Characterization of Printer Banding in Regions of Complex Image Content

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Abstract

This paper presents algorithms for estimating parameters that characterize weak levels of a printer artifact referred to as banding. Flat field test images are typically used as test patterns for banding evaluation; however, the images of this study contain complex image content to demonstrate the algorithm's robustness and extend the utility of the defect characterization methods. The test images are from color printers in the development phase and include multiple visible defects such as banding, grain, and streaking. The banding characterization includes an estimation of the fundamental frequency and average power extracted from local regions dominated by low frequency content where banding is likely to be most visible and offensive. Grain and mottle defects combined with other image content form a difficult noise environment from which the quasi-periodic banding characteristics must be extracted. The algorithm is based on the autocorrelation function and uses special averaging and a pre-whitening filter designed to minimize the influence of the interfering factor. Experimental results show that this method provides accurate banding frequency and power characterization even for multiple banding sequences that are present in the image test area. This new algorithm proves computationally efficient and more accurate than parameter estimates based on frequency domain analysis using the power spectrum. Experimental results show accurate banding characterizations for periods ranging between 0.93 and 10.5 mm over a range of banding-to-noise ratios from 5.5 to -6.5 dB.

1. Introduction

Printer banding artifacts are typically most visible and offensive in uniform areas of a printed image, such as the sky regions or flat-fields in business graphics. Regions dominated by low frequency content offer the minimal masking to the human observer for the higher frequency artifacts, which can include other artifacts like grain and mottle. Banding often appears as quasi-periodic density fluctuations in bands that extend across the printed image horizontally or vertically depending on the underlying printer mechanism imperfections. Multiple banding patterns can occur concurrently at independent fundamental frequencies. Current Inkjet and Electrophotographic (laser) printers continue to be affected by banding defects, especially as the printer components wear with use.

The Discrete Fourier Transform (DFT) magnitude and the Power Spectrum (PS) of a line of image pixels running normal to the banding direction are common analysis tools for characterizing banding. In previous work the PS has been used to simulate banding and separate it from other print defects such as grain and streaking [1, 2, 3]. Other work has considered estimates of fundamental banding frequency in relationship to printer components that cause the banding [4, 5, 6, 7]. The visibility and offensiveness of banding patterns of various waveform shapes and frequencies has been investigated as well; however, human visual system sensitivity to real banding patterns requires further investigation [8, 9, 10, 11].

This paper describes algorithms for estimating the fundamental frequencies of banding artifacts in local regions of real images dominated by low frequency content, such as the sky in a natural scene. The estimate of fundamental frequency can be used to characterize and reconstruct the banding pattern to remove it from the image for the purpose of analyzing additional defects [1]. The proposed algorithm relies on spatial domain autocorrelation analysis of a filtered image profile. It has some advantages over frequency domain operations, which show significant sensitivities small changes in the tapering window shape, amount of zero-padding, and signal positioning within the window. The autocorrelation method can be used to identify and estimate the frequencies of multiple banding patterns, and has the potential to estimate banding power for intra-image (constant noise levels) detection, and banding signal-to-noise ratio (SNR) for inter-image (variable noise levels) comparisons.

The harmonics of a periodic banding pattern appear as regular peaks in the PS. The peak heights can be viewed as an indication of banding power; however, noise energy levels can artificially bias this measure. Furthermore, if two independent banding patterns occur together, it can be shown that the two peak groups can interfere to the point where the weaker pattern might not be detectable in the PS. Also, transient image features and noise processes spread throughout the frequency domain causing locations to vary with noise levels, which lead to inaccurate estimates [1]. The autocorrelation method has an advantage here in that
such noise processes primarily affect the lags near zero, and can be more easily dealt with to separate it from the lags associated with banding.

