# Qualitative Performance Evaluation of Visual Models in an Iterative Halftoning Procedure *

*T. Mitsa and J. R. Alford*
*Department of Electrical and Computer Engineering*
*University of Iowa, Iowa City, Iowa*

## Abstract

Visual models are increasingly being incorporated in digital halftoning algorithms. With the variety of visual models available, algorithm designers must select one that is consistent with desired results and computational requirements. In order to select the most appropriate visual model, it is important to gain an understanding of the visual effects of the different visual models on the halftone output. This work compares the effects of several single-channel visual models on halftone output by using an iterative technique that explicitly shapes the quantization error in the Fourier domain. By operating on the spectrum of the quantization error, we are able to directly apply a visual model as a threshold function. Our results clearly indicate that low-pass visual models produce much better quality halftones than conventional contrast sensitivity function models. This method also provides insight into the effects of constraining error in individual bands of a multichannel visual model. In addition, we introduce a technique that combines filters to shape the error spectrum in a way that preserves perceptually important high frequencies without sacrificing the desirable attenuation of low frequencies. The combination of filters can be implemented in an image adaptive manner by using the spectrum of the grayscale image or in an image independent manner by using weighted combinations of multiple channel filters.

## Introduction

Visual models are increasingly being incorporated in digital halftoning algorithms. A wide variety of visual models have been defined. Quantitative studies[1] indicate that choice of visual model is important in generating error metrics to assess halftone quality. This implies that the choice of visual model for designing a new halftoning technique is also a non-trivial issue. In order to choose an approriate model, an algorithm designer must gain an understanding of the visual effects of the different visual models of the halftone output.

It has been shown[2] that the spectrum of the quantization noise of a halftone is

$$Q\,(\mathbf{k}) = G\,(\mathbf{k}) - F\,(\mathbf{k})$$

where $\mathbf{k} = (k,l)$ are discrete sampling points in the spectrum plane and $G\,(\mathbf{k})$ is the spectrum of the halftone image and $F\,(\mathbf{k})$ is the spectrum of the input grayscale image. Reformulating this shows that the spectrum of the binary image is

$$G\,(\mathbf{k}) = F\,(\mathbf{k}) + Q\,(\mathbf{k})$$

It is well established that the shape of the quantization error spectrum affects the perceived quality of the halftone[3].

By explicitly constraining $Q(\mathbf{k})$ with visual models, we can directly assess the effects of different frequency domain characteristics. In this paper, we report on two classes of constraints. First we apply constraints based solely on established image-independent visual models in order to compare bandpass versus loupes characteristics. Next, we introduce an image adaptive technique that preserves perceptually important high frequencies without sacrificing the desirable effects of visual model based constraints on halftoning algorithms.

## Methods

The algorithm used to generate the halftones is an iterative Fourier transform technique described by Broja and Bryngdahl.[2] In this technique, the input grayscale image is halftoned with a pseudo-random threshold function. The spectrum of the original image $F_i(\mathbf{k})$ is then modified to produce the spectrum of the input grayscale image to the next iteration $F_{i+1}(\mathbf{k})$.

It is the filtering of the error spectrum where we focus our attention. Each input grayscale is generated from modification of the error spectrum, formally

$$F_{i+1}(\mathbf{k}) = F_i(\mathbf{k}) + Q_i(\mathbf{k}) * H(\mathbf{k})$$

where * represents convolution and $H(\mathbf{k})$ represents the constraints on the error spectrum. We consider two distinct formulations of $H(\mathbf{k})$. First, $H(\mathbf{k})$ is the transfer function of a visual model. By modifying the visual model represented by $H(\mathbf{k})$, we can observe the effects of different visual models. Second, $H(\mathbf{k})$ represents a two level cascade of filters, the first of which represents an image-independent visual model and the second of which is an image-dependent filter which restores perceptually important high frequencies.

