Chapter 4

Deblurring (Two-Tone Images)

4.1 Introduction
Images get blurred because of the degradations due to the imaging system and environment including an out-of-focus camera or an imaging instrument of insufficient resolution [122]-[224]. If the blur is not properly removed, the performance of recognisers can deteriorate severely. Classical deblurring procedures assume a priori knowledge of the blur parameters. In many cases, the blur can be more complicated and generally unknown even to within a parametric family of models. In this chapter, we consider the problem of isolating the linear blur noise. A number of methods have been proposed in the past to deal with blind image restoration problem i.e. recovery of the original image from a linearly degraded version without complete a priori knowledge of the degradation process for a recent review on this subject. The blur filter is also known up to an additive error term, which is Gaussian white noise. The blurring, or degradation, of an image can be caused by many factors:
- Movement during the image capture process, by the camera or, when long exposure times are used, by the subject
- Out-of-focus optics, use of a wide-angle lens, atmospheric turbulence, or a short exposure time, which reduce the number of photons captured
- Scattered light distortion in co focal microscopy
A blurred or degraded image can be approximately described by this equation
\[ g = Hf + n, \quad \ldots \quad 4.1 \]

\[ G \] The blurred image
\[ H \] The distortion operator, also called the point spread function (PSF). This function, when convolved with the image, creates the distortion.
\[ F \] The original true image
\[ N \] Additive noise, introduced during image acquisition, that corrupts the image

Wiener deconvolution can be used effectively when the frequency characteristics of the image and additive noise are known, to at least some degree. In the absence of noise, the Wiener filter reduces to the ideal inverse filter

4.1.1 WIENER FILTERING

The most important restoration technique for removal of blur in images due to linear motion or unfocussed optics is the Wiener filter. Wiener filtering is a method of restoring Images in presence of blur as well as noise. In other words wiener filtering is an approach that incorporates both the degradation function and statistical characteristics of noise into
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the restoration process. From a signal-processing standpoint, blurring due to linear motion in a photograph is the result of poor sampling. Each pixel in a digital representation of the photograph should represent the intensity of a single stationary point in front of the camera. Unfortunately, if the shutter speed is too slow and the camera is in motion, a given pixel will be an amalgam of intensities from points along the line of the camera's motion. The method is founded on considering images and noise as random processes, and the objective is to find an estimate \( y \) of the uncorrupted image \( f \) such that the mean square error between them is minimized. This error function is given by

\[
e^2 = E\{ (f - y)^2 \} \tag{4.2}
\]

Where \( E \{ \} \) is the expected value of the argument. It is assumed that the noise and the image are uncorrelated; that is one or the other has zero mean; and that the gray levels in the estimate are a linear function of the levels in the degradation image.

4.1.2 Two-Tone Images

A new statistical method is proposed for deblurring two-tone images, i.e., images with two unknown gray levels, that are blurred by an unknown linear filler. The key idea of the proposed method is to adjust a deblurring filter until its output becomes two-tone. Two optimization criteria are proposed for the adjustment of the deblurring filter. A three-step iterative algorithm (TSIA) is also proposed to minimize the criteria. It is proven mathematically that by minimizing either of the criteria, the original (non-blurred) image, along with the blur filter, will be recovered uniquely (only with possible scale/shift ambiguities) at high SNR. The recovery is guaranteed not only for i.i.d. Images but also for correlated and non-stationary images. It does not require a priori knowledge of the statistical parameters or the tone values of the original image; neither does it require a priori knowledge of the blur filter.

4.2 Various Techniques

The key idea of the method explained is to linearly filter the blurred image until a two-tone image is obtained at the filter output. Two optimization criteria are employed to guide the adjustment of the filter (or its parameters). Under very mild conditions, we prove mathematically that the minimization of either criterion leads to the desired solution of the problem: unique recovery of the original image and the blur filter (with only possible scale and/or shift ambiguities), which is guaranteed when the SNR is sufficiently high. The criteria can be minimized numerically by standard optimization routines. As an example, a three step iterative algorithm (TSIA) is considered that repeats the cycle of image filtering, tone updating, and filter updating.

