Direct Binary Search for Print Mask Design in Inkjet Printing

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Abstract

Since the advent of multiple nozzle print-heads there have been efforts to utilize the added degree of freedom that comes with multiple-pass printing, the mode of printing where the print-head visits each pixel of the media more than once. The direct binary search (DBS) algorithm has been used as an optimal searching mechanism for signal design in digital holography, matched filtering for target recognition, digital halftoning, as well as location dependent sensor placement. An application of the DBS algorithm to optimal print mask design is proposed and an example is provided. The example showed that the number of operations for 100 trials of the DBS was 8 orders of magnitude smaller than that for the previously proposed exhaustive search. Future efforts are needed to improve number of operations required to confidently (> 95% confidence) obtain a globally minimizing print mask.

Introduction

With the numerous inkjet printed devices [1], the throughput associated with multiple nozzle arrays is necessary for large scale manufacturing. The capability of inkjet printers to possess multiple nozzle print-heads provides print jobs with higher throughput relative to single nozzle print-heads. Since the advent of multiple nozzle print-heads there have been efforts [2–6] to utilize the added degree of freedom that comes with multiple-pass printing, the mode of printing where the print-head visits each pixel of the media more than once. These efforts focused on designing a print mask (PM), a matrix used to map each media pixel to the pass of the print-head during which ink is deposited, to reduce artifacts (e.g. banding) caused by drop placement errors and ink migration.

In an ideal situation, we would have the print-head travel over the media in the print-head scan direction until reaching the width of the image, advance the length of the print-head in the media advance direction, and repeat this process until reaching the end of the image (i.e. the print-head would visit each pixel of the image once and only once). However, hardware limitations and print quality requirements make it difficult to print from all nozzles or even adjacent nozzles at a given time. Print modes are established to trade-off between print speed and print quality requirements based on different media, ink, and image content. A multiple-pass print mode optimized for halftoned images may not be desirable or have adequate throughput for text or line art documents, which have higher requirements on swath alignment.

Since not all nozzles should be fired at any given pass for a multiple-pass print mode, the print-head must pass over each pixel more than once so that there is more than one opportunity for ink deposition. Figure 1 shows how an image can be printed by two passes of a print-head with six nozzles. The top left image of Fig. 1 is the image to be printed. On the first pass, the bottom three nozzles pass over the image filling in the top left pixel with the fourth nozzle, the middle pixel with the fifth noz-



Figure 1. Example of printing an image with two passes of a print-head.

zle, and the bottom right pixel with the sixth nozzle (i.e. all of the pixels requiring ink which are labeled with pass number 1) as shown in the bottom left image of Fig. 1. The substrate then moves three nozzles in the media advance direction relative to the print-head. The print-head then passes over the image pixels its second and final time, printing the top middle pixel from the first nozzle and the middle left pixel from the second nozzle (i.e. all of the pixels requiring ink which are labeled with pass number 1) as illustrated in the bottom right image of Fig. 1. The top right image of Fig. 1 is the (PM) used for printing the image, which is referred to in the literature [2,3] as the checkerboard design because of the checkerboard pattern of 1's and 2's in the PM. The checkerboard PM design is often used to avoid consecutive firing of the same nozzle and in some cases to avoid print artifacts. Due to hardware limitations and print quality requirements, PMs other than that of the checkerboard design may be needed.

In 1999, Yen et. al. [2] introduced two methods for *PM* design. First, in order to produce an imperceptable (by the human visual system) printed pattern that covers up banding artifacts caused by defective print-head nozzles, a two-pass 4 by 4 *PM* with triangular clusters, derived from halftoning techniques [7], was used. Second, an alternative *PM* was derived from generating a super smooth dithering matrix [8], which proved to address artifacts associated with ink migration by guiding the ink migration into a super smooth dithereing pattern indetectable by the human eye. Subsequently, Yen et. al [3] formulated the automatic selection of a *PM* as a general constrained optimization problem applicable to multiple-pass print modes for multiple-level (multiple drops per pixel), multiple-drop (multiple drops per pixel, per pass) technologies. The method begins with a random initial solution found by means of a greedy algorithm, followed by neighborhood

search techniques. However, no specific guidlines were given to consider drop placement error, which can be on the same order of magnitude as the drop radius, or to consider the occurrence of coalescence between neighboring drops, which affects the performance of printed electronics (e.g.'s shorted or open circuits).

