CHAPTER 2

ANALYSIS

Many techniques have been developed for removing degradations from images. Most of them have been developed for a particular problem in a specific field. Hence, the underlying algorithms differ from each other in many aspects. Some techniques have been developed to improve on other existing methods, while others use a completely different paradigm. This chapter focuses on some common algorithms/techniques used for the removal of degradations from images. To be able to carry out an analysis, the methods are briefly described in terms of the types of defects they aim to restore, the complexity, the degree of user involvement, the speed of execution and the results that has been obtained from known experiments.

2.1 Restoration with commercial software

Many professional photo retouchers commonly use commercial software for restoring damaged photographs [ADAI02, BRAV98, COBU98, KAYS03]. The user needs to perform all operations manually i.e. the user needs to detect the defect and provide correction manually. The process is very complex and time consuming, and usually requires some training. However, the results are impressive as almost any type of defect can be restored.

2.2 Bayesian Methods

Bayesian methods [DJAF93, MOLI01] are probabilistic methods that use the concept of prior knowledge (or expectations) on the expected structure within an image such that assumptions about the real underlying image are made and thereafter, the validity of the image model is tested. The term '*prior* 'is used since this prior knowledge makes no reference to the data and hence, can be decided on *a priori*, i.e. before the act of making the measurement. The *a priori* information can be either in a deterministic form or in a probabilistic form like mean values, variance values or in general some constraints on the probability density functions.

After modeling the available prior knowledge by means of probability density functions, the Bayes formula provides a posterior probability density function that contains all information concerning the uncertainty in the measured data and available prior knowledge. In other words, Bayesian methods use all the available information to constrain the range of solutions and then select the most likely solution given what is known. The resultant image is an optimal trade-off between the measured data and the imposed prior knowledge. In cases where no specific prior knowledge is available, it is impossible to impose a probability density function for individual object pixels. Hence, general image characteristics must be used and incorporated to impose some global characteristics upon the image. Bayesian methods are used in the restoration of blurry and noisy (with specific distributions) images. Two popular methods that are based on the Bayesian model are the maximum likelihood method and the maximum entropy method.

The likelihood of a set of data is the probability of obtaining that particular set of data given the chosen probability model. **Maximum likelihood methods** [FRIE72] seek the maximization of this likelihood function, resulting in an image for which the measurements have the highest probability. However, given the ill-posed nature of the image reconstruction problem, the maximum likelihood solution is very sensitive to noise. To avoid this problem, it is necessary to stop the iterations of the algorithm before reaching the point of maximum likelihood.

The **maximum-entropy method** (MEM) [PUYA98, FRIE72] adopts an entropic form as prior distribution. Entropy is a measure that assigns a positive weight to all possible configurations not excluded by the given information. The MEM prior is a global constraint and therefore MEM enforces an average smoothness on the entire image and does not recognize that the density of information content in the image varies from location to location. Unlike other methods, such as maximum likelihood, this maximum entropy method returns a unique solution even for ill-posed problems.

2.3 Richardson-Lucy Method

One of the most widely used image restoration method in astronomy is the Richardson-Lucy algorithm [RICH72, LUCY74]. This algorithm was initially derived from Bayes theorem and shown to increase the likelihood assigned to the observed image. The method restores blurry images, assuming that the blurring function is known. The original algorithm has been improved into several other techniques [LUCY94, SHEP82, VARD85] mainly to reduce the computational requirements and to deal with other types of noise distribution.

2.4 Pixon-based Methods

The Pixon Method [PUET95a, PUYA98] was originally developed by research physicist Richard Puetter and graduate student Robert Pina at the University of California San Diego (UCSD) in 1992/93. Pixon-based methods are derived from the Bayesian model but also integrate information theory concepts. The Pixon representation of an image is the one with the smallest number of parameters necessary to completely specify the signal in the data. The goal of the Pixon method model is to construct the simplest, i.e. smoothest, model for the image that is consistent with the data. Unlike Bayesian methods, the Pixon method does not assign explicit prior probabilities to image models. Instead, it restricts them by seeking minimum complexity which not only enables an efficient representation of the image but is also the best way to separate signal from noise. The selection of the simplest plausible model of the image can be viewed in this way: if the signal in the image can be adequately represented by a minimum of P parameters, adding another parameter only serves to introduce artifacts by fitting the noise. Conversely, the removal of a parameter results in an improper representation of the image, since adequate fits to the image require a minimum of P parameters.