The image samples are from printers in the development phase and contain a natural scene with most of the elements likely to be present in images the device must faithfully reproduce. The model adopted for representing the complex image content is [1]:

$$I(y) = b(y) + n(y) + h(y),$$  \hspace{1cm} (1)

where $I(y)$ is a series of image points through the region of interest (ROI) and normal to the banding process, $y$ is the index of the series, $b(y)$ denotes periodic artifacts such as banding, and $n(y)$ describes random artifacts such as grain and mottle, and $h(y)$ denotes for the image content or transient artifacts. The grain and mottle noise in such regions is more complex than simple additive noise because it is affected by image content and the interaction of the individual color halftone screens of the printer’s CMYK components. Initial noise reduction is achieved through averaging across several columns/rows in the local ROI for characterization of horizontal/vertical banding. Residual random noise and image content remains in the resulting 1-D profile and interferes with the banding signal. The low frequency artifacts that contribute the most to the profile are gradients, mottle, streaks, and coarse grain. Detrending the profile with a linear fit helps remove the effects of image content gradients, while a low-order linear prediction (LP) error filter can be used as a whitening filter to remove the effects of colored noise that ordinarily effect autocorrelation at non-zero lags. This second noise reduction step enhances banding frequency detection and power estimation as long as the LP filter order is smaller than the banding period (in pixels) of interest. The LP error filter uses the correlation in the colored noise to predict the profile value from a sequence of adjacent samples. The sequence of errors between the actual sample and predicted values is a white noise sequence, since the correlation has been removed. The first significant peak height of the filtered autocorrelation is typically a good estimate of banding power. Multiple banding patterns are signified by multiple peak groups with different periods. The paper is organized as follows. Section 2 describes the experiment, where the autocorrelation and power spectrum methods are compared, and Section 3 presents details on applying the algorithms to an example ROI. Section 4 shows experimental results of banding characterization, and Sections 5 presents summaries of results and conclusions.

2. Experimental Design

Several print samples from printers in the development phase were analyzed. They were printed on different paper grades on printers with various print parameters and exhibit combinations of grain, streaking and banding artifacts. The samples are 19x19 cm square and contain an image of a park with elements of flat, transient, and textured regions that can be found in real images. A test page with such content can be useful for examining various aspects of printed image quality in a scenario closest to field deployment requirements. Figure 1 shows the complex image content and the square ROI in the sky area. This ROI has a side length 43.3x43.3 mm, which corresponds to 1024 pixels – given that the test images were scanned at 600 dpi (on an HP ScanJet C7710A flatbed scanner).

The images for Figs. 1 and 2 show the luminance component of the CIE L*a*b* decomposition of the color image [12, 13]. The challenge lies in characterizing banding power and frequency in the presence of colored grain, random streaking, and image content. The grain produced by printing the image content using the printer’s CMYK colors is more complex than simulated monochrome grain due to effects of halftone screen interaction and image content color. In this example, the image content of the sky is evident in the gradual change in color levels in the vertical direction.
The next section describes how the applied algorithm manages the presence of grain noise and image content, while preserving the effect of the periodic banding signals.

3. Algorithm

The banding characterization algorithm assumes the ROI contains horizontal banding patterns embedded in grain and streaking noise, as well as, low-frequency image content such as regions of sky in a natural scene. The ROI, such as the one shown in Fig. 2 is converted to the CIE L* color space channel and modeled as an \(N \times N\) image matrix \(I(x,y)\), with \(x\) and \(y\) corresponding to the column and row pixel indices, respectively. The first step applies profile-based averaging (PBA) to the ROI. The two dimensional image is collapsed into a one dimensional image profile \(I_p\) by averaging over all columns denoted by \([1]\):

\[
I_p(y) = \frac{1}{N} \sum_{x=0}^{N-1} I(x,y). \tag{2}
\]

For the power spectrum method, a Kaiser window (with \(\beta=5\)) is applied to the analysis profile, which is zero-padded, to avoid edge effects while computing the DFT for the power spectrum estimate [14]. The DFT of \(I_p\) is computed as follows:

\[
S_p(k) = \sum_{y=0}^{N-1} I_p(y) \cdot e^{-j \frac{2\pi y k}{N}}. \tag{3}
\]