The main difficulties in the application of the TV penalty methods are related to the solution of a highly nonlinear second-order PDE and to the non-differentiability of the TV functional. Many attempts to overcome such difficulties can be explained. Here it is suggested that an alternative approach can be used which is based on an approximation of the TV functional. The solution, as in the classical approach, is formulated as a time-dependent nonlinear PDE, and it produces an isotropic diffusion of the initial data. It is
well known that the classical and isotropic diffusion method is ill posed, in the sense that
it corresponds to the steepest decent method applied to the minimization of an energy
functional having an infinite number of global minima, which are dense in the image
space. Instead, Murli derived filter from the minimization of a convex functional having a
unique global minimum. The idea is based on the fact that the edge-preserving property
of the total variation functional, as in other discontinuity adaptive regularization methods.
It depends on the behavior of the so-called potential function at infinity, rather than its
behavior at the origin. Murli proposed a nonlinear iterative smoothing filter based on a
second-order partial differential. It smoothes out the image according to an isotropic
diffusion process. The approach is based on a smooth approximation of the total variation
(TV) functional, which overcomes the non-differentiability of the TV functional at the
origin. In particular, the method performs linear smoothing over smooth areas but
selective smoothing over edges. By relating the smoothing parameter to the time step,
they arrive at a condition, which guarantees the causality of the discrete scheme. This
allows the adoption of higher time discretization steps, while ensuring the absence of
artifacts deriving from the non-smooth behavior of the TV functional at the origin. It is
possible to avoid the typical staircase effects in smooth areas, which occurs in the
standard TV scheme.

In many image restoration/resolution enhancement applications, the blurring process, i.e.
point spread function (PSF) of the imaging system, is not known or is known only to
within a set of parameters. PSF parameters for this ill-posed class of inverse problem is
estimated from raw data, along with the regularization parameters required to stabilize
the solution, using the generalized cross-validation method (GCV). Few techniques are
based on the Lanczos algorithm and Gauss quadrature theory, reducing the computational
complexity of the GCV. Data-driven PSF and regularization parameter estimation
experiments with synthetic and real image sequences have been demonstrated. Robust
techniques for solving restoration and resolution enhancement in imperfectly known
imaging conditions should be considered.

A new class of the “frequency domain” – based signal/image enhancement algorithms
including magnitude reduction, log-magnitude reduction, iterative magnitude and a log-
reduction zonal magnitude technique can also be used. These algorithms are known and
applied for detection and visualization of objects within an image. These techniques are
based on the so-called sequence ordered orthogonal transforms, which include the well-
known Fourier, Hartley, cosine, and Hadamard transform, as well as new enhancement
parametric operators. A wide range of image characteristics can be obtained from a single
transform, by varying the parameters of the operators. We also introduce a quantifying
method to measure signal/image enhancement called EME. This helps choose the best
parameters and transform for each enhancement.

A new class of the fast trigonometric systems is used for performing the transform
coefficients manipulation operations. A quantitative of image enhancement is introduced.
The techniques developed has been successfully employed on NASA’s Earth Observing
system, satellite data products for the purpose of anomaly detection and visualization.
These satellites collect a Tera-byte of data per day, and fast and efficient methods are crucial for analyzing these data.

A new wavelet-based image denoising method, which extends a recently emerged "geometrical" Bayesian framework can also be used. The new method combines three criteria for distinguishing supposedly useful coefficients from noise i.e. coefficient magnitudes, their evolution across scales and spatial clustering of large coefficients near image edges. These three criteria are combined in a Bayesian framework. The spatial clustering properties are expressed in a prior model. The statistical properties concerning coefficient magnitudes and their evolution across scales are expressed in a joint conditional model. The three main novelties with respect to related approaches are 1) the interscale-ratios of wavelet coefficients are statistically characterized and different local criteria for distinguishing useful coefficients from noise are evaluated, 2) a joint conditional model is introduced, and 3) a novel an isotropic Markov random field prior model is proposed. The results demonstrate an improved denoising performance over related earlier techniques.

The geometrical Bayesian approach may be further extended. The three main novelties are 1) a statistical characterization of different significance measures for wavelet coefficients and a comparative evaluation of their performance, 2) a joint conditional model, which combines local inter and intrascale statistical properties, and 3) a novel, an isotropic MRF prior model. Such a performance evaluation clearly motivates a joint significance of measure, which relies on both coefficient magnitudes and on their evolution across scales. The resulting, joint conditional model offers a superior denoising performance with respect to earlier ones that use interscale ratios only, or coefficient magnitudes only. A new an isotropic prior model preserves well finest image details. As compared to the isotropic one, it introduces minor increase in complexity, but preserves image details significantly better.

The problem of phase image denoising can be addressed through nonlinear (NL) filtering. There are various imaging systems in which the phase information is utilized to generate useful imaging data. However, the presence of noise makes difficult to obtain the appropriate phase image. The authors apply NL vector filtering techniques to denoise the complex data from which the phase image is extracted. A study was realized in which several NL filters were applied to a simulated complex image. The effects of filtering were determined through a Monte Carlo simulation in which the image was successively contaminated with six different noise models. The effectiveness of the filters was measured in terms of normalized mean square error, signal-to-noise ratio and the number of eliminated phase residue. Results indicate a significant noise reduction, especially when NL filters based on angular distances are applied to the noisy input.

