Moire Patterns in Scanned Halftone Images

Cormac Herley, Qian Lin
Computer Peripherals Laboratory
HPL-96-29
February, 1996

scanning, halftone, moire, interference

In this report we examine the origin of moire patterns that occur when scanning halftone images. By analysing the halftoning and sampling processes in the frequency domain we find that halftone images typically have spectral copies of the baseband in the high frequencies, and the moires are aliases of these generated by the sampling. We analyse the kind of effects that are generated for monochrome and color halftones and scanners. We discuss how moire effects may be detected and eliminated in an automatic fashion.
Moire Patterns in Scanned Halftone Images

Cormac Herley and Qian Lin

Abstract

In this report we examine the origin of moire patterns that occur when scanning halftone images. By analysing the halftoning and sampling processes in the frequency domain we find that halftone images typically have spectral copies of the baseband in the high frequencies, and the moires are aliases of these generated by the sampling. We analyse the kind of effects that are generated for monochrome and color halftones and scanners. We discuss how moire effects may be detected and eliminated in an automatic fashion.

1 Introduction

In scanning halftone images it is often noted that beat frequencies or moire patterns arise in the form of visible periodic or almost periodic patterns in the final image. In this report we examine the origin of these patterns and point out some ways in which they can be avoided or alleviated. By way of illustrating the kind of problem that we are talking about example Figure 1 shows two versions of an image that has been scanned from a halftone. They have been sampled at the same rate, but have been processed differently after sampling. Figure 1 (a) shows very visible and objectionable moire patterns, while in Figure 1 (b) they are almost completely invisible.

Since moire patterns are (by definition) periodic phenomena we find that the problems and their solutions are most clearly illustrated in the Fourier domain, i.e. using Fourier transforms or Discrete Fourier transforms (DFTs). Most of the problems we have encountered can be easily explained in terms of classical two-dimensional sampling theory. While this subject is somewhat mathematical we will attempt to illustrate all of the ideas by example, and without assuming any knowledge of Fourier or sampling theory.

We will focus mostly on screened images such as are common in magazines and brochures, and on flatbed CCD scanners, such as the HP ScanJet 2c and 3c. We will begin the discussion with the
Figure 1: Example illustrating the importance of proper processing of a scanned halftone image after sampling. Both images come from an original scanned at the 400 dpi. (a) Result of downsampling to 300 dpi using more sophisticated interpolation. (b) Result of downsampling to 300 dpi using linear interpolation.

monochrome case, since the essential ideas are most simply conveyed in that way, but we will deal also with color prints and color scans. We will be particularly interested in the very common scenario of scanning using RGB filters an image that was printed using CMYK inks.

An outline of the report is as follows: in Section 2 we introduce the basic sampling relations that are needed to understand the frequency domain pictures of halftoned images. We show how screened images look in the frequency domain, and how this frequency domain picture changes as a function of screen frequency and angle. In Section 3 we show how scanned images look in the frequency domain, and how scanned halftones differ from continuous tone images. In Section 4 we examine some of the approaches to eliminating moire effects.
2 Frequency Domain View of Screened Images

2.1 Relation between space and frequency domain

The essential view that we would like to convey in this section is that the process of screening resembles the process of sampling very closely, and that there are clear and simple relationships (which we list) between the type of screen that is used to print an image, and how it looks in the frequency domain. Most of what we need can be developed using the following two facts from sampling theory (see for example [1])

- If an image is sampled using a rectangular grid of spacing \((T_1, T_2)\) then in the frequency domain the sampled image is \((2\pi/T_1, 2\pi/T_2)\) periodic.

- Rotating the spatial sampling grid by an angle \(\theta\) counterclockwise corresponds to rotating the frequency domain picture by an angle \(\theta\) clockwise.

