Chapter 5

Autocorrelation-driven restoration of scanned color halftones

"An optimist is a person who sees a green light everywhere, while a pessimist sees only the red stoplight... The truly wise person is colorblind."

—Albert Schweitzer

Color is experiencing a renaissance in the world of document image understanding. This renewed interest is due, in part, to the ubiquity of inexpensive color scanners on desktops, as well as the availability of cheap disk space and powerful CPUs. Compounding this, the proliferation of mass produced color documents, in concert with advances in commodity color scanning technology, creates the expectation that document understanding systems cope effectively with color. The increasing computation power and storage capacity of desktop workstations at least admits the possibility that color document understanding systems can be built.

Color documents, particularly scanned halftone documents, present unique challenges to document understanding systems. Switching to color analysis immediately causes a combinatorial increase in representation alone, and solved problems in the binary or greyscale domain become open issues again. Even the problems of foreground/background separation and layout segmentation are affected by uncertainty introduced by color. Indeed, most research on the topic has been limited to attempting to cope with the complexity introduced by color, and researchers have not begun exploiting the potential richness in representation that color offers. Typical approaches to reducing this complexity include color clustering in RGB-space [100, 119], which clusters colors that are close in the RGB-cube under the assumption that they are close spatially; adaptive partitioning of RGB-space [43], which adaptively identifies clusters in RGB-space and assigns them a unique label; and chromatic/achromatic color classification [118], which identifies chromatic elements in a document image in order to segment foreground from background. All of these of these techniques reduce the image complexity to a handful of colors, or even directly to greyscale or binary, so that from there known techniques can be applied.

Color clustering and quantization rely on the assumption that small variations in colors within a local spatial region result from noisy measurements of the same color. Halftone color reproduction, however, deliberately varies color in a region to create the perception of continuous tone color. Colorspace reduction is essentially a very simple
model of the human visual system, which is very adept at averaging out minute sub-resolution variations in color. Halftone color reproduction exploits this spatial low-pass behavior to create the perception of continuous tone color using a precise arrangement of sub-resolution colorant dots. Colorspace reduction approaches that do not take these high-frequency patterns into account can actually accentuate halftone patterns, resulting in visible distortions, known as moiré patterns, that are more prominent than in the original scan. This also has the undesired effect of simplifying color images in color resolution only, but not spatially. In other words, the number of colors is reduced, but high-frequency patterns in space remain that do not represent the original, perceived color document.

We will show how increasing scanning resolution of color halftone reproductions introduces noise to local shape measurements, and propose in this chapter a non-linear diffusion approach to recapture continuous tone color representations. The technique is motivated by the sub-resolution averaging process of the human visual system. We do not aim at straightforward or focused averaging, but rather at an averaging process driven by the local geometry of color images. Hence we are using geometry-driven diffusion.

This chapter is organized as follows. The next section describes the halftone process of color reproduction, and discusses some of the resulting artifacts affecting the interpretation of scanned color halftones. Section 5.2 gives the diffusion framework used to correct for these discrepancies. Section 5.3 describes our technique for computing local autocorrelations that is used to drive the diffusion of color halftones. Several examples of our diffusion results are given in section 5.4, and we conclude in section 5.5 with some directions for further research.

5.1 Halftone process color

In this section we describe the process of reproducing colors using halftone screens. This color reproduction technique is still the most common method of reproducing colors in high-throughput color printing environments [96], and most mass-produced periodicals are reproduced using this technique. We begin by describing the general technique for halftone color reproduction.

5.1.1 Halftone color reproduction

The halftone color reproduction process exploits the spatial low-pass character of the human visual system to create the perception of continuous tone color. This is achieved by precisely arranging a collection of dots in primary ink colors in a region that, when spatially averaged, create the illusion of a continuous color. Most commercial halftone printing systems use cyan, magenta, and yellow colorants for reproducing color. A fourth black colorant is also usually incorporated to reduce the use of the more expensive inks, prevent over saturation of the paper, and to produce denser blacks [96]. Each primary color is deposited independently on paper using a screen of dots or varying sizes aligned at a specific angle.
The primary screens are oriented at standard, pre-specified angles:

- Yellow: 0°
- Cyan: 15°
- Magenta: 75°
- Black: 45°

The primary inks are screened in the order listed above, i.e. lightest to darkest, and at the specified angles. These angles are selected to minimize the formation of moiré patterns. Figure 5.1 illustrates this process.

