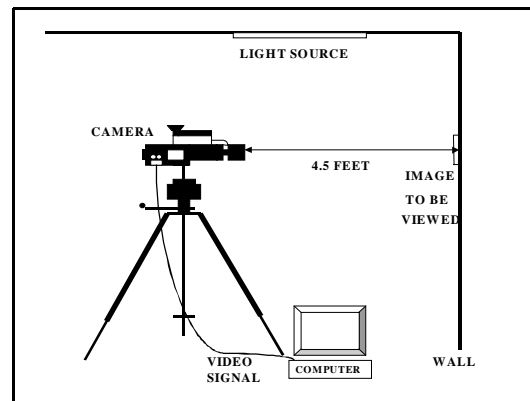


Figure 4.1: Experimental setup

5. PREPROCESSING STEPS

The imaging environment may not necessarily be an ideal setup. The object of interest is not always illuminated by a single uniform source of light. Also, there may be undesirable effects such as the misalignment of the axis of the imaging system with respect to the object of interest. It becomes necessary, therefore, that the image be preprocessed or compensated for such practical limitations of the imaging environment before applying any image restoration algorithm. Section 4 describes the imaging environment used for the experiments conducted during this work. Various preprocessing steps, viz. illumination correction, filtering, image registration, and gray level correction for compensating the camera sensor and printer nonlinearity were performed.

To correct the observations for uneven lighting effects, an intensity image of a plain white paper with same texture as the other test images was taken for each set of observations. This image was then fitted to a two dimensional surface, which served as the illumination pattern for the corresponding set of observations. The illumination pattern was subtracted from each of the observations and a constant value was added to avoid nonnegativity of pixel values. A black square marking the boundary of the image inserted in each of the test images served as the registration mark. Image registration was performed by locating the corners of the registration mark using some morphological operations and projections. A test image with sixteen known gray levels was used for deriving the nonlinear sensor response of the camera. The plot of observed gray levels versus the input gray levels was fitted to a third order equation and the inverse of this function was applied to each of the observations to obtain gray level correction.

6. EXPERIMENTAL RESULTS

The imaging set-up as described in Section 4 is used throughout the experiments. The test image is selected by examining the results from the simulation as stated in Table 3.1. According to the simulation results, the single pixel wide random noise gray level test image gives the least mean square error. Ideally, this should be used as a test image. But, the printer proved to be a limiting factor here. The half-toning effects and resolution limitation would smear the gray levels together, thus distorting the original test image. Therefore, the second best test image, which is the single pixel wide black and white random noise image, is chosen as the test image. The observation taken for this image is preprocessed and deconvolved using Wiener filter defined with the original test image to obtain the blur estimate. The amount of out of focus blur was varied in 8 steps during this experiment. The blur estimate for the second case is shown in Figure 6.1.

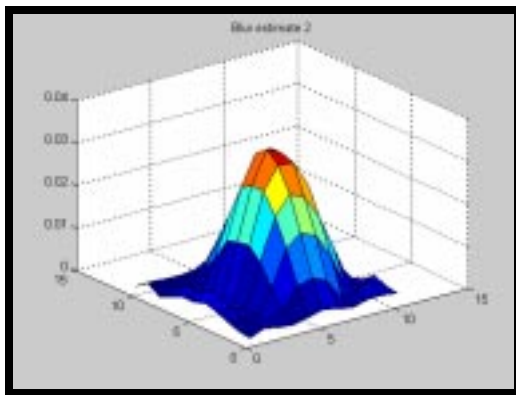


Figure 6.1 Estimated Blur Function for Given Imaging System

It was observed that the blur estimate becomes wider in spatial domain and decreases in the peak magnitude with increase in amount of defocus.

Image restoration was then performed on observations for other test images, using the estimated blur function. The optimum Wiener parameter was found in each case as described in Section 2.2. Figure 6.2a shows the original ‘cameraman’ image. Figure 6.2b and 6.2c show the corresponding observation and restored images.



Figure 6.2a Original Image 0



Figure 6.2b Observation 0



Figure 6.2c Restored Image

The performance of the restoration was evaluated by using two criteria, namely, the Mean Square Error (MSE) and the Signal-to-Noise Ratio Improvement (SNRI). Equation (6.1) and (6.2) define the MSE and SNRI respectively.

$$MSE(\hat{f}) = 100 \frac{\sum [a \hat{f}(x, y) - f(x, y)]^2}{\sum f^2(x, y)} \quad (6.1)$$

where, \hat{f} is the restored image, f is the original image, and 'a' is defined by (4.2).

$$a = \frac{\sum f(x, y) \hat{f}(x, y)}{\sum \hat{f}^2(x, y)} \quad (6.2)$$

The MSE between the observation and the original image is also calculated by substituting the observation $g(x, y)$ in place of $\hat{f}(x, y)$ in (6.1) and (6.2). The performance evaluation criterion called the signal-to-noise ratio improvement (SNRI) is then calculated using (6.3).

$$SNRI = \frac{MSE(g)}{MSE(\hat{f})} \quad (6.3)$$

Table 6.2 lists the MSE and SNRI for the restoration results shown in Figure 6.2.

Table 6.2: MSE and SNRI for Case 0

	$MSE(\hat{f})$	$MSE(g)$	SNRI
Observation 0, 'cameraman'	0.0221	0.1066	4.82749

7. CONCLUSION

The purpose of this work was to simulate and implement an image enhancement method, which measures the blur function of the imaging system. Evaluation of the

performance and investigation of possible methods of improvement were also the important tasks. The Wiener filtering technique is used successfully to model out of focus blur introduced by the given imaging system. Wiener filter is used for estimating the blur function as well as for image restoration. Advantages of the Wiener filter over the simple inverse filter are evident due to the ability of the Wiener filter to suppress noise.

The computer simulations give a good insight to the deconvolution problem. Choosing a test image with all frequencies in it simplifies the problem of finding a unique solution to a deconvolution problem. The simulation results demonstrate that a random noise test image with 256 gray levels is the best test image. But in the experiments conducted with the real imaging system, this image had to be thresholded to binary levels owing to limitations with the printer resolution. This alters the frequency content of the test image, but is still satisfactory.

The out of focus blur function for the imaging system used in the experiments can be approximated by a Gaussian function. Ideally, a circular disc models an out of focus blur function. The electronic circuitry in the digital camera has a low pass filter effect, which explains the Gaussian nature of the actual blur function as opposed to a uniform circular disc.

The out of focus blur function becomes wider in spatial domain with increase in amount of defocus. This leads to a narrower PSF in the frequency domain, making the data over a larger frequency range unrecoverable. The data at higher frequencies is not only attenuated but also is highly corrupted due to a very low signal-to-noise ratio. There is no way to recover the data, which is lost.

The percentage Mean Square Error (MSE) and Signal-to-Noise Ratio Improvement (SNRI) are effective criteria to evaluate the performance of restoration algorithm as long as the image registration is accurate. The restoration results show significant improvement perceptually as well as with the MSE and SNRI criteria. Thus, the proposed method for estimating the blur function and improving the quality of restoration works successfully. It is also clear that further improvements are possible, though beyond the scope of this paper.

8. REFERENCES

- [1] Andrews H. C. and Hunt B. R., *Digital Image Restoration*. Englewood Cliffs, NJ: Prentice Hall, 1977.
- [2] Gonzalez Rafael C. and Woods Richard E., *Digital Image Processing*. New York: Addison-Wesley Publishing Company Inc., 1993.