An illustration of the first property is given in Figure 2 where we show the frequency domain picture of an image in Figure 2 (a). It is assumed that most of the images energy is clustered at low frequencies. In Figure 2 (b) and (c) we show two different sampling frequencies together with their frequency domain pictures. Essentially, we end up with copies, or replicas, of the baseband image repeated periodically. An illustration of the second property is shown in Figure 3. Here we rotate the sampling grids used in Figure 2 and show that the corresponding frequency domain pictures are rotated by the same amount, but in the opposite direction.

Strictly speaking, of course, "periodic" implies that the spatial sampling pattern and the frequency replication patterns are repeated infinitely. In practice, the image has finite support in space. The effect of this spatial limitation on the frequency domain picture is to alter somewhat the intensity of the spectral replicas, but it does not alter their location. Since this is largely a second-order effect we will not emphasize it in our analysis.

An example of an screened versions of an image with frequency domain images as predicted from the sampling model are shown in Figure 4. Screening can be seen as being very closely related to sampling in that the illusion of continuous tone is created by using a periodic array of dots. In amplitude modulated (AM) screening the gray (or color) level is controlled by varying the size of the dots. Thus the
Figure 2: Comparison of the frequency domain views of an image and its sampled versions. (a) The support of an image which has energy mostly in the low frequencies. (b) If the image is sampled with a rectangular grid as shown on the left, the sampled version of the image has a periodic frequency domain picture. The original spectrum is repeated (infinitely in both directions) with period $2\pi/T_1, 2\pi/T_2$. (c) If the distance between samples is increased, then the distance between the replicas of the baseband image decreases.
Figure 3: Rotation of the sampling grid causes rotation of the frequency domain picture also. (a) The sampling pattern used in Figure 2 (b) rotated counterclockwise by 15 degrees. This causes clockwise rotation of the frequency domain picture by 15 degrees. (b) The sampling pattern used in Figure 2 (c) rotated counterclockwise by 25 degrees. This causes clockwise rotation of the frequency domain picture by 25 degrees.
Figure 4: Examples of different screened versions of an image with their frequency domain depictions. (a) Original image and its spectrum, which is predominantly lowpass. (b) Screened version with 22 lpi screen at 45 degree angle. (c) Screened version with 60 lpi screen at 85 degree angle.
difference between sampling and screening is that in sampling the signal is represented by a “dot” which is vanishingly small and has amplitude proportional to the amplitude of the signal at that location, while in screening the dots have binary amplitude, but have size proportional to the amplitude of the signal.

In sampling the “dots” are theoretically vanishingly small, while in screening they can be large enough that they completely overlap, leaving little or no white space in between. In areas of constant gray in a screened image the dots will all be approximately the same size. To a first order we can model the gray level of the image as being slowly varying, or constant over small areas. Thus we can model the screened image as being equivalent to some sampled image that fixes the location of the dots convolved with some dot profile function that fixes their size. To see how varying the dot size alters the frequency domain picture we need the following additional property

- Convolving by a function in the spatial domain corresponds to multiplying by its Fourier transform in the frequency domain.

The dot profile function can have circular or square or diamond shaped support for example. To illustrate the idea consider the simple case of a one-dimensional rectangular profile function. The Fourier transform of a rectangular function is a Sinc function as shown in Figure 5. We can see that convolving by a rectangular profile function corresponds to a crude form of lowpass filtering. Here we have a boxcar in the spatial domain, and a Sinc in the frequency domain; this is in a sense the dual of the ideal filtering case where we desire a boxcar in frequency, and use a Sinc spatially. That is, there is a rolloff as we go to higher frequencies. Notice that the wider the boxcar in time (the larger \( a \)) the narrower the Sine function in frequency. This has the natural interpretation that convolving by a wider pulse, corresponds to more averaging, which implies a greater degree of lowpass filtering.