## Results

In order to assess differences in visual models, we begin by selecting a widely used contrast sensitivity function introduced by Mannos and Sakrison.[4] This function is defined in cycles per degree and obtains its peak value at about 8 cycles per degree. Since we are working to minimize visible error, we invert the contrast sensitivity function so that it reaches its minimum value at 8 cycles per degree. By filtering with an inverted form of the contrast sensitivity function, we shape the quantization error spectrum so that errors are reduced where the eye is most sensitive and we allow errors to pass where the eye is least sensitive. This has the effect of minimizing changes to the original grayscale image in frequencies where the eye is most sensitive and allowing quantization error energy to remain where the eye is least sensitive. Figure 1(c) is an intensity representation of the inversion of the contrast sensitivity function. The brightest intensity represents a value of 1.0; the dark values represent zero value. As seen from the bright intensities near the center of the figure, much low-frequency energy is allowed to remain from the quantization error. The familiar “lena” image was the original grayscale input for the first iteration. Figure 1(b) is the halftone that was produced after modifying the input grayscale with the filtered quantization error using the Mannos and Sakrison contrast sensitivity function seen in Figure 1(a).

Next, we modified the Mannos and Sakrison function to be a low-pass filter as described in [1]. That is, we “flattened” the peak by setting the function to its maximum value at all frequencies lower than the peak frequency. Again, after inverting the function as described above, the filter applied to the quantization error is shown as in intensity image in Figure 1(c). The halftone produced with this modification is shown in Figure 1(d).

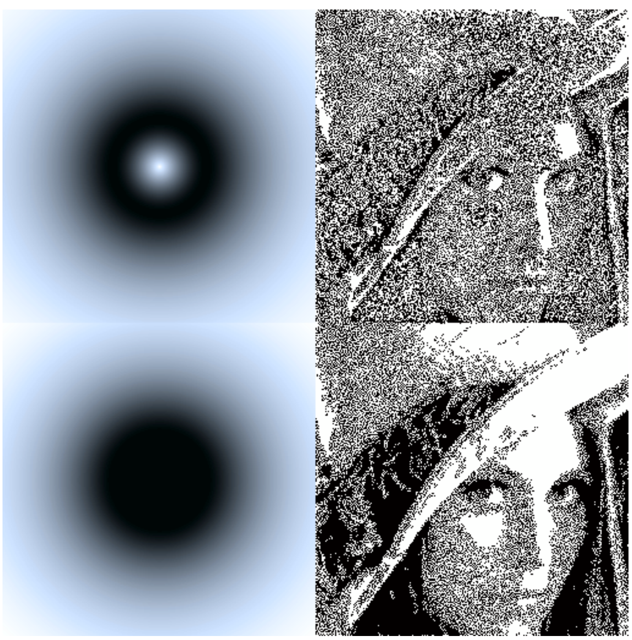

*Figure 1. From left to right and top to bottom: (a) inverted CSF filter (b) halftone output using inverted CSF filter (c) inverted low-pass modified CSF filter (d) halftone output using inverted low-pass modified CSF filter.*

Comparing the two results shown in Figures 1(b) and 1(d) clearly shows improvement by using a low-pass filter rather than a bandpass-type conventional contrast sensitivity function. These result also indicate that the iterative Fourier transform method is a good vehicle for assessing the effects of different visual models.

Next, we extended the concept of $H(\mathbf{k})$ to a two-level cascade of filters, each level designed to achieve a different goal. The first level is simply a lowpass visual model as described above. While this achieves the attenuation of low-frequency error that is well accepted as undesirable in halftones, it allows unconstrained error in the high frequencies. This is a problem because there are some images in which the high frequencies provide perceptually important information, For example, the periodicity of the lines in a brick wall provide important information to an observer. Minimizing error in just low frequencies will reduce errors in the representation of each brick surface but will degradation of the lines which serve to distinguish the wall as one made of bricks.

An image adaptive method to preserve distinguishing high frequency information is achieved by extending $H(\mathbf{k})$ is extended to include a second filter. The second filter is generated from the inversion of the normalized spectrum of the grayscale image. Where the original spectrum has peaks, indicating distinctive features, the second level filter has valleys, which will serve to attenuate errors at the specific frequencies that characterize image features. This is illustrated graphically in Figure (2). For simplicity, only a single slice of the image spectrum is depicted.