Color printing systems are calibrated using the *spectral Neugebauer model* [91], which models the predicted spectral distribution of a patch on the final printed page as a function of the wavelength $\lambda$:

$$R(\lambda) = \sum_{i=1}^{N} w_i R_i(\lambda),$$

where $R_i$ is the spectral reflectance of the $i$th Neugebauer primary and $w_i$ is proportion of area in the given patch of the corresponding Neugebauer primary. $N$ is the number of Neugebauer primaries, and in a four colorant system $N = 2^4 = 16$, corresponding to all possible combinations of colorants (e.g. yellow and cyan, yellow and magenta, etc.).

The specifics of the Neugebauer calibration procedure are not relevant, however, as we will not be using the model explicitly. What is important is the linearity of the model, which links the physics of color reproduction to the physics of human color perception. As printers are calibrated to reproduce colors by modeling a spatial averaging process of known primaries, we can recapture continuous tone colors using a similar spatial averaging procedure.

### 5.1.2 Scanned color halftones

In most document understanding tasks, it is convenient to assume that a scanned image is an accurate perceptual representation of the original page. For binary, or indeed even grayscale images, this is a fairly simple requirement to satisfy. For halftone process color documents, however, there is an interaction between the scanning process and the halftone dot patterns used to create the perception of continuous tone colors.

Consider the image in figure 5.2. When viewed at the scale intended, the viewer will perceive two continuous tone regions separated by a crisp edge. When scanned at even moderately high resolutions, however, the scanner begins to resolve the individual dots constituting the continuous colors. The edge boundary itself is no longer well defined as the dots or its contour become visible. The situation becomes more noticeable in more complex images. In figure 5.3 we can see the complex arrangement of “interesting” features such as edges and text superimposed on convoluted patterns of halftone dots.

Note that the original print in figure 5.3 was generated using only the three primaries described in section 5.1, and the the green color is produced by spatial averaging of the scanner sensors.
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Figure 5.1: Example of halftone color reproduction. The rather putrid green color on the left is translated into a pattern of halftone dots. The combination of each of the primaries (cyan, magenta and yellow in this example) creates the perception of the desired color when viewed at the appropriate resolution. Note that the simulated halftone screen on the right is not an accurate halftone of the green patch, as in reality printer colorants are semi-opaque, causing colors to blend more subtly.

Figure 5.2: A simple example of a scanned color halftone. The image was created by scanning a color magazine page at 600dpi. While there is only one feature of interest (the edge), the scanning resolution is high enough to resolve the dots of the halftone pattern quite distinctly.

Figure 5.3: A complex example of scanned color halftones.
5.1 Halftone process color

Figure 5.4: Local average squared difference images for a simple color edge. At the top left is the original image at 75dpi. The local neighborhood variance images are shown at 75, 150, and 300dpi.

We can begin to quantify what is happening by examining the evolution of local image statistics as a function of scanning resolution. For each pixel in a scanned color image, we compute the average squared difference in a local neighborhood $N_x$:

$$V_u(x) = \frac{1}{|N_x| - 1} \sum_{y \in N_x} (u(x) - u(y))^2. \tag{5.1}$$

The local variance images for a range of scanning resolutions are shown in figure 5.4 for a simple color edge between a mustard yellow patch and paper. Even at very low scanning resolutions, 75dpi, the halftone dots are being partially resolved. While these relatively minor variations could be easily discounted as noise, as the scanning resolution increases, the shape of the halftone dots begins to dominate the local statistics.