An illustration of the screening process is shown in Figure 6. For simplicity we show a one dimensional example; this can for example be considered as a cross section of a real screened image. In Figure 6 (a) we show an example function \( f(t) \) and its Fourier transform \( F(w) \); in Figure 6 (b) the function has been sampled to give \( f_s(nT) \) and \( F_s(w) = \sum_k F(w - 2\pi k/T) \), which is periodic with period \( 2\pi/T \). In Figure 6 (c) we show the dot profile function, which is rectangular, and its Fourier transform which is a \( \sin(w)/w \) function. In Figure 6 (d) the sampled image has been convolved by the dot profile function. This makes it look like a screened image in the spatial domain, and has the effect of attenuating the periodic replicas in the frequency domain. This essentially explains a fact that will prove important: \textit{while in theory the}
spectrum is periodic, with all copies having the same amplitude, in practice the copies decay rapidly with increasing frequency.

2.2 Cluster Dot Dither

In order to demonstrate the efficacy of the model we have been using, we now briefly examine the frequency domain images obtained from real images which have been screened using the cluster dot dither method. First, in Figure 7 we show an example image together with its frequency domain picture. As is common for many images, much of the energy is concentrated in the low frequencies (for all of the frequency domain plots that we show zero frequency is at the center).

In Figure 8 (a) we show the same image after it has been screened using a cluster-dot dither, with a screen angle of 45°. Firstly observe that (except for spacing) the replicas of the baseband occur at locations similar to those of Figure 3 (b). This was predictable from the first two Fourier properties that we introduced in Section 2.1. Also observe, that the frequency replicas of Figure 8 (a) become attenuated at higher frequencies. This is owing to the third Fourier property, as we demonstrated in Figure 6.

2.3 Dispersed Dot Dither and Error Diffusion

Halftoning algorithms other than the traditional screen exhibit different frequency characteristics. We illustrate this with an example.

Figure 7 shows the image of a couple from the USC database, as well as its discrete Fourier transform. Figure 5 shows halftone images as well as their discrete Fourier transforms using clustered-dot dither [2],
Figure 6: Process in one dimension. Space domain signals are shown on the left, with the frequency domain counterpart on the right. (a) A continuous-time signal prior to sampling, together with its Fourier transform. (b) After sampling this signal with sampling interval $T = 1$, the discrete-time version has a $2\pi$ periodic frequency domain picture. (c) If the dots on the page have non-zero support, this is equivalent to convolving by a boxcar function shown. The boxcar has support (in space) $(-1/5, 1/5)$ giving the frequency domain version that is a $\text{Sinc}(w)$ function that crosses zero at intervals of $5\pi$. (d) Convolution the discrete-time sampled signal, with the boxcar dot profile gives this bar-graph plot in space, and a frequency domain version where the periodic replicas of the baseband signal have been attenuated.
super smooth dither [3], and a randomized-weight error diffusion implemented by Andy Fitzhugh of HPL.

Both clustered-dot dither and super smooth dither employ dither matrices that are used periodically to cover the image. The main difference is that the periodicity of super smooth dither is much larger, and the halftone dot distribution is much more scattered. Hence, in the frequency domain, both spectra has periodic components. However, the number of periodic components in super smooth dither is much larger, and the amplitudes of the periodic components are much smaller. The frequency spectrum of the error diffused image, on the other hand, does not have periodic components. Both the super smooth dithered image and the error diffused image have spectra that resembles that of the original image more than the spectrum of the clustered-dot dithered image.

Analytically, the Fourier transform of a binary image halftoned by a dither algorithm can be represented as a function of the dither matrix and the original continuous tone image [4]. The Fourier transform consists of a low frequency component and several high frequency components. The low frequency component is the Fourier transform of the quantized original gray scale image. The high frequency components are distributed on a grid corresponding to the size of a halftone cell. The amplitude of a high frequency component depends on the halftone dot pattern. The frequency distribution of a high frequency component is the distorted Fourier transform of the original gray scale image. The Fourier transform of an error-diffused image does not have an analytical expression since the error diffusion algorithm is not linear, not periodic, and not point-to-point, i.e. the binary output of halftoning a pixel
Figure 8: Renderings of an image with their frequency domain pictures. (a) Cluster dot dither. (b) Error diffusion. (c) Super-smooth dither.
depends on the adjacent pixels.