In other work, a stochastic model considering drop evaporation, drop impact, and drop placement error has been developed in efforts to establish threshold values for deposition time differences between adjacent drops [4, 5]. These threshold values were then used as constraints in a multiple-pass single-level PM design problem formulated to maximize throughput (minimize the total number of passes) while maintaining a minimum probability of drop coalescence [6]. This exhaustive search resulted in a set of admissible PM's. However, the required computational intensity deemed this approach applicable only for PM's with less than 16 elements for a four-pass print mode.

The direct binary search (DBS) algorithm has been used as an optimal searching mechanism for signal design in digital holography [9], matched filtering for target recognition [9], digital halftoning [9], as well as location dependent sensor placement [10].

This paper poses the DBS algorithm as a less computationally intensive alternative to the exhaustive search *PM* design discussed earlier [6]. The exhaustive search study required a number of operations proportional to $p_1 \cdot p_2 \cdot n^{p_1 \cdot p_2}$; where p_1 is the number of rows of the *PM*, p_2 is the number of columns of the *PM*, and *n* is the total number of passes in the print mode. However, the DBS algorithm requires a number of operations proportional to $p_1 \cdot p_2 \cdot n$, exponentially smaller than that required for the exhaustive search. The iterative nature of the DBS results in the highest of quality of images in digital halftoning when compared to point algorithms and neighborhood algorithms [11], which is desirable for printing. In future work, the DBS may be used to gain insight into improving the image quality of *PM* design with faster algorithms (point and neighborhood), similar to digital halftoning [9, 11].

The remainder of the paper is as follows. The next section discusses generally how the DBS can be applied to PM design. The third section gives an example of applying the DBS to PM design with an objective of minimizing the drop coalescence and the drop placement error. The final section gives the concluding remarks on the results found herein.

Direct Binary Search in Print Mask Design

As discussed in the literature [9, 11, 12], the DBS is an iterative search algorithm that begins with a randomly generated initial image with a uniform distribution of 1s and 0s. The algorithm continues by sweeping through every element of the initial image lexicographically and computes the difference in a prescribed error measure or cost function between changing the value of the image element and keeping the value of the image element. If changing the value of the image element improves the error measure or cost function, then the new value replaces the old value. Otherwise, the old value is kept. An iteration is considered complete once the algorithm has swept through every element in the image. The algorithm has converged to a local minimum of the error measure or cost function when no changes to the image are accepted during an iteration [11].

The flowchart for the DBS algorithm taylored for PM design



Figure 2. Flowchart of DBS Applied to Print Mask Design.

is displayed in Fig. 2. An initial random print mask PM_{ij} is generated from a discrete uniform distribution on [1, n]. The prescribed error measure, e, resulting from PM_{ij} is then computed. The print mask is then scanned in raster fashion. For each element in the print mask, a loop is conducted through $\{1, 2, ..., n\}$. At each instance in the loop the element in the print mask is changed to the current loop value and the resulting error measure e' is computed and compared to the previous error measure. If the error measure decreases and the constraints imposed onto the print mask are satisfied, then the modified print mask PM'_{ij} and the new error measure e' are kept. Otherwise, the print mask remains at its previous value. An iteration is complete when the algorithm has addressed every element in the print mask. The algorithm terminates once an iteration results in no modification to the print mask result from the previous iteration.

In reference to the originaly DBS [12], slight modifications have been made to make the algorithm applicable to PM design. The difference between the DBS as is and the DBS applied to PMdesign is the inherent difference between the values that the elements in each application can take. Since a PM is a base n matrix, all possible values for each element in the print mask must be considered, resulting in the additional c loop in the algorithm. Also, Fig. 2 includes the satisfying of constraints before accepting a change. It should be noted that the constraints can be lumped into the error measure. However, we have chosen to show them separately. The next section discusses an application of this algorithm for designing a PM with the objective of minimizing coalescence and drop placement error.