Such local differences are then averaged for the entire image to compute an average measure of neighborhood variance for an entire image

$$V_u = \frac{1}{MN} \sum_x V_u(x),$$

where $M$ and $N$ are the width and height of the image. Figure 5.5 plots the evolution of such local difference measurements for the same edge image as in figure 5.4. As scanning resolution is increased, local shape information is influenced as individual halftone dots are resolved. The critical point in the graph is at 300dpi, where there is a sharp jump in the measured neighborhood variance.

Increasing scanning resolution is done primarily to increase shape resolution in the resulting scan. That is, we increase scanning resolution in order to resolve more relevant details about structures in the original image. For document analysis it is desirable to increase shape resolution of characters and layout features in order to improve segmentation and recognition performance. To a human observer there is
Figure 5.5: Average neighborhood variance as a function of scanning resolution. The average local variance of each color channel (in CIE L*a*b color space) is shown.

no shape information at all to be resolved in perceptually continuous regions. If the original pages were actually continuous tone images – as they appear to the human eye at observation scale – such local image statistics would not be influenced by increasing scanning resolution. The patches of the image of constant color would remain as constant. For process halftone color, however, this is not the case. At even moderate scanning resolutions the halftone dot patterns are resolved and begin to interfere with the actual structures we are trying to measure. The degree to which, and scanning resolution at which, such dot pattern interfere with the actual structure depends on a number of factors, such as the original halftone screen resolution and the ink density at a particular location.

### 5.2 Diffusion of scanned color halftones

The Neugebauer model used for calibrating color reproduction systems is based on a linear spatial averaging of the spectral reflectances of the primaries present in a given patch. This is how CCD sensors in color scanners operate [96], and there is much evidence supporting the belief that the human front-end visual system operates in a similar way [60]. The critical process at work here is the linear spatial averaging of sub-resolution measurements. This is why halftoning works, and why it doesn’t when we increase scanning resolution beyond the point at which halftone dots become visible.
5.2.1 Linear diffusion filtering

Gaussian diffusion filtering has received much attention in the computer vision literature, and is considered to be a good model for the spatial low pass behavior of the human front end visual system. Given an input image \( I \), we embed it in a one parameter family of diffused images:

\[
 u_I(x; \sigma) = \int_{y \in \mathbb{R}^2} I(y) g(x - y; \sigma) dy
\]

where \( g(x; \sigma) \) is the isotropic two dimensional Gaussian:

\[
 g(x; \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{|x|^2}{2\sigma^2}}.
\]

The scale parameter \( \sigma \) controls the amount of smoothing applied to the image. Increasing \( \sigma \) results in simpler images with details below a certain spatial scale being reduced and eventually removed.

Figure 5.6 shows the result of smoothing a color halftone image for a range of scales \( \sigma \). Gaussian filters of this type have the desired effect of removing the halftone dot details by averaging the observed tristimulus values within each neighborhood. The color patches are partially diffused to a continuous hue for larger values of \( \sigma \). The scale \( \sigma \) at which this occurs will depend on the distribution of dot sizes in the region. Eventually, Gaussian diffusion filtering has the undesired effect of blurring image details that we are interested in preserving. In the case of the image shown in figure 5.6 it is difficult to balance blurring the halftone dot patterns into a continuous hue against the preservation of the crispsness of the edge.

5.2.2 Nonlinear diffusion filtering

What is clearly needed is a diffusion process that does not treat all regions equally. Gaussian diffusion filtering can also be formulated as the solution to a partial differential equation (PDE). In fact, it is well known that Gaussian convolution is the unique solution to the diffusion equation:

\[
 u_t = \text{div}(\nabla u) = u_{xx} + u_{yy}.
\]

Perona and Malik were the first to rigorously address the problems of unwanted blurring in linear diffusion filtering [88]. They introduce an "edge stopping function" into the diffusion PDE, regulating diffusion at edges using a decreasing function \( g \) of the edge indication function:

\[
 u_t = \text{div}(g(|\nabla u|^2)u)
\]

They use the gradient function \(|\nabla u|^2\) to indicate discontinuities in the image, and they propose a diffusivity function:

\[
 g(s^2) = e^{-\frac{s^2}{\lambda^2}} \quad (\lambda > 0).
\]
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Figure 5.6: Example of linear isotropic diffusion of scanned color halftones. As the scale of diffusion increases the dot structure disappears, but interesting features (i.e. the edge) are also blurred.

