Printer Model Integrating Genetic Algorithm for Improvement of Halftone Patterns

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Abstract- The paper describes a genetic algorithm to search for halftone patterns that would print with the least visual granularity. Our approach automatically generates dithers optimized for use in specific printing hardware. A semi-empirical model of electrophotographic printing process is applied as a fitness criterion used in evaluating performance of individual dithers. The printer model includes a function for visual contrast sensitivity and also for random print noise. Genetic searches were begun with halftone patterns of very low spatial frequency, very high frequency, and white noise random patterns. All of these converged to quasi-random patterns with noise power maximized just below the visual threshold. Our experiments demonstrate ability of genetic algorithms to find high fitness dithers irrespective of the printing hardware being considered. This work is part of an on-going project to develop printer calibration procedures to optimize print image quality.

I. Introduction

Traditionally development of dithers for different printing hardware systems has been a tedious manual process. Coupled with the rapid growth in the total number of developed printing systems this prevented creation of optimized dithers for each and every particular system. Genetic algorithms have been previously employed in the search for improved halftoning masks [1], [2], [5], but unfortunately limitations of the printing hardware prevent accurate transfer of images developed in such a way to a printed page. The advantage of our system is that the printer model we utilize takes into account the changes produced by the printing process itself such as smearing of ink and appearance of noise artifacts due to hardware limitations of printer.

II. The Genetic Algorithm

The developed GA is generational, based on the ideas in Goldberg [6].

1) A population of N possible solutions is developed.
2) The fitness value of each individual (dither) is determined.
3) Repeat the following steps $N/2$ times to create the next generation.
   a) Choose two parents using tournament selection.
   b) With probability p_c, crossover the parents to create two children; otherwise simply pass parents to the next generation.
   c) With probability p_m for each child, mutate that child.
   d) place the two new children into the next generation.
4) Repeat new generation creation until a satisfactory solution is found or the search time is exhausted.

By continually selecting dithers with higher fitness values and creating new dithers through the genetic operators of crossover and mutation the population of dithers increases in quality. This procedure is usually given a specific amount of time and is then halted, at which time the best mask found is reported.

A. Dither Representation

A dither, D, is a 2-dimensional binary array with ones signifying the existence of ink in that particular region of the pattern and zeros obviously being regions where no ink should be deposited. Our algorithm aims at developing dot patterns within the dithers, which can be reproduced by the printing hardware without introducing any visible artifacts into the final printout. While theoretically any size dithers can be evolved, due to the computational requirements of the printer model, all our experiments were performed on the dithers of at least 50×50 units.

B. Creation of the Initial Population

Initial population necessary to begin the genetic search can be generated in a number of ways. For example, after the size of the initial population is decided on, the necessary number of individuals can be produced in a random fashion. Random number generator can be used to decide the value of every element in the binary array representing each dither. This results in the gray-level value of about $.5$ if a normal distribution random number generator is utilized. Gray-level is calculated by dividing the number of ink dots in the dither by the total size of the dither. Overall, any value gray-level dither can be produced as follows: first an array of zeros of the desired size is produced. Afterwards zeros at random locations are converted to ones, until the total number of ones in the binary array approaches that expected from the dither at this gray-level.

An alternative approach to creation of the initial population is to assign manually designed dithers to be the initial binary arrays. The designed dithers could be based on a certain property such as high degree of blue noise, or be constructed to represent an anticipated well printable pattern such as for example checkerboard pattern of particular dot cluster size. It is also possible to seed the initial population for the GA run with superior individual from previous successful runs. This approach tends to produce high initial fitness values, but may result in faster stagnation of the exploration process.

In general we aimed at random generation of the initial population. This approach removes any need for manual design of the halftone patterns and so is especially valuable, as it allows automatic development of dithers for each and every hardware printing system.

C. Fitness Function

The most complicated and certainly most important part of our search system is the fitness function, which is based on the semi-empirical model of electrophotographic printing model of the printing process. We have developed a parameterized printer model, which takes into account such factors as dot gain, toner transfer, paper and ink effects, reflectance, noise, and even the contribution from the human visual system [4], [