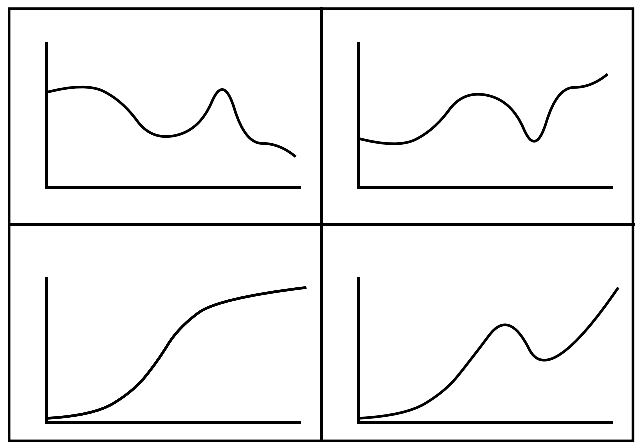

*Figure 2. From left to right and top to bottom: (a) normalized grayscale spectrum (b) second-level filter (c) first-level lowpass filter (d) combined effect of both filters with attenuation in all low-frequencies and at distinctive peaks.*

To illustrate the effects of constraining some high frequency error in an image adaptive manner, we applied the iterative Fourier technique to the picture of the rings of a tree. We tested three cases as illustrated in Figure (3). Figure 3(a) is the original grayscale image of a cross section of a tree. Figure 3(b) shows the results of using just a lowpass visual model error constraint. Figure 3(c) shows the results of bypassing the lowpass visual model and filtering the error with the inversion of the normalized power spectrum of the image. Figure 3(d) shows the results of combining the filters used in Figures 3(b) and 3(c). Specifically, the lowpass visual model constraint was cascaded with the second level filter constructed from the grayscale power spectrum. The second level constrains image-specific high frequencies. The poor quality of 3(c) indicates that attenuation of low-frequencies is important to overall halftone quality. The improved quality of 3(d) indicates that halftones can be improved by constraining some high frequency error. High frequency error can be reduced in an image independent way by constructing $H(\mathbf{k})$ from weighted combinations of individual channels in a multichannel model of vision.

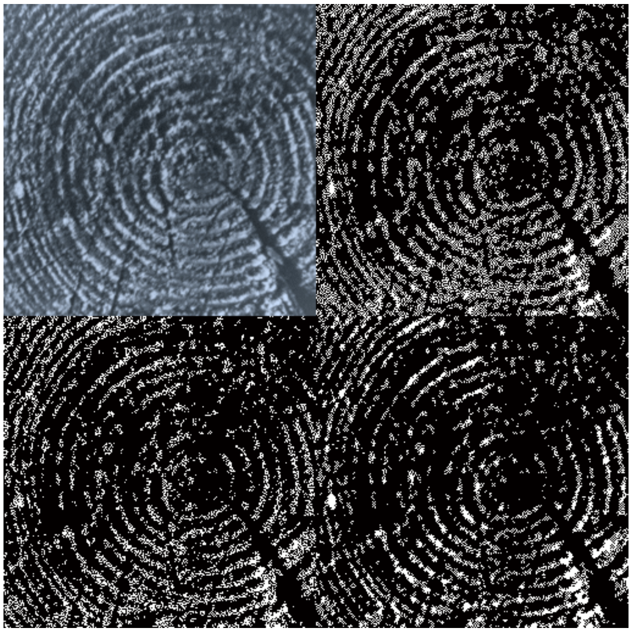

*Figure 3. From left to right and top to bottom: (a) grayscale image of tree (b) halftone produced with error constrained only by first level filter (c) halftone produced with error constrained only by second-level filter (d) halftone produced with error constrained by both first and second level filters.*

## Conclusions

The specific visual model selected for implementation in a halftoning algorithm can have a dramatic effect on the quality of the output. Qualitative results achieved here are consistent with previously obtained quantitative results[1] in concluding that a low-pass type visual model is much more appropriate than a conventional bandpass-like visual model for halftoning applications. Since the iterative Fourier technique allows explicit control of the quantization error spectrum, it can be a powerful tool for assessing the effects of various visual models in halftone algorithms. It can be used to assess the effects of single channel models and the individual channels of multichannel models. A new image-adaptive method is introduced which preserves perceptually important high frequencies without sacrificing the desirable effects of constraining error with a lowpass visual model. This is accomplished with a two-level cascade of filters, one level designed to support the lowpass nature of the visual system and the other level designed to restore high frequency information that characterizes the image. The improved results of the two-level filter indicate that for some images, constraining error at some high frequencies improves image quality. High frequency error can be reduced in an image independent way by constructing a cascade of filters from weighted combinations of individual channels in a multichannel model of vision.

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## References

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