In this diffusivity function $\lambda$ plays the role of a contrast parameter regulating forward (low contrast) and backward (high contrast) diffusion locally. At locations where the gradient falls below $\lambda$ diffusion is allowed. When the gradient is above $\lambda$ diffusion is reversed and edges are enhanced.

Figure 5.7: A comparison of natural and halftone edges. Shown on the left is an idealized edge. On the right is the same edge after performing simulated halftoning. In both graphs, the ideal edge is shown along with a diffused version and the (squared) first derivative.

Consider the graph of figure 5.7. Two idealized one dimensional edges are shown. On the left is an edge that might appear in a natural image, and on the right is the same edge after transformation by a simulated halftoning process. The gradient, or in
the case of 1D signals the square of the first derivative, does a good job of characterizing the difference between constant regions and the edge in the example on the left. For the halftone signal, however, the edge is indicated in the original signal by a change in the width of the individual impulses. In this example the gradient signal is corrupted with noise from the halftone pattern resulting from constant regions in the original. In order to dampen the noise caused by the discrete character of the signal, the scale used for computing the gradient must be increased to the point where edge articulation is lost.

### 5.3 Measuring local autocorrelation

As discussed in the previous section, gradient based edge indicators do a poor job of articulating edges in halftone images. The reason for this is that edges, when reproduced using halftone, do not necessarily result in dramatic variations in intensity. Rather, they result in a change in primary ink concentration, i.e. halftone dot width, at the edge boundary. The Perona and Malik diffusion model starts with the assumption that diffusion should be unrestricted in constant regions. If we examine the plots of ideal edges in figure 5.7 we see that is the repetition of halftone dots that determine regions to be diffused. It is at points where this pattern of repetition, or self-similarity, changes where we want to restrict diffusion.

One way the self-similarity of a signal \( u(x) \) can be effectively characterized by its autocorrelation:

\[
R_u(t) = \int_{-\infty}^{+\infty} u(x)u(x + t)dx. \tag{5.2}
\]

The autocorrelation function \( R_u(t) \) measures how similar the signal \( u \) is to itself at distance \( t \). This approach is not directly applicable to our problem, however, because the autocorrelation function provides no locality in measuring correlation.

Starting with (5.2) above, we introduce locality into our autocorrelation measurement by modulating the original signal with a Gaussian. A new spatial parameter, \( x_0 \), is introduced to indicate the point about which we are computing the autocorrelation, and the image is replaced with \( u \) modulated by a Gaussian aperture centered at \( x_0 \):

\[
R_u(t, x_0) = \int_{-\infty}^{+\infty} u(x)g(x - x_0; \sigma)u(x + t)g(x + t - x_0; \sigma)dx
\]

\[
= \int_{-\infty}^{+\infty} u(x)u(x + t)g(x - x_0; \sigma)g(x + t - x_0; \sigma)dx \tag{5.3}
\]

Taking the derivative of \( R_u(t, x_0) \) with respect to \( x_0 \) gives us a measure of the local change in self similarity:

\[
\frac{\partial}{\partial x_0}R_u(t, x_0) = \frac{\partial}{\partial x_0} \int_{-\infty}^{+\infty} u(x)u(x + t)g(x - x_0; \sigma)g(x + t - x_0; \sigma)dx
\]

\[
= \int_{-\infty}^{+\infty} u(x)u(x + t) \frac{\partial}{\partial x_0} [g(x - x_0; \sigma)g(x + t - x_0; \sigma)]dx
\]
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Figure 5.8: The family of convolutions \( K'(x - x_0, \tau; 3) \) for a range of \( \tau \) values about \( x_0 = 0 \) (see figure 5.9 for the three dimensional version of this family).