2.4 Color Screens

We have seen that the frequency domain picture of screened images are clearly predictable from the screen frequency, screen angle and the dot profile function. So far we have mentioned only the monochrome case, but obviously the same ideas apply without problem to the frequency domain picture of the different color planes when handling color images, provided that the color planes are independent. In practice there is considerable overlap between the color planes. However, we defer until Section 3.3 a discussion of the complications that arise because of the interactions between color planes in the scanning process.

3 Scanning Screened Images

We have examined the spectra of halftoned images and found that they resemble the spectra of sampled images. The scanning process is itself, of course, a sampling, so we will be able to make use of the properties that we have already developed in Section 2. We shall assume for the moment that the sampling grid of the scanner (i.e. the spacing between the samples or the dpi setting) can be varied at will. Many scanners can sample only at certain preset dpi settings and interpolate to get others, and some (in particular flatbed) scanners have different sampling processes for the horizontal and vertical dimensions. We examine first the ideal case where any desired dpi setting can be achieved and afterwards look at deviations from this assumption and the associated problems.

3.1 Replication of the frequency domain image

In our idealized model of the scanner sampling process we assume that the scanner uses a rectangular sampling grid, with spacing $S_1$ horizontally, and $S_2$ vertically. Of course, using the first of our Fourier properties from Section 2.1 this gives that the frequency domain version of the scanned image will be $(2\pi/S_1, 2\pi/S_2)$ periodic, as shown in Figure 2. Now, we see the difference between scanning a halftone, and scanning a continuous tone image. Re-examine the frequency domain plot of the continuous-tone image in Figure 7. When we scan such an image we will generate replicas of the baseband image with periodicity $(2\pi/S_1, 2\pi/S_2)$. So long as $S_1$ and $S_2$ are small enough (fine sampling) the spectral replicas will be far apart $(2\pi/S_1$, and $2\pi/S_2$ are large) and there will be little aliasing energy carrying over from
any of the spectral copies to the baseband.

Consider, by contrast, scanning the halftoned image of Figure 8 (a). Here the frequency domain already has replicas at periodicity \((2\pi/T_1, 2\pi/T_2)\), where \(T_1\) and \(T_2\) are determined by the screen frequency. Even if we scan at the same \(S_1\) and \(S_2\) as for the continuous-tone image, periodic replication of the frequency plot in Figure 8 (a) is obviously a lot more likely to generate interference, since it has large frequency components at many frequencies, not just the baseband. Since the replicas have concentrated energy (corresponding to attenuated versions of the baseband image) they will create very coherent periodic patterns if they are not masked in some way. It is for this reason that they are called moire patterns.

We have identified then the main source of moire patterns as the following:

The resampling at \((S_1, S_2)\) owing to a scanner causes replication of the spectrum at \((2\pi/S_1, 2\pi/S_2)\). Since a halftoned image already has replicas at \((2\pi/T_1, 2\pi/T_2)\) many new replicas appear.

In the design of halftone techniques great care is generally taken to ensure that the high frequency replicas that derive from the halftone periodicity are spread apart (in frequency) so that they are as imperceptible as possible. When a scanner resamples the image, these aliases can appear in frequency locations that are very perceptible, thus creating irritating periodic effects.

Recall that the scanner carries out a conventional sampling of the image. We know from sampling theory that if the image is bandlimited to some frequency range \((\Omega_0, \Omega_1)\) we can reconstruct the signal exactly if we sample at a rate equal to or higher than twice \((\Omega_0, \Omega_1)\). In practice real images are not bandlimited, but their spectra generally falls off fairly rapidly. If we sample at \((S_1, S_2)\) then all frequencies above \(2 \times (2\pi/S_1, 2\pi/S_2)\) will be aliased to lower frequencies, but the consequences of this are not so severe if the energy is falling off rapidly. This is the case with a majority of natural images, for example that shown in Figure 7. For halftone images such as in Figure 8 (a) the situation is very different. Here the spectrum does not fall off anything like as rapidly, owing chiefly to the aliased copies of the spectrum that have been generated by the halftone. Allowing the frequencies above \(2 \times (2\pi/S_1, 2\pi/S_2)\) to alias to lower frequencies can have much more serious consequences in this case. In Figure 9 we show an example of the spectrum of a halftoned image, which shows the spectral copies decaying with increasing frequency. In Figure 10 we show the spectrum of this image after sampling; the original spectrum is still present, but periodic replicas are also shown.