Figure 3. Neighborhood of Interest for Image Pixel q_i, q_2 .

An Example of Direct Binary Search for Print Mask Design

The choice of error measure is application dependent. In previous applications the goal was to keep all image errors [9–11] or embedded signals [13] imperceptable to the human eye. The human vision system has also been considered in previous print mask designs [2]. However, this example focuses on designing a PM via DBS with an error measure which considers drop coalescence and drop placement error.

Let the image, *I* be of size $m_1 \times m_2$ pixels. To address drop coalescence and drop placement error, the neighborhood of image pixel q_1, q_2 shown in Fig. 3 is considered. Typically, $p_1 < m_1$ and $p_2 < m_2$. As a result, the *PM* is tiled up to match the the size of the *I*. This tiled up matrix is referred to as the canvas [6]. For this example, we take $m_1 = 2k - \frac{k}{n}$ and $m_2 = 2p_2$; where *k* is the total number of nozzles in the print-head.

Let

$$repi = \begin{cases} \left(\left\lfloor \frac{2k - \frac{k}{n}}{p_1} \right\rfloor - 1 \right) \cdot p_1 + i, & \text{if } i > mod \left(2k - \frac{k}{n}, p_1 \right) p_1 \\ \\ \left(\left\lfloor \frac{2k - \frac{k}{n}}{p_1} \right\rfloor \right) \cdot p_1 + i, & \text{otherwise} \end{cases}$$
(1)

denote the number of times element (i, j) in the *PM* repeats itself throughout the height of the canvas and

$$Q = \{(q_1, q_2) : q_1 = i, i + p_1, i + 2p_1, \dots, repi; q_2 = j, j + p_2\}$$
(2)

be the set of all pixels in the canvas where element (i, j) of the *PM* appears. Then we write the error measure for element (i, j) to be

$$e = \sum_{Q} \left(\sum_{w=1}^{4} f(q_1, q_2, w) \right);$$
(3)

where *w* represents the member of the neighborhood shown in Fig. 3 and *f* is point and neighbor dependent error function. Let γ_c be a weighting on the importance of drop coalescence, γ_{dp} be a weighting on the importance of drop placement, $\varepsilon_{q_1q_2w}$ be the relative biased drop placement error between the nozzle responsible for printing image pixel (q_1, q_2) and the nozzle responsible for printing neighbor pixel *w*, $\sigma x_{q_1q_2}^2$ and $\sigma y_{q_1q_2}^2$ be the variance of the drop placement error associated with the nozzle that prints image pixel (q_1, q_2) in the print-head scan and media advance directions, respectively, and σx_w^2 and σy_w^2 be the variance of the drop placement error associated with the nozzle that prints neighbor *w* in the print-head scan and media advance directions, respectively.

For this example, we have

$$f(q_1, q_2, w) = \gamma_c \cdot f_c(q_1, q_2, w) + \gamma_{dp} \cdot f_{dp}(q_1, q_2, w); \quad (4)$$

where

$$f_c(q_1, q_2, w) = \begin{cases} T_{min} - |T_{q_1q_2} - T_w|, & \text{if } |T_{q_1q_2} - T_w| < T_{min} \\ 0, & \text{otherwise} \end{cases}$$
(5)

is the point and neighbor dependent error function for coalescence and

$$f_{dp}(q_1, q_2, w) = \varepsilon_{q_1 q_2 w} + \sqrt{\sigma x_{q_1 q_2}^2 + \sigma y_{q_1 q_2}^2 + \sigma x_w^2 + \sigma y_w^2}$$
(6)

is the point and neighbor dependent error function for drop placement. T_{min} is the deposition time difference threshold between image pixel (q_1, q_2) and neighbor w in order to avoid drop coalescence, $T_{q_1q_2}$ is the deposition time of image pixel (q_1, q_2) , and T_w is the deposition time of neighbor w. The methods used in this example to find T_{min} , $T_{q_1q_2}$, T_w , and the nozzle responsible for printing each image pixel are the same methods discussed in [6].