Re-writing the derivative of the Gaussian products then gives us:

\[
\frac{\partial}{\partial x_0} R_u(\tau, x_0) = \int_{-\infty}^{+\infty} u(x)u(x + \tau)K'(x - x_0, \tau; \sigma)dx, \quad (5.4)
\]

where

\[
K'(x - x_0, \tau; \sigma) = \frac{\partial}{\partial x_0} [g(x - x_0; \sigma)g(x + \tau - x_0)] = \frac{2(x - x_0) + \tau}{2\pi\sigma^4} e^{-\frac{(x-x_0)^2+(x+\tau-x_0)^2}{2\sigma^2}}. \quad (5.5)
\]

From equations (5.4 and 5.5) we can see that what is occurring is actually the convolution of the signal by a family of modulated Gaussian derivative like functions. Figure 5.8 illustrates the family of convolution kernels used to compute \( R_u(\tau, x_0) \) for a range of \( \tau \) values. Note the similarity of each curve in this figure to a Gaussian derivative kernel. In our case, each derivative kernel is globally modulated by the original Gaussian introduced in equation (5.3) above to mute the contribution of measurements taken away from \( x_0 \).

In two dimensions we have an additional spatial parameter \( y_0 \), two offset parameters \( \tau_x \) and \( \tau_y \), as well as two partial derivatives:

\[
(R_u)_x(\tau_x, \tau_y, x_0, y_0) = \int_{x,y} u(x, y)u(x + \tau_x, y + \tau_y)K_x(x - x_0, y - y_0, \tau_x, \tau_y; \sigma)dxdy
\]

\[
(R_u)_y(\tau_x, \tau_y, x_0, y_0) = \int_{x,y} u(x, y)u(x + \tau_x, y + \tau_y)K_y(x - x_0, y - y_0, \tau_x, \tau_y; \sigma)dxdy,
\]

where \( K_x \) and \( K_y \) are the partial derivatives of the two dimensional kernel in the \( x \) and \( y \) directions, respectively:

\[
K_x(x, y, \tau_x, \tau_y; \sigma) = \frac{2x + \tau_x}{4\pi\sigma^6} \exp(-\frac{(x^2 + y^2) - (\tau_x + x)^2 - (\tau_y + y)^2}{2\sigma^2}),
\]

\[
K_y(x, y, \tau_x, \tau_y; \sigma) = \frac{2y + \tau_y}{4\pi\sigma^6} \exp(-\frac{(x^2 + y^2) - (\tau_x + x)^2 - (\tau_y + y)^2}{2\sigma^2}). \quad (5.6)
\]
5.3. Measuring local autocorrelation

Figure 5.9: Visualizing $K_x$ for a range of offsets $\tau_x$ and $\tau_y$ (see also figure 5.8).

We have omitted the spatial parameters $x_0$ and $y_0$ in the derivative kernels above for brevity, as well as the fact that in practice we will be computing them in a local neighborhood translated so $x_0 = 0$ and $y_0 = 0$. Some samples of $K_x$ for a range of $\tau_x$ and $\tau_y$ values are shown in figure 5.9.

To use the change in local autocorrelation directly in the Perona and Malik nonlinear diffusion equation, we obtain a scalar-valued function from $(R_u)_x$ and $(R_u)_y$ (which are functions of $\tau_x$ and $\tau_y$ at every point in space), we integrate the square of the change in local autocorrelation over all offsets $\tau_x$, $\tau_y$:

$$|\nabla R_u|^2 \equiv \iint \left[ ((R_u)_x(\tau_x, \tau_y, x_0, y_0))^2 + ((R_u)_y(\tau_x, \tau_y, x_0, y_0))^2 \right] d\tau_x d\tau_y$$

The symbol $\nabla R_u$ is used to emphasize the association with the gradient, in whose place we will be using the above directional local autocorrelation measures in our diffusion.

An illustration of the ability of local autocorrelation to articulate edges is shown in figure 5.10. For small $\sigma$ the local autocorrelation is very similar to the gradient. As the scale increases, however, the gradient is unable to articulate the edge, while the local autocorrelation remains stable at the edge.
Figure 5.10: A comparison of edge articulation using the gradient and local autocorrelation. Shown on the left are the gradient and local autocorrelation functions for a 1D edge similar to that shown in figure 5.7, computed for $\sigma = 4$. On the right are the gradient and local autocorrelation for $\sigma = 8$. Both functions are re-normalized to attain a maximum of 1 to facilitate comparison.

