A Novel Algorithm for Detecting Streaks in Mottled and Noisy Images

Hector Santos Rosario[1], Eli Saber[1], Wencheng Wu[2]
1. Department of Electrical Engineering, RIT, Rochester, NY, 14623, USA
2. Xerox Corporation, 800 Phillips Road, Webster, NY, 14580, USA

Abstract

This paper describes an algorithm for detecting streaks in printed images using adaptive window-based image projections and maximization of mutual information. To this effect, projections are computed across the entire image at different window sizes. The traces collected from the projections are correlated using maximization of mutual information to pinpoint streak locations and width using a peak detection algorithm. Finally, for a given peak, the window size is changed adaptively to identify and locate the intensity and length of the corresponding streak while maximizing signal to noise ratio. Results on synthetic and real-life images are provided to demonstrate the effectiveness of our proposed technique.

1.0 Introduction

The standards for image quality have increased significantly over the past decade, and will continue to do so for years to come. Present day print engines are required to produce consistent and stable image quality requirements as measured by various metrics and ultimately evaluated by customers. Generally speaking, print shops place image quality as one of the most important aspects of any printing system. However, even though the quality of the documents produced using current print engines far exceeds what was generated a decade or two ago, the current devices still possess a variety of image quality defects and artifacts (e.g. spots, streaks, etc.) that often result from a fault or degradation in the underlying imaging and electrophotographic processes. The artifacts come in a variety of sizes and shapes and occur at different spatial locations. Operator or Engineer's intervention is usually required to visually or instrumentally diagnose the defect and perform corrective action as quickly as possible to minimize downtime.

Methods for image quality assessment can be generally classified as qualitative or quantitative. Qualitative measures are widely utilized for diagnosing artifacts and evaluating perceived image quality. These measures are highly subjective [1, 2], time consuming, and require expert knowledge. Quantitative measures, on the other hand, often utilize sophisticated instrumentation to measure the quality of the image or exploit the difference between pixel values of the original and reconstructed image in order to provide some measure of closeness between them. Mean squared error, least mean square, and peak signal to noise ratio (PSNR) are among the most common measures for assessing the objective quality of images [3, 4]. These usually require expensive laboratory setups, highly trained operators and are generally limited to a small subset of artifacts.

In this paper, we present a new algorithm for detecting the location of streaks in printed documents and assessing their corresponding length, width, and intensity. The proposed algorithm uses adaptive window-based image projections and maximization of mutual information (MMI) [5] for detecting "straight line" streaks in noisy and mottled grayscale and RGB color images. The traces, collected from the various projections, are correlated using maximization of the mutual information [5] to build a confidence vector that indicates the location and width of the streak(s). Finally, for a given peak position, the window size is changed adaptively to determine the intensity and length for the corresponding streak thereby maximizing the underlying signal to noise ratio. The effectiveness of our proposed algorithm is demonstrated on a series of images with varying degrees of streak intensity, length and width.

The remainder of this paper is organized as follows. Section 2 discusses the proposed algorithm. Our results are presented in Section 3 and conclusions drawn in Section 4.

2.0 Proposed Algorithm

A block diagram of our proposed algorithm is shown in Figure 1. It is divided into three major steps. In the first step, horizontal and vertical projections are computed using varying window sizes for the image at hand. The resulting 1-D profiles are correlated, in step 2, using MMI yielding a confidence vector that serves to indicate the location and width of the streak(s). Finally, the length and intensity of each streak are calculated, in step 3, using an adaptive window size selection technique to maximize the signal to noise ratio (SNR). The steps of the algorithm are discussed in detail in the following paragraphs.

2.1 Computation of Horizontal and Vertical Projections

Given an M x N grayscale or RGB color image (M = number of rows and N = number of columns), we start by computing the vertical projections across all rows and columns for a window size initially chosen to equal the entire image. A vertical projection is defined as the average intensity value of all pixels for a given column bounded by the window size. The window size is then reduced vertically by a factor of 2 yielding an M/2 x N window, and projections are computed using the M/2 x N window in a sliding fashion starting at the top of the image and moving downward in steps that are equal to M/4 (i.e. half of the window size in the vertical direction). This process is again repeated using an M/4 x N window size and continuing until the number of rows in the window is less than 8 pixels. The above computed projections are utilized collectively to generate the confidence vectors as described in the following section in order to pinpoint vertical streak(s). Similarly, the above process is also repeated in the horizontal direction yielding horizontal type projections.