Then it is normalized by its root-mean-square (RMS) value to ensure comparability of profiles from different test images:

\[
S_{np}(k) = \frac{S_p(k)}{\sqrt{\langle S_p(k)^2 \rangle}}, \tag{4}
\]

where the \(< >\) denotes the mean over the frequency variable. The normalized frequency spectrum yields the profile’s normalized PS:

\[
P_{np}(k) = \frac{|S_{np}(k)|^2}{L}, \tag{5}
\]

where \(L\) is the profile length in mm. The vertical analysis profile usually contains gradients due to image content — thus, it is detrended by removing the best fit line from it before computing the FT. Fig. 3 shows the vertical analysis profile for the image region in Fig 2, before and after detrending. The visible spikes in the profile correspond to the 6.27 mm banding discussed earlier. This signal is represented in the power spectrum plot in Fig. 3 as a peak around 0.16 cyc/mm. On the other hand, the 0.93 mm banding pattern is not visually apparent in the analysis profile or the PS. The PS does not indicate a peak at 1.07 cyc/mm because this second banding pattern is relatively weak and is drowned out by the peak of the first banding’s 7th harmonic and other noise processes.

\[\text{Figure 3. Raw (top) and detrended (center) vertical analysis profile. The power spectrum of the profile (bottom) shows harmonic banding peaks. Circles locate two fundamental banding frequencies.}\]
This example illustrates a case where the PS is ill-suited for detecting multiple banding patterns in a single profile – especially when one pattern is considerably weaker than the other. Another problem with the PS in this case, is that the grain noise power spectrum (NPS) is manifested as a gradual downward trend from the zero-frequency out to the low-frequency areas [1, 5, 15]. This grain energy (colored noise) artificially biases peaks of the PS that might be due to banding, thus causing inaccurate banding power estimation or fundamental frequency detection.

The other algorithm (introduced in this work) that will be compared to the PS approach is a spatial domain procedure for detecting the fundamental frequencies and power of multiple banding patterns. The algorithm also detrends the profile as in the case of the PS, but then uses the detrended profile sequence to estimate coefficients for a 20th order LP filter. This was implemented with the LPC algorithm provided by MATLAB (The MathWorks, Inc. in Natick, MA) [16]. The whitening process used the coefficients in an FIR filter and applied it to whiten the analysis profile. After whitening the sequence the autocorrelation was computed as follows:

$$R_{pp}(m) = \frac{1}{R_0} \sum_{y=0}^{N-1} I_p(y) \cdot I_p(y + m),$$

(6)

where $I_p(y)$ is the whitened profile sequence, and $m$ is the sample lag, which is greater than or equal to zero. Note that $R_{pp}$ is normalized by the zero-lag energy $R_0$ to have the value of unity at $m=0$. Note that $R_0$ is the total energy and is equal to the sum of squared elements of the profile $I_p$.

In this work, the LP error filter order was chosen as 20. Here, the linear predictor uses the past 20 sample values of $I_p$ to predict to the next sample. As long as the banding periods of interest are greater than the filter order, they will not be predicted and removed in the whitening process. In general, selecting the filter order requires knowledge of the minimum expected banding period and the correlation length of the interfering noise processes. Let $k$ be the LP error filter order, then in this case for $k=20$, the minimal period length detectable is 0.85 mm according to the formula:

$$T_B \geq \frac{k}{f_s},$$

(7)

where $T_B$ is the detectable banding period (in mm), $k$ is the filter order (or the prediction window size in pixels), and $f_s$ is the sampling frequency. In this work the scans were made at 600 dpi which is equivalent to 23.6 samples per mm.

As seen in Fig. 4, the autocorrelation of the non-whitened profile, $R_{pp}$, is subject to the effects of grain energy, which introduces elevated levels from the zero-lag up to $m=15$. The filtered autocorrelation, also shown, reduces this problem. Now, the periods of the two banding patterns can be clearly read from the lag axis. In this case, they are located at the first peaks of regular peak groups – namely, at 0.93 mm and 6.27 mm as indicated by the circles. The whitening filter allows accurate reading of the individual banding powers, since the underlying noise slope has been reduced and likewise its variable contribution to the autocorrelation peak height. Therefore, the overlapping banding periods can be more clearly resolved.