5.4 Experiments

There is no good, objective quality measure for the recovery of scanned color halftones. In the absence of such a performance metric, we discuss here some qualitative experiments we have performed to illustrate the effectiveness of our proposed technique. The experiments are designed with many applications in mind, focusing on the potential users of scanned halftones, their requirements and expectations.

All example images were scanned using a Hewlett Packard ScanJet model C7716 color scanner. The resolutions used are actual optical scanning resolutions of the device, and no interpolation or other post-processing was performed to artificially obtain higher scanning resolution. Images are acquired in 24-bit RGB TrueColor format, and all processing is performed in the RGB colorspace.

To illustrate how our diffusion process is treating edges and constant regions in images, a diffused version of the image from figure 5.3 is shown in figure 5.11. Also shown is the diffused image quantized to only size unique colors. The example shows how edges are preserved by maintaining the halftone dots supporting their boundary, while the halftone dot patterns in perceptually constant regions are diffused.

In section 5.1.2 we defined a simple measure of variance within a neighborhood of a scanned color image (see equation (5.1) and figure 5.4). This measure of local structure shows how the local image statistics change unexpectedly as a function of scanning resolution. We computed this measure for a sample color image at a number of scanning resolutions before and after applying our diffusion technique. Figure 5.12 shows the results of this comparison for all color channels in the original and diffused sets of images. The results of this comparison indicate that our diffusion approach performs well across a broad range of scanning resolutions, and effectively mutes the resolution of unwanted shape at high resolution. The critical point in this example
5.4. Experiments

Figure 5.11: Diffusion and quantization of high resolution halftone scans. The top image is the result of performing autocorrelation-driven diffusion on the image of figure 5.3. On the bottom is the top image quantized to only six colors.

occurs at 300dpi. Up to this point the local variance in the original scans is increasing, and quite dramatically between 150 and 300dpi. Until this point, more and more halftone shape is being resolved. At 300dpi the halftone dots become fully resolved and the local variance stabilizes. For the diffused images, the local variance remains stable across all scanning resolutions.

A qualitative measure of the quality of scanned images can be gained by visual inspection of reconstructed halftones reproduced at appropriate resolution. This is relevant not only for aesthetic reasons, as it is also a reflection of how such color scans will appear to document analysis algorithms. Figure 5.13 provides examples of the improvement in visual quality gained by applying our proposed technique. Note how even at the lowest shown scanning resolution the halftone dot patterns interfere with the continuous color of the solid blue and green regions. The effect is even more pronounced at the higher resolutions. After applying the diffusion the continuous tone colors are recaptured. Note also how our technique is able to preserve details in the diffused images.

An original color page that appears to an observer to only contain four colors should ideally be presented to an analysis algorithm with those four colors. Figure 5.14 illustrates how interference from resolved halftone details can affect the results of color quantization. The technique of minimum variance color quantization was applied [109], attempting to quantize the image to only four colors. Quantization accentuates the
Figure 5.12: Stability in evolution of local image statistics. The average neighborhood variance from equation (5.1) is plotted as a function of scanning resolution for a single source image before and after diffusion. Each color channel in the L*a*b color representation is plotted separately for both images. Scanning resolutions of 75, 150, 300, and 600dpi are shown. Neighborhood sizes used for computing the average local variance are 3x3, 7x7, 15x15, and 31x31, respectively.

Halftone noise in the constant color regions of the original scan, while after diffusion these regions can be quantized without introducing noise. This is directly related to the evolution of local image statistics mentioned above. As more halftone shape is resolved, the color quantizer becomes more confused.