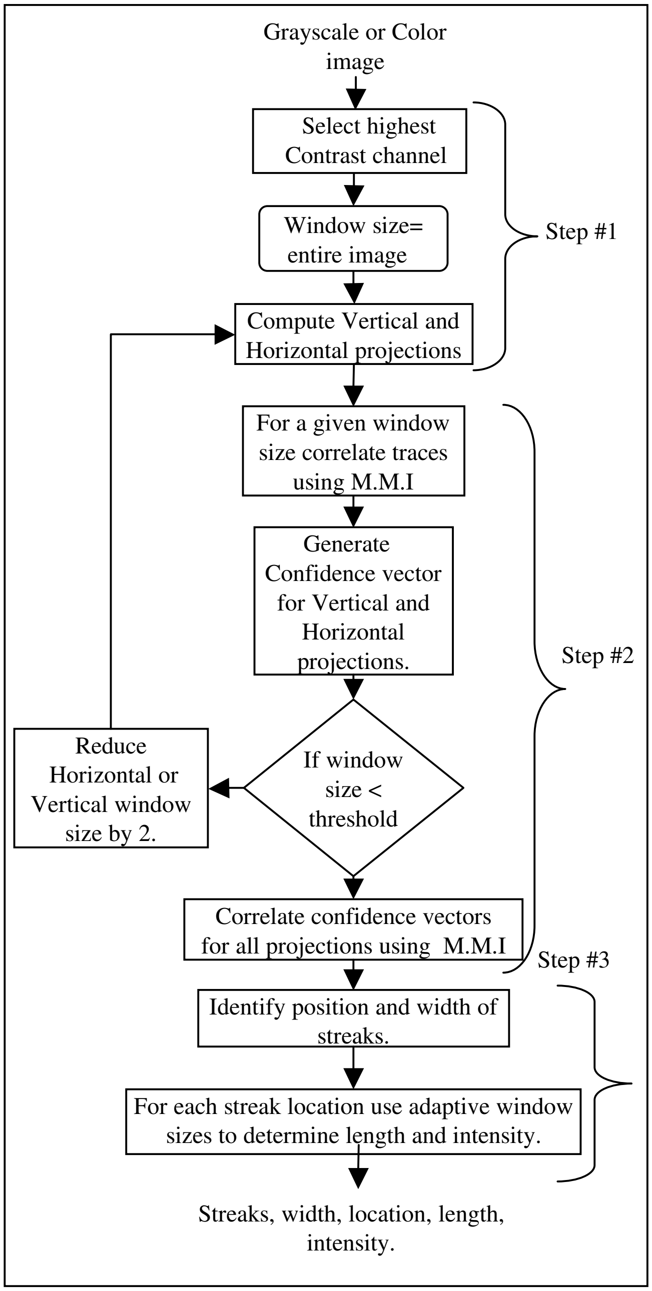

Fig. 1: *Block Diagram of the Proposed Streak Detection Algorithm*

2.2 Correlation of Projections using MMI

Once the projections have been collected for various window sizes as described in Section 2.1, we proceed to generate confidence vectors using MMI [5,6] in order to pinpoint horizontal and vertical streak locations. Let x and y define two random variables. The mutual information [5], which is a measure of general interdependence between random variables, is defined as:

$$I(x,y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log_2 \left(\frac{p(x,y)}{p(x)p(y)} \right) \tag{1}$$

where $p(x), p(y)$ are the marginal probability density functions (pdf), and $p(x,y)$ is the joint pdf of the random variables x and y. The projections collected above for various window sizes are correlated using MMI [5] to yield a horizontal and vertical confidence vectors that indicates the location and width of the streak(s) in the image for both horizontal and vertical directions, respectively. To this effect, for a given window size and direction (i.e. horizontal or vertical), we correlate the traces by computing the mutual information between peaks in two consecutive projections to obtain an intermediate confidence vector. The reasoning for selecting two consecutive projections is based on the fact that a given streak may not extend across the entire image and thereby is “visible” in only certain projections. We then correlate the intermediate confidence vectors from the various window sizes to obtain our final confidence vector as shown in Fig. 2. Locations that exhibit a confidence value greater than a user specified threshold are selected as streak(s). The width of the streak is defined by the width of the peak in the final confidence vector.