To avoid the trivial situation where a pass is associated with no nozzle firing, the following constraint is applied to this example [6].

$$\bigcup_{i,j} \{ PM(i,j) \} = \{1,2,\dots,n\}.$$
(7)

Next we assume bidirectional printing, equivalent ink properties, substrate properties, image resolution, and the same 12-nozzle print-head as in [6]. In addition, we assume the print-head scan speed to be 15in/s, 2in margins, a minimum acceptable probability of coalescence to be 10%, n = 4, and $p_1 = p_2 = 4$. To maintain comparable magnitude scaling between Eq.'s 5 and 6, the weightings were set to $\gamma_c = 1$ and $\gamma_{dp} = 0.001$. It should be noted that these weightings depend on the units and magnitudes of the cost functions. In this case, the units for Eq. 5 are in seconds and the values maintained are on the order of 1s; the units for Eq. 6 are in μm and the values maintained are on the order of $10\mu m$. Additionally, $\varepsilon_{q_1q_2w} = 0$.

To achieve a sense of performance with this example, the proposed DBS algorithm was run 100 times. The values for the number of iterations required before convergence and minimal e were recorded for each trial. The *PM* associated with the smallest vaue for the minimal e is

	(4	2	4	1	
DM		1	4	1	4	
$PM_{min} =$		4	1	3	1	ŀ
	$\left(\right)$	1	4	1	4	

It should be noted that only two of the elements in PM_{min} are neither 1 nor 4. By default one of these should be 2 and the other should be 3 so that the constraint in Eq. 7 is satisfied. The reason for a large populations of 4's and 1's in PM_{min} is due to the coalescence objective (no more than 10% coalescence). Using the argument of adjacency constraints [3], to satisfy the coalescence objective, each element in the PM_{min} must be at least two passes from its horizontal and vertical neighbors. It should also be noted from the application of the exhaustive search [6] that PM_{min} is in the set of admissible PMs with a minimum acceptable probability of coalescence of 72%, nothing lower. This is because of the high print-head scan speed (15in/s) compared to the ratio of the size of the image to the time scale of evaporation of water on glass (0.02in/s) and the presence of 2 in $PM_{min}(1,2)$ and 3 in $PM_{min}(3,3)$, resulting in deposition time differences less than the threshold values for 72% occurrence of coalescence, violating the coalescence constraint. However, the constraint is violated only for these two elements.

The statistics for the recorded values are given in Table 1. In this example, the DBS has a fast rate of convergence, requiring only 3 to 5 iterations to converge to a local optimum, as seen with previous applications [9,11]. However, the resulting PM will only minimize e locally, not globally, which requires multiple runs of the algorithm to confidently (>95% confidence) obtain a globally minimizing PM. This explains the large standard deviation (33% of the mean) of the minimum *e*, especially in this case when the smallest minimized e is more than two standard deviations from the mean. On the other hand, the DBS is its much lower number of operations when compared to the previous exhaustive search (smaller by a factor of $n^{p_1 \cdot p_2 - 1}$) [6]. For this example, the exhaustive search requires $O(6.9 \times 10^{10})$ operations to complete, 8 orders of magnitude higher than running 100 trials of the DBS (10 orders of magnitude higher than 1 trial of the DBS (O(64)). Because of its drastic reduction in computation resources compared to the exhaustive search, future efforts will be made on improving the number of operations required to confidently obtain a globally minimizing *PM*.

Summary of DBS Statistics for 100 Trials

Statistic	Minimum e	Iterations		
Minimum Value	3.94	3		
Maximum Value	16.68	5		
Mean Value	10.62	3.11		
Standard Deviation	3.42	0.35		

Conclusion

In this work, the DBS has been adopted and applied to print mask design. In addition, an example print mask design with an objective to minimize drop coalescence and drop placement error was conducted via DBS. The number of operations for 100 trials of the DBS was 8 orders of magnitude smaller than the previously proposed exhaustive search. Future efforts are needed to improve the number of operations required to confidently (> 95% confidence) obtain a globally minimizing *PM*.

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