![Figure 4. Autocorrelation plots of the raw (top) and filtered (bottom) analysis profiles with peaks showing energies of multiple banding patterns.](image)

The average power of the banding signal can be determined from the filtered autocorrelation by simply noting the height of the peak $E_B$ located at the lag equal to the banding period. In the example in Fig. 4, the banding energies are $E_{B1} = 0.1727$ and $E_{B2} = 0.5280$. Note that $E_{B2}$, the banding with the larger 6.27 mm period, is more than three times stronger than the banding with the 0.93 mm period. For comparisons between ROI’s from different test images, however, it is useful to express banding strength in terms of SNR. This is due to the fact that the total energy at the zero-lag, which is set to equal unity, contains the energy from the entire image’s elements including the banding “signal”, and “noise” contributions of grain, streaking, and image content – and it cannot be assumed, that this noise is constant over a set of test images. The SNR is defined as follows in this work:

$$SNR = 10 \cdot \log_{10} \left( \frac{E_B}{E_T - E_B} \right),$$

(8)

where $E_B$ is the banding energy defined as the height of the fundamental banding peak in the filtered autocorrelation, and $E_T$ is to total energy and is defined as unity (zero lag
peak height). Note that the denominator can be viewed as the energy of noise, i.e. from all image elements except the banding signal. It is evident that given a constant banding signal, its peak in the filtered profile autocorrelation will lose height with increasing noise, since the total energy is always set to equal unity. The experimental results show, however, that the SNR measure correlates with basic human ranking of banding visibility in the available samples. Additional investigation is required for a better understanding of this connection.

4. Results

A total of 17 natural scene test images from various printer settings were analyzed. Since the selected ROI’s (from the “sky” area) contained visible banding that was real (not synthesized), the ground truth of present banding periods had to be determined through manual investigation. A combination of spatial and frequency domain tools was used to establish the visible banding periods. The most basic being, counting the average length between spikes in the image profile $I_p$ defined in Eq. (2) and shown in Fig. 3. This approach yielded good estimates of the banding periods; however, it was not as accurate as examining the autocorrelation of $I_p$. Hence, these methods were combined and used to establish the ground truth of banding in each of the samples. The PS was an intuitive tool for detecting the fundamental frequencies of banding patterns; however, it does not perform well when a contribution of a periodicity is biased by noise levels or overpowered by harmonics of a different and more dominant periodic signal, as has been discussed in the context of Fig. 3. Another limitation of the PS lies in the fact that the location of the fundamental frequency peak might not be accurate due to interference with noise elements of similar frequency.

The PS peak locations of two banding frequencies over a range of SNR values are shown in Fig. 5. It can be seen that the variation in peak location is close to 10% for the lower-frequency banding. The higher-frequency banding, however, has a much smaller location estimation error (less than 1%). This confirms earlier simulations and suggests that banding patterns of low frequency are more susceptible to the effects of colored noise, particularly from grain and mottle artifacts.

Analysis of the described filtered autocorrelation algorithm showed that it successfully detected the fundamental frequencies of several banding patterns at various SNR values. The data points shown in Fig. 6 summarize the range of successful application. The figure shows banding-SNR points that range between 5.5 and -6.5 dB, and 0.93 to 10.5 mm periods.

![Figure 6. Summary of detected banding periods at various SNR's using the proposed algorithm.](image)

The performed analysis over this range did not expose problems with the proposed method. A more thorough analysis with synthesized banding of known power and frequency embedded into a natural flat field (such as the sky region) will help answer questions of method robustness. For such experiments, it is advisable to use a dedicated printer and scanner of high performance to minimize device induced variability and artifacts. A matter of interest here is that the grain of a natural color scene is more complex than synthesized monochrome grain, and it is unclear how human perception of it is affected by the interaction of the individual color half-tone screens of the printing process.

5. Conclusions

This paper introduced a noise reduction process to enhance the reliability of estimating parameters associated with banding artifacts in printer output. The LP error filter effectively whitened the extracted profile sequence, thereby reducing the colored noise contributions from other artifacts, such as mottle, grain, streaking, and low-frequency image content. The results, based on
comparisons with manual and human investigation of the raw image scans, demonstrated that the autocorrelation methods with the preprocessing for noise reduction was superior to power spectrum techniques in terms of accuracy and variability. In addition, when multiple banding processes were present, the power spectrum failed to detect the weaker banding, whereas the algorithm introduce here successful detected these secondary banding processes.

While further investigation is warranted to find the performance limits of the algorithm, it has relatively few parameters that need to be set and a robust performance with real data has be clearly demonstrated with the implementation presented in this paper. The method presented here has the potential to assess printer quality as a final metric to marketing the printer and also in the development phase to identify the periods of the banding and relate them other subcomponents in the printer that may be generating them.

6. References