One might imagine that this merely involves relocating the aliases due nto the halftone to other
Figure 9: Spectrum of a halftoned image showing the periodic replicas of the baseband, which decay with increasing frequency.
Figure 10: Spectrum of a halftoned image after sampling showing the periodic replicas of the baseband, and the interference copies. The additional frequencies shown are due to a copy of the original spectrum (shown in Figure 9) copied to the right (in red), to the left (in green), above (cyan) and below (magenta).
locations, and that the outcome would not be very severe. However recall that design of good halftoning techniques involves careful placement of the aliased spectra; thus allowing the aliasing to occur in an uncontrolled way is far more likely to generate displeasing artifacts. Also the aliases due to the halftone will appear at frequencies that are separated from the baseband by \((2\pi/T_1, 2\pi/T_2)\) where \((T_1, T_2)\) is the halftone dot spacing. The aliases due to the resampling can appear at much lower frequencies. In general aliases that occur at low frequencies are more likely to be noticeable and displeasing.

The moires introduced by sampling a halftone are obviously classical aliasing phenomena. If we were to lowpass filter the image to \((2\pi/S_1, 2\pi/S_2)\) prior to scanning, obviously the problem would be avoided.

### 3.2 Interpolation to intermediate dpi

We have seen that a principle cause of moire effects in scanning halftones is that the halftone information at high frequencies can alias to lower frequencies in the sampling process. Scaling an image through interpolation is also a form of resampling, and thus care must be taken when scaling such images not to introduce additional aliasing.

An illustration of the problem in the one dimensional case is given in Figures 11 and 12. In Figure 11 we illustrate the interpolation process in both the spatial and frequency domains, for pixel replication, and a scaling factor of 4/3. Observe that pixel replication is equivalent to convolving the original signal (shown in Figures 11 (a)) with a boxcar function (shown in Figures 11 (b)) to get a piecewise constant function (shown in Figures 11 (c)). Resampling this function at the desired rate gives the pixel replicated output (shown in Figures 11 (d)). The frequency domain versions of these operations are shown on the right hand side. We have assumed that the signal has some lowpass characteristic.

In Figure 12 we have repeated the analysis, but this time assuming a spectrum that has the high frequency energy localizations usually associated with a halftone. It can be seen that while the halftone energy in the original may not be objectionable, it may alias in the resampling process to lower, more sensitive frequencies.

Recall the two examples shown in Figure 1. These were the results of resampling using two different interpolation filters. Figure 1 (b) was done using bilinear interpolation, while the output in Figure 1 (a) was done using an interpolation filter that nulled the halftone energy, preventing it from aliasing to sensitive locations.
Note that interpolation is automatically performed by certain scanners. For example flatbed scanners generally have a fixed imaging bar in the horizontal dimension which fixes the horizontal resolution. To reach other desired dpi settings interpolation is necessary.
Figure 11: One dimensional example of resampling a signal. Here we downsample by a factor of 3/4 using nearest neighbour interpolation. This is equivalent to first convolving the sampled signal with a boxcar function, and resampling the resulting signal at the new rate. (a) The sampled signal and its spectrum. (b) Boxcar function and its spectrum. The boxcar is chosen to be the same width as the sampling rate of the signal in (a). (c) Result of convolving sampled signal with boxcar. Observe that the $2\pi$ replicas of the original spectrum are nulled. (d) Resampling of the signal in (c). Observe that the final spectrum resembles the original except the frequency axis is compressed.
Figure 12: One dimensional example of the moires introduced when resampling a signal. Here we downsample by a factor of 3/4 using nearest neighbour interpolation. This is equivalent to first convolving the sampled signal with a boxcar function, and resampling the resulting signal at the new rate. (a) The sampled signal and its spectrum. The spectral contributions from the halftone are shown in red (compare for example with Figure 6). (b) Boxcar function and its spectrum. The boxcar is chosen to be the same width as the sampling rate of the signal in (a). (c) Result of convolving sampled signal with boxcar. Observe that while the $2\pi$ replicas of the original spectrum are nulled, the halftone frequencies are not. (d) Resampling of the signal in (c). Observe that the halftone frequencies may now alias even into the baseband.
3.3 Color Halftones