While the performance of the original Pixon method was very good, the computational speed of the method was quite slow. Consequently, the method could only be used on small imaging projects unless very powerful computers were used, and even then the computation times could last days or more. Faster versions of this method (like the Accelerated Pixon method or the Quick Pixon method) have been implemented since then. For example, the Quick Pixon method is reported [PIXO02] to take about 200 seconds to restore the 512x512 pixel image of 'Lena' on a desktop computer (200 MHz Pentium Pro). The Pixon methods are used to reconstruct images from blurred, noisy data. Although the initial application of the Pixon method was to astronomical imaging, it can provide strong benefits to all kinds of imaging systems: medical, geophysical, surveillance, radar, and sonar, as well as to data archiving and communication, for example, image compression, and voice and video encoding and playback.

2.5 Wiener Filter

The Wiener filter [WIEN49] is used to restore images degraded by additive noise and blurring. The objective of the Wiener filter is to find an estimate of the original image such that the mean square error between the original image and the degraded image is minimized in the process of inverse filtering and noise smoothing. The following equation characterizes the Wiener Filter:

$$R_w(u,v) = \frac{H^*(u,v)}{\left|H(u,v)\right|^2 + \left[\dfrac{S_n(u,v)}{S_I(u,v)}\right]}$$

where

(i) $H^*(u,v)$ is the complex conjugate of $H(u, v)$

(ii) $\left|H(u,v)\right|^2 = H^*(u,v)\ H(u, v)$

(iii) $S_n(u,v) = \left|N(u,v)\right|^2$ = power spectrum of the noise

(iv) $S_I(u,v) = \left|I(u,v)\right|^2$ = power spectrum of the original image

The Wiener filter is usually applied in the frequency domain. Hence, the filter is applied by multiplying it by the Fourier transform of the degraded image, *D(u,v)*, and the restored image is obtained by taking the inverse Fourier Transform of the result:

$$\hat{I}(r,c) = \Im^{-1}\left[\hat{I}(u,v)\right] = \Im^{-1}\left[R_w(u,v)D(u,v)\right]$$

where $\hat{I}(r,c)$ is the restored image and $\Im^{-1}$ is the inverse Fourier transform. To be able to apply the Wiener Filter, some knowledge of the original image must be known in order to perform the restoration effectively. But in practical cases, the power spectrum of the original image is not known. Hence the power spectrum ratio $\left[\frac{S_n(u,v)}{S_I(u,v)}\right]$ is often approximated by a parameter *K*, which is a specified constant.

2.6 Digital Image Inpainting

2.6.1 Technique 1

Bertalmio *et al.* [BERT00] developed the very first digital image inpainting algorithm, which is based on a partial differential equation model. The user must specify the portions of the input image to be retouched. The algorithm then treats the input image as three separate channels (R, G and B) and for each channel, fills in the areas to be inpainted by propagating information from the outside of the masked region. The restoration procedure is completely automatic, since the user does not have to specify where the novel information comes from. Another special type of diffusion is also applied in the same algorithm to preserve edges across the inpainted region. Applications of this technique include the restoration of old photographs and damaged film; removal of superimposed text like dates, subtitles, or publicity; and the removal of entire objects from the image like microphones or wires in special effects. But as it is the case with all inpainting techniques, the technique does not take into consideration any information present in the region to be inpainted. The CPU time required for inpainting depends on the size of the region to be inpainted only. From [BERT00], the image shown in Figure 2.0 took approximately 7 minutes to be restored, but if a two-level multiresolution approach is used[1], the processing time can be reduced to 2 minutes only. These times were measured on a 300 MHz Pentium II PC (128 MB of memory under Linux).

[1] The converged result of a lower resolution stage is used to initialize the higher one.

Figure 2.1: A*n old photograph to be restored. The red region represents the noise mask.*

2.6.2 Technique 2

Oliveira *et al.* [OLIV01] developed an inpainting technique that aims to fill in missing areas in an image by a diffusion process. The border of the region to be inpainted is convolved with a predefined mask for a number of iterations (the authors suggest a value of 100). This operation is repeated until the whole region is processed; each time the border already processed is removed from the noise region so that a new border is defined from the remaining area. The technique requires manual identification of the area to be inpainted and also requires the user to indicate where edges are located so that the boundaries between any two distinct regions remain sharp. The technique can be used in the restoration of old photographs and damaged film and removal of unwanted objects in images, provided the region to be inpainted is locally small. The image shown in Figure 2.0 was restored with this algorithm in 1.21 seconds (measured on a Pentium III, 450 MHz using 128 MB of memory under Windows 98).