Independence of our technique from a specific halftoning model is demonstrated by a common quality measure used for describing the fidelity between compressed (and halftoned) images and originals is the peak signal-to-noise ratio (PSNR) in the luminance channel [89]. The root-mean-squared error between an original image $u$ and reconstructed image $\hat{u}$ is:

$$\text{RMSE}(u, \hat{u}) = \left( \sum_{x,y \in \text{dom}(u)} [(u(x,y) - \hat{u}(x,y))^2] \right)^{1/2}$$

The PSNR between $u$ and $\hat{u}$ is then defined as:

$$20 \log_{10} \left( \frac{1}{\text{RMSE}(u, \hat{u})} \right).$$
5.5. Discussion

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<th>Jarvis</th>
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Table 5.1: Peak signal-to-noise ratio (dB) for reconstructed continuous tone images after halftoning. Results for classical halftone screening as well as the Floyd-Steinberg, Jarvis, and Stuki error diffusion halftoning techniques. The peak signal-to-noise ratio of the synthetic halftone is given in parentheses.

Several standard images were halftoned using classical and error diffusion halftoning algorithms [24, 40]. The halftoned images were then processed with our proposed technique. Figure 5.15 shows an example image along with a halftoned version generated using the Floyd-Steinberg error diffusion halftoning algorithm. The image, as reconstructed by our diffusion is also given.

Table 5.1 gives the PSNR values for synthetically halftoned images and images reconstructed from them using our diffusion technique. The results illustrate how our technique can be applied under different halftoning conditions with identical effectiveness.

5.5 Discussion

In this chapter we have proposed a non-linear diffusion approach for recovering continuous tone color images from scanned color halftones. The technique uses a measure of local autocorrelation to drive and limit the diffusion. The reason for this is that at higher scanning resolutions the shape of halftone dots becomes resolved, and interferes with the actual shapes we wish to analyze. At high scanning resolutions, color measurement become a matter of texture measurement as well as intensity.

A simple measure, the local neighborhood variance, was introduced to quantify how local shape statistics change unexpectedly when increasing scanning resolution of halftones. The proposed diffusion technique stabilizes this local variance measure across scanning resolution by diffusing halftone texture corresponding to perceptually continuous colored regions. Experiments show that the visual appearance of scanned halftones can also be improved when reproduced. Our diffusion technique mutes the high-frequency halftone signal, while preserving important visual details. By comparing the fidelity of images reconstructed from synthetically halftoned images, it has also been shown that our diffusion technique performs similarly on a variety of non-classical halftoning algorithms.

An important aspect of evaluation of halftone restoration algorithms is visual appearance. The behavior of our diffusion approach at edges is predictable. At halftone edges, where the autocorrelation changes rapidly, the halftone dots supporting the edge boundary are preserved. While this creates unpleasant visual effects when viewed at
Figure 5.13: Reproducing scanned color halftones on a laser printer. The images in the top row are the original scanned images, the bottom row are the best results obtained from our proposed diffusion technique.

Figure 5.14: Original and diffused images after color quantization. The left image is the quantized original scan at 300dpi, on the right is the quantized image after applying our diffusion technique. The images are quantized to four colors and displayed at their intended size.

Figure 5.15: Reconstruction of original from halftoned image. The original image (a) was halftoned using Floyd-Steinberg error diffusion. The version of the image reconstructed with our technique is shown in (c).
high resolutions, the effect is not noticeable in the reproduced version. In fact, these edge dots preserve edge definition at reproduction resolution.

The visual appearance of scanned halftones is not only important for document analysis algorithms, but is also of interest in production printing environments. Providing an accurate representation of the original continuous color source will result in higher color fidelity in reproductions, and images that scale much better across a broader range. Consider the fact that all of the halftone image examples provided in this chapter were reproduced on a color laser printer. The printer is doing its best to reproduce the high frequency components of a foreign color reproduction model.

We have also shown how diffused images can be much more effectively quantized to the number of perceptually salient colors in an observed document page. This results in images that are more visually appealing, reproduce better, and scale predictably because high frequency distortions induced by the halftone patterns are eliminated. It also allows us to simplify the representation of scanned color images, while preserving fidelity with the original.

An advantage of our approach is that it is based on a model of color perception, and is not at all specific to a particular halftoning algorithm. This independence from a halftoning model enables our technique to perform well on halftone models other than classical halftone screening.