The chief cause of moires is a classical aliasing phenomenon as described above. When a color page is scanned using a flatbed or drum scanner, the page is typically sampled on a regular grid through red, green, and blue filters. Examples of the transmittance of the filters for a ScanJet 3c scanner are shown in Figure 13. When the page is printed with cyan, magenta, yellow, and black (CMYK) halftone dot patterns, then different filters pick up different halftone patterns. Figure 14 shows the spectral response of CMYK offset inks used in printing a magazine page, measured by a Gardner Color Machine. Both the cyan and the black halftone patterns absorb light in the red part of the spectrum. Thus, through the red filter, cyan and black dot patterns will be picked up. Similarly, through the green filter, magenta and black dot patterns will be picked up, and through the blue filter, yellow and black dot patterns will be picked up. However, since there usually exists cross contamination among CMY inks, and RGB filters overlap spectrally, the red filter may also pick up some magenta or even yellow dot patterns. However, the effect seems secondary, and we have not observed strong moire components as a result of this.

![Transmittance of Red, Blue, and Green Filters](image)

Figure 13: The transmittance of red, blue, and green filters.

Hence, for convenience of analysis, we can use the following simplified multiplicative model:

\[
    r(i, j) = c(i, j) * k(i, j)
\]

\[
    g(i, j) = m(i, j) * k(i, j)
\]
where $r(i, j), g(i, j), b(i, j)$ are scanner output at position $(i, j)$, and $c(i, j), m(i, j), y(i, j)$, and $k(i, j)$ are cyan, magenta, yellow, and black halftone dot patterns respectively, with values between 0 and 1. When the scanner sample is taken completely from within a halftone dot, its value is one. When the scanner sample is taken completely from outside a halftone dot, its value is zero. Otherwise, it takes a value in between. This is an extension of the model used in [5], where the superposition of monochromatic images is considered. However, the analysis remains the same. The multiplication in spatial domain translates into convolution in the spectrum domain. Frequency vectors of the original vector are added, while their corresponding amplitudes are multiplied.

An example of the spectrum of a real scanned halftoned image is shown in Figure 15. The strongest set of components, located in a circle are the spectral copies due to the halftone. All the other significant components are due to moire.

This nonlinear behavior as a result of the interaction between the black plane and one of the other
Figure 15: Frequency domain picture of a CMYK halftoned image which has been scanned along red, green and blue planes. The FFT of each of the red, green and blue channels has been combined for this composite frequency plot.

ink color planes creates the inner circle of moire components.

4 Moire Removal

We have spent most of the report so far developing the idea that moire patterns are chiefly alias phenomena generated by sampling a halftone patterned image. Since they are inherently periodic, frequency domain analysis is the natural tool to analyze them. Having developed an understanding of the mechanisms that generate moire patterns we will address in this section means for removing or suppressing them.

4.1 Analog anti-aliasing

Aliasing is an unavoidable consequence of sampling a signal below the appropriate Nyquist rate. What is true in most sampling situations also holds here: prevention is better than cure as far as aliasing is concerned. It is generally much better to prevent aliases from appearing, than to attempt to remove them afterwards. Good A/D systems will generally lowpass filter an incoming signal at a frequency that
is half the sampling frequency, thus preventing aliasing. Such a filtering before sampling would eliminate the problem. In the context of scanners it appears that this is not always easily achieved and so we must consider what post-sampling means are available to us. Nonetheless it should be emphasized that some form of optical lowpass filtering could prove very effective in eliminating high frequencies from the image of the halftone before they alias to lower frequencies after sampling.