2.7 Image Noise Removal Algorithm

The image noise removal method [HITO96a, HITO96b] has been initially developed to remove scratches or wires (for special effects purposes) in films. The user needs to identify the noisy region manually, and needs to indicate a reference sample subimage, as well as a repair subimage, based upon which the restoration process will operate. The repair subimage is a region that contains the noise pixels and some part of the area surrounding these pixels. The sample subimage is another region in the same image that is similar to the repair subimage, but which does not contain the noise pixels. The method combines information from both the frequency and the spatial domain to restore the defective area. Processing in the frequency domain involves comparing the Fourier spectrum of the repair subimage with that of the sample subimage, and consequently reshaping the repair subimage spectrum according to defined conditions. Spatial domain processing involves clipping intensity values and replacing pixels around the noise region. The algorithm deals mainly with texture synthesis, and not with structured background [BERT00]. The method can be used to remove cracks, scratches, blotches and small objects from images, provided an appropriate reference subimage can be identified by the user.

2.8 Line Scratch Correction Algorithm

The Line Scratch Correction Algorithm (LSCA) [TENZ03] has been specifically developed to remove line scratches from old films. Since these line scratches are mostly due to particles in the projector mechanism, the scratches run more or less in the vertical direction. This method is applied to each video frame, and does not take into account previous or succeeding frames. Therefore, it can also be applied to images, but its effect is limited to vertical lines only. The location of the line needs to be specified by the user, but the restoration process thereafter is completely automatic. LSCA aims to reconstruct the degraded image via an approximation of the uncorrupted image by horizontally interpolating the values in the line and thereafter applying an additive-multiplicative model.

2.9 Semi-Transparent Blotch Removal Algorithm

This algorithm was developed by Stanco *et al.* [STRT03] to restore semi-transparent blotches (or water blotches) in vintage photographic prints. It works in two steps:

1. The first step is based on an additive-multiplicative model, the optimal parameters of which are searched for around the area to be restored. This step restores pixels inside the semi-transparent blotch.

2. The second step performs an interpolation along the gradient direction on the contour to restore the darker contour.

Only the region where the blotch is situated is processed and only one iteration of the above algorithm is required, hence, the method executes quickly.

2.10 Summary

In this chapter, we have presented some techniques that are used in image reconstruction and image inpainting. Techniques that have been developed for a particular field usually remove only specific types of degradation. For example, the Pixon-based methods or the Richardson-Lucy technique are used in the restoration of noisy or blurry images that are common in astronomical imaging. Techniques which are used for the removal of defects like scratches, cracks or blotches usually require manual detection of the defect but thereafter most of them provide an automatic restoration process. Table 2.1 summarizes the different techniques presented in this chapter.

	Author(s)	Works on whole/part of image	Type of degradation targeted for restoration	Defect detection	Restoration process	Takes into account original image information
Restoration with commercial software	[ADAI02, BRAV98, COBU98, KAYS03]	Both	All	Manual	Manual	Yes
Bayesian Methods	Frieden [FRIE72]	Whole	Noise, blur	Automatic	Automatic	Yes
Digital Image Inpainting Techniques	Bertalmio *et al.* [BERT00], Oliveira *et al.* [OLIV01]	Part	Damages in old photographs and films; superimposed objects; removal of entire objects	Manual	Automatic	No
Image Noise Removal Algorithm	Hirani and Totsuka [HITO96a]	Part	Scratches, blotches, wire removal	Manual	Semi-automatic	No
LSCA	Tenze and Ramponi [TENZ03]	Part	Straight lines (scratches, cracks)	Manual	Automatic	No
Pixon-based Methods	Puetter and Pina [PUET95a]	Whole	Noise, Blur	Automatic	Automatic	Yes
Richardson-Lucy Technique	Richardson and Lucy [RICH72, LUCY74]	Whole	Noise, Blur	Automatic	Automatic	Yes
Semi-transparent Blotch Removal Algorithm	Stanco *et al.* [STRT03]	Part	Semi-transparent blotches	Manual	Automatic	Yes
Wiener Filter	Wiener [WIEN49]	Whole	Blur, additive noise	Automatic	Automatic	Yes

Table 2.1: *Existing restoration techniques*