In many situations, the complex data from which the phase image is extracted. In these cases, the application of NL vector filters can be a valuable alternative for noise filtering. NL vector filters have demonstrated excellent noise reduction properties in applications to color image and multi-channel signal processing. The problem of phase image denoising can be addressed through nonlinear filtering. A number of NL vector filters
commonly used for multi-channel signal processing were applied to the complex images. Their properties in reducing phase image noise and eliminating phase residues are studied. The latter problem is important, as phase unwrapping. Results indicate a significant noise reduction in terms of signal to noise ratio (SNR) and suppression of phase residues. Especially for the angular-distance based NL filters.

Signal and image enhancement is considered in the context of a new type of diffusion process that simultaneously enhances, sharpens, and denoise images. The nonlinear diffusion coefficient is locally adjusted according to image features such as edges, textures, and moments. As such, it can switch the diffusion process from a forward to a backward (inverse) mode according to a given set of criteria. This results in a forward and backward (FAB) adaptive diffusion process that enhances features while locally denoising smoother segments of the signal or image. Another method, using the FAB process, can be applied in a super-resolution scheme. The FAB method is further generalized for color processing via the Beltramin flow, by adaptively modifying the structure tensor that controls the nonlinear diffusion process. The proposed structure tensor that controls the nonlinear diffusion process. The proposed structure tensor is neither positive definite nor negative, and switches between these states according to image features. This results in a forward-and-backward diffusion flow where different regions of the image are either forward or backward diffused according to the local geometry within a neighborhood. The aim of this study is to further extend the nonlinear PDE-based filtering methods, and to apply them in signal and image enhancement and sharpening. We focus on enhancing and sharpening blurry signals, while still allowing some additive noise to interfere with the process. We may minimize the effect of amplification of noise—an inherent byproduct of signal sharpening—by combining backward and forward diffusion processes. We may then generalize the analysis of by the introduction of a generalized local adaptive criterion for the forward-and-backward diffusion in sharpening and denoising of color images.

4.3 MUSIC & ESPRIT for deblurring

Pole-zero models assume a linear time-invariant system that gets excited by white noise. However, in many applications the signals of interest are complex exponentials contained in white noise for which the sinusoid or the harmonic models are more useful. Signals consisting of the complex exponentials are termed as formant frequencies in speech, moving targets in radar.

4.3.1 ESPRIT Algorithm

A frequency estimation technique that is built upon the same principles as other subspace methods but further exploits a deterministic relationship between subspaces is the estimation of signal parameters via rotational invariance techniques (ESPRIT) algorithm. This method differs from the other subspace methods in that the signal subspace is estimated from the data matrix $X$ rather than the estimated correlation matrix $\mathbf{R}_x$. The essence of ESPRIT lies in the rotational property between staggered subspaces that is invoked to produce the frequency estimates. In the case of a discrete-time signal or time
series, this property relies on observations of the signal over two identical intervals staggered in time. This condition arises naturally for discrete-time signals, provided that the sampling is performed uniformly in time. We first describe the original, least-squares version of the algorithm (Roy et al. 1986) and then extend the derivation to total least-squares ESPRIT (Roy and Kailath 1989), which is the preferred method for use. Since the derivation of the algorithm requires an extensive amount of formulation and matrix manipulations, we have included a block diagram in Figure 4.1 to be used as a guide thorough this process.

**FIGURE 4.1**
Block diagram demonstrating the flow of the ESPRIT algorithm starting from the data matrix through the frequency estimates.
4.3.1 Results

\textbf{Figure 4.2} (Normalized Frequency of the blurred image)

\textbf{Figure 4.3} Result of ESPRIT ALGORITHM

\textbf{Figure 4.4} a) Blurred Sample  b) DeBlurred Sample of 4.4(a)
Figures 4.4 and 4.5 demonstrate the detection of the blur-noise frequency. Once the frequency of the Linear White Noise has been found there after it becomes very easy to design a spatial filter for blur removal. Spatial-Filter will be applied to the row vector in an image. Being a two-tone image there are two possibilities of change in the grey scale i.e either black to white or white to black. Let us call the spatio-filter term as below:

$$S = \frac{1}{NF} \quad \text{(4.3)}$$

In case of black to white this 1D filter has to be additive and in the second case it will subtract. Figure 4.6 show the length of the blur noise and the detected blur normalized frequency, which makes the things clear.

**Figure 4.5** a) Damping Factor using Esprit Algo. On Figure 4.4(a) b) Noise Frequency of Sample 4.4(a)

**Figure 4.6** a, b, c, d, e are 2, 4, 6, 10 and 18 point blur sequences and a', b', c', d' and e' shows the normalized frequencies of the blur.
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Table 4.1 Linear Blur Sequence

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Figure 4.7 Graph showing the detected linear blur.

4.4 Summary

This method shows an easy approach to remove the linear blur due to scanner-produced blur. Of course in case of Non-Linear blur, this method will not work. Method is not the replacement of the Weiner filters rather this design and simulation work is much simpler and secondly the original image is not required to be predicted as in the case of Weiner Filter. Here the noise term is detected from the non-signal area, which is much safer as compared to the earlier designs.