4.2 Detecting and removing moire components in the frequency domain

The most straightforward way of reducing the moire pattern is to null the moire components in the frequency domain. This involves detecting moire components automatically from the Fourier transform of the scanned halftone image, removing them, and then taking the inverse Fourier transform.

The moire components are characterized by relatively high-energy peaks that spread a few pixels, with a profile as shown in Figure 16(a). Hence, to detect the moire components automatically from the Fourier transform, we can use a matched filter, as shown in Figure 16(b). When the output of the matched filter exceeds a threshold, then there is a local peak.

(a)

(b)

Figure 16: A typical profile of moire component and its corresponding matched filter.

However, the output of the matched filter alone is prone to noise, and will result in many false detections. To make the detection more robust, we add second constraint related to the total energy, i.e. the ratio of the matched filter output to the sum of the amplitude of the Fourier transform in the
Figure 16 window should exceed a threshold. Further, to make sure that the image content, mostly in
the low frequency domain, is affected as little as possible, we will not change the Fourier transform in
the very low frequency domain.

As an example, we show an advertising page scanned with ScanJet IIC scanner. The upper left
corner of Figure 17 is the scanner image, while the lower left corner of the figure is its Fourier transform.
The page was printed with 130 lines per inch (lpi), with cyan plane at 67.4°, magenta plane at 7.3°, yellow
plane at 82.5°, and black plane at 37.3°. The frequency range on the Fourier transform is from -150 lpi to
150 lpi both vertically and horizontally, so the moire components corresponding to the original halftone
are easily identifiable from the Fourier transform image. Two prominent low frequency components at (30,
17)lpi and (-30,-17)lpi are created by the interpolation from native to non-native frequencies. The upper
right corner of Figure 17 shows the processed image after zeroing out the detected moire components,
while the lower right corner shows what happens in the Fourier transform domain. The matched filter
threshold is set at 1.0 and the ratio threshold is set at 0.6. The protected very low frequency domain has
a radius of 18 lpi.

Comparing the images at the upper left and upper right of Figure 17, it is easily seen that both the
low frequency moire at 34.5 lpi (spanning 8.7 pixels) that results from the interpolation, and the high
frequency moire at 130 lpi that results from the original halftone are removed.

Of course taking a two dimensional FFT of the image can be computationally expensive, and is in
fact unnecessary in most cases. It is possible to get an accurate view of the halftone information by taking
the one dimensional FFTs of several rows and several columns, since the two dimensional periodicity will
also imply one dimensional periodicities. A simple thresholding scheme along the one dimensional FFTs
also allows accurate detection of the halftone information.

4.3 Notched filters

Nulling of FFT components can be undesirable as a means of removing moire effects. Firstly it generates
a spatial aliasing pattern (quite different from the frequency aliasing we have been dealing with). In
zeroing components of the FFT we are attempting to implement convolution by an ideal filter. Since
multiplication in the FFT domain corresponds to circular convoluuion in the spatial domain we will get
aliasing at the borders of the reconstructed image owing to the poor decay of the coefficients of the
ideal filter. A second reason for not desiring to null FFT components is that it may be computationally unrealistic to buffer the whole image, take an FFT, identify and null the undesired components, and take an inverse FFT. Breaking the image into blocks before transforming can help, but can generate blocking artifacts.

An alternative approach is to design a notch filter, which attempts to remove the undesired components. Such a filter would have frequency response close to zero at the location of the moire phenomena, and should be close to one everywhere else. Such a filter could then be implemented in the spatial domain, or in the frequency domain using a method such as overlap-and-add or overlap-and-save [6]. Thus only a few rows would have to be buffered and there would be no need to carry out the full two-dimensional forward and inverse FFTs (although detection of the moire locations would still be required).