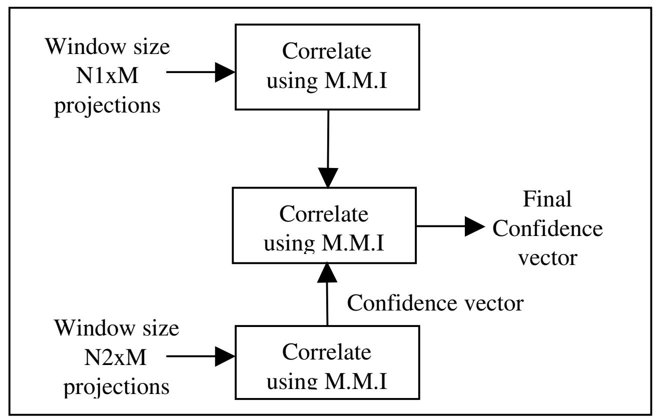

Fig. 2: *Final Confidence*

2.3 Computation of Length and Intensity of Streaks

To compute the length and intensity of a given vertical streak, we start by constructing a window that spans the streak horizontally and extends vertically to the full image height. We then compute the vertical projection of the streak of interest for the selected window size. The height of the window is then reduced sequentially and the above process is repeated in a sliding scenario yielding a set of projections as a function of vertical window size. The projection that yields the maximum or minimum value (dependent on whether the streak intensity is greater or smaller than the surrounding background) is utilized to determine the length and intensity thereby maximizing signal to noise ratio. To this effect, the height and average projection value of the window employed to compute the selected vertical projection is selected as the length and intensity of the streak, respectively. This focused approach is selected to minimize the number of computations that would be required for sliding window projections. The process is repeated in a similar fashion for horizontal type streaks.

3.0 Results

We tested the performance of our proposed algorithm on two sets of images. The first set consists of synthetic images that are constructed with various streak locations, lengths, width and intensities. This is utilized to test the robustness of our algorithm to varying degrees of noise, streak intensities, and lengths. The second set encompasses several scanned images that contain varying degrees of streaks, noise and mottle. In addition, some also contain a halftone periodic structure. These “real life” images were acquired from several electro-photographic based print engines. In the sections to follow, we will demonstrate our approach for detecting vertical streaks since the detection of horizontal streaks is identical assuming the image is pre-rotated by ninety degrees.

3.1 Analysis on Synthetic Images

Figure 3a shows a synthetic image created with a background gray value equal to 128 and different streaks lengths and intensity values as shown in Table 1. The streaks are numbered from left to right. Gaussian noise with different variances ranging from 1 to 80 (see Table 1) was added. Our proposed algorithm was applied to the image shown in Fig. 3a and the resulting streaks and final confidence vector, for ^{2} = 20, are shown in Figure 3b and 3c respectively. The detected streak lengths are compared using absolute error to the streaks manually segmented by a human operator, and the outcome is displayed in Table 1. Note that our algorithm was able to detect the location of the streaks effectively with the exception of streak #6 which is 5 pixels in length. Our ability to detect the streaks is inversely proportional to the level of noise added as seen in Table 1 and depends heavily on the streak length. The longer the streak, the more likely it is to be detected in the presence of noise due to the increase in signal to noise ratio.

Table 1: Length vs. Noise

Streak Information				Absolute error as a function of Noise level (σ^2)				
No.	L	I	W	1	20	40	60	80
1	110	136	1	0	5	76	76	-
2	80	120	1	0	0	2	8	-
3	60	136	1	0	0	2	2	-
4	40	120	1	2	2	5	5	-
5	20	136	1	0	1	-	-	-
6	5	120	1	-	-	-	-	-

L: Length, I: Intensity, W: Width

- : Indicates that the streak was not detected

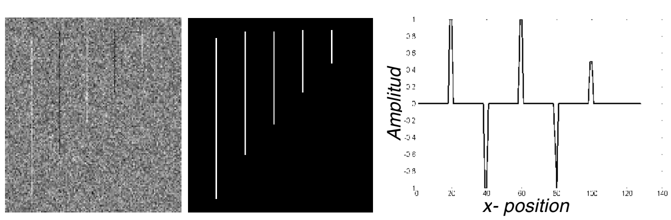

***Fig. 3** (a) Input image (b) Output image (c) Final Confidence*

Similarly, Figure 4 shows a synthetic image created with a background gray value equal to 128 and different streaks lengths, widths, and intensity values as shown in Table 2. Once again, the streaks are numbered from left to right and Gaussian noise with different variances ranging from 1 to 260 (see Table 2), instead of 1 to 80, was added. Our proposed algorithm was applied to the image shown in Fig. 4a and the resulting streaks and final confidence vector, for ^{2} = 20, are shown in Figure 4b and 4c respectively. The detected streak lengths and widths are compared using absolute error to the streaks manually segmented by a human operator, and the outcome is shown in Table 2. Similar results were observed in this experiment with one exception. The widths of the streaks increased the likelihood of detection in the presence of noise as observed from Table 2.

Table 2: Width vs. Noise Variance

Streak Information				Absolute error as a function of Noise level (σ^2)				
No.	L	I	W	1	40	120	200	260
1	110	136	25	0	0	1	1	-
2	80	120	15	0	0	0	1	-
3	60	136	10	0	1	1	2	-
4	40	120	5	0	1	1	2	-
5	20	136	2	0	-	-	-	-
6	5	120	1	-	-	-	-	-

L: Length, I: Intensity, W: Width

- : Indicates that the streak was not

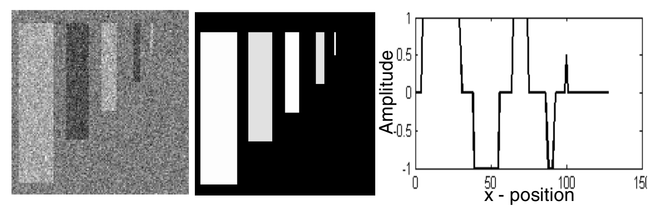

Fig. 4 (a) Input image (b) Output image (c) Final Confidence

We also tested our algorithm on a synthetic image created with a background gray value equal to 128 and several streaks of a fixed length and width and varying intensity values ranging from 134 to 150. Gaussian noise with variances ranging form 1 to 80 was added. The detected streaks were compared using least mean square error to those manually segmented by a human operator. The results indicate that the probability of detection increased with the increase in intensity.

3.2 Analysis on Real Images

In addition to the synthetic images discussed above, we tested our algorithm on several real life RGB scanned images that contain mottle, noise, halftone structures and varying degrees of streaks length, width, and intensity. Note that our algorithm selects the channel with the highest contrast for analysis. Fig. 5b and 5d show a “blow-up” of the region highlighted by the blue square in Fig. 5a and 5c respectively. The superimposed red lines indicate the location of the major streaks found in each of the images. Figures 6, 7, and 8 display three images with three different major types of streaks: i) a wide streak (Fig. 6a), ii) several narrow streaks (Fig. 7a), and iii) a set of streaks embedded in a periodic halftone structure (Fig. 8a). The detected streaks are superimposed using read lines on the corresponding figures, namely Fig. 6b, 7b and 8b. In Fig. 8b, we have only superimposed some of the lines for legibility. The detected streak in Fig. 6a has a length of 512, width of 20 and intensity of 76. Similarly, the results for the streaks detected in Fig. 7a are tabulated in Table 3. The length, width and intensity of the streaks found in Fig. 8a ranged from 470 to 512, 2 to 5, 30 to 70 respectively. Note that in each of the images, our algorithm was able to effectively detect the major streaks and accurately specify their length, width and intensity.

Table 3: Streak Information

Streak ID	Length	Width	Intensity
1	512	2	98
2	512	2	96
3	512	3	100

The threshold utilized to detect the location of the streaks was derived using a receiver operating characteristic (ROC) curve scenario as described in detail in [7, 8]. In summary, we selected thresholds for the final confidence vector ranging from 0.2 to 1; and for each threshold we computed the probability of detection and false alarm respectively.

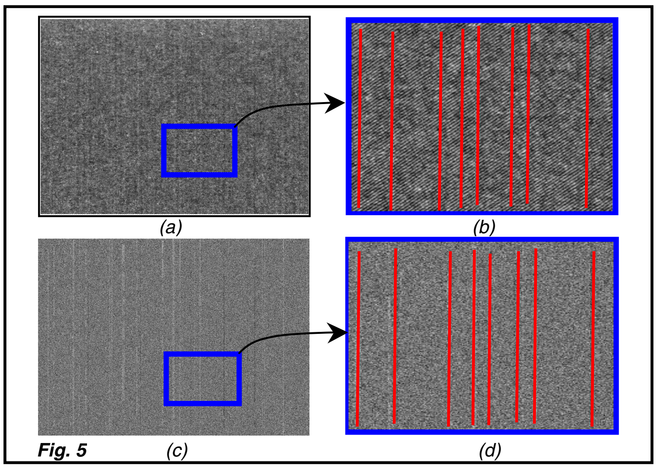

Fig. 5 (a) (b) (c) (d)

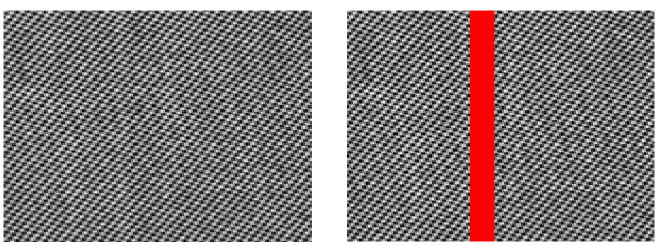

Fig. 6 (a) (b)

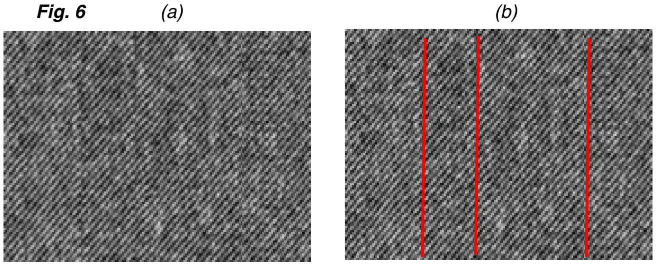

Fig. 7 (a)

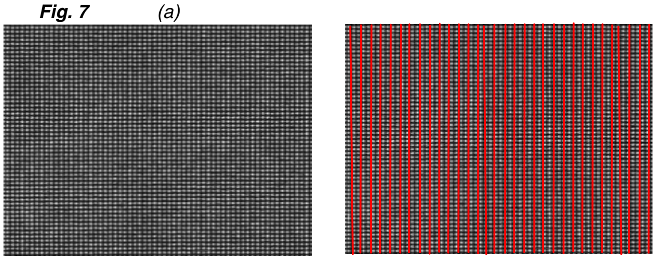

Fig. 8 (a) (b)

The optimum threshold utilized in the results discussed above was selected to minimize the probability of error between a set of training images and their corresponding human segmented gold standard.

4.0 Conclusion

This paper presented a new method for detecting streaks in mottled and noisy images by utilizing adaptive window-based image projections and maximization of mutual information. The proposed algorithm has been successfully demonstrated on a series of synthetic and real-life images that contain varying degrees of noise, mottle, and streaks. It is robust and effective for "straight line" streaks and proven superior to gradient or Hough transform based techniques due to its ability to detect streaks in noisy and mottled images.

5.0 Acknowledgments

This work was supported by the Center for Electronics Imaging System, a NYSTAR-designated Center for Advanced Technology, Xerox Corporation and the Electrical Engineering Department at RIT.

6.0 References

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Biography

Hector Santos received the B.S and M.S degrees in Electronic and Telecommunications Engineering from Pontificia Universidad Catolica Madre y Maestra, Santiago, Dominican Republic in 1993 and 2004, respectively. He is currently pursing an M. S. degree in Electrical Engineering at the Rochester Institute of Technology, Rochester, NY. From 1993 to 2004, he worked for the Civil Aviation Administration as a radar and communications system engineer. From 1998 to 2000, he was a communications engineer for Micro-Ondas Nacionales. From 2000 to 2002, he was a Project Manager in the Santiago International Airport responsible for the installation of the runway lighting systems and Precision Approach Path Indicators. From 1997 to 2004, he was an Adjunct Professor of Electrical Engineering at Pontificia Universidad Catolica Madre y Maestra.