There has been some work on the design of notch filters [7], and we examined the applicability to removing moires. They did not work out to be the best approach for a number of reasons.

- Implementation of good notch filters is difficult, often requiring long filters, and accurate floating point implementation.
- In an automated algorithm the filters cannot be designed in advance, since we must first detect the moire frequencies before designing the filters.
- Many of the moires generated are at higher frequencies and a simple lowpass filter does an adequate job of removing them for much less complexity (and far less sensitivity to the accuracy of implementation).
- When moires occur at low frequencies attempting to remove them by a notch filter often generates unacceptable amounts of ringing and distortion; raising the possibility of removing the moire, but nonetheless making the image worse.

When we deal with very low frequency moire effects it should be pointed out that nulling frequencies in the Fourier domain usually works better than a notch filter.

4.4 Lowpass filtering

Since the moires are alias phenomena, they involve a "wrapping around" of the frequency information in the halftoned image. Since the information wraps from high to low, and the spectrum is in any case
decaying, commonly there will be much more moires at high frequencies than at low. Often, while they sit at the higher frequencies the moires are responsible for a graininess in the image. These are quite easily removed by lowpass filtering. It is important not to destroy the sharpness of text and edges when doing so. Thus, we can first detect the location of the moire and halftone patterns in the frequency domain, as discussed previously, and then lowpass using a filter with a cutoff frequency chosen to be lower than the moire frequencies. The lowpass filtering will almost certainly destroy much of the halftone information also, but this has a negligible effect on image quality.

We found that using a two-dimensional McClellan transformation of a one-dimensional filter designed using a windowing or Remez exchange approach worked considerably better than separable filtering along the rows and columns.

An example of the effect of lowpass filtering is shown in Figure 18. The original image has the grainy appearance typical when the moire locations are in the high frequencies. After filtering by a simple 7 by 7 lowpass filter the appearance is very considerably improved. Notice that even the sharpness of the text has not been degraded. A second example is shown in Figure 19. An alternative approach to suppression of grainy moire patterns is documented in [8]

4.5 Rendering as a means of moire suppression

While we have discussed the acquisition of images in some detail we have not yet mentioned the effect that rendering and printing has on the perceived moire effect. If rendering is done using error diffusion, or super smooth dither this certainly helps break up somewhat the coherent structure of the moires. Recall from Figure 8 that for both of these techniques the high frequency region of the image will have a blue noise appearance, and if there are moire in the high frequencies this appears to make them less noticeable. For example the same images as were shown in Figure 19 are printed again in Figure 20; this time the rendering is done using cluster dot dither. Not only are the moire effects much more noticeable in the original before filtering, but there are still somewhat more visible after halfband lowpass filtering.
5 Conclusions and Acknowledgements

5.1 Conclusions

We have examined the origins of moire patterns in scanned halftone images; we found they are explained as an aliasing pattern in the resampling (through the scanner) of an image that has already been "sampled" (from the halftone). We suggested how they may be suppressed using simple filtering or frequency domain processing.

5.2 Acknowledgements

We would like to acknowledge helpful discussions with several people. Ed Snow, Dave Childs, and Carlo Mastrogiacomo of SPR and Dan Allen of SDD were helpful, in explaining the color copier pipelines. Bob Sobol and Bob Gann of Greeley Hardcopy division provided us with information on the workings of the HP ScanJets. We thank Dan Tretter of HP Labs for a number of discussions.

References


Figure 17: Upper left: scanned image; lower left: Fourier transform of the scanned image; upper right: image after moire reduction; lower right: Fourier transform of the image after moire reduction.
Figure 18: Result of lowpass filtering an image with high frequency moire effects. (a) Original image. (b) 4:1 zoom in. (c) Filtered using a 7 by 7 halfband lowpass. (d) 4:1 zoom in.

Figure 19: Result of lowpass filtering an image with high frequency moire effects. (a) Original image. (b) Filtered using a 7 by 7 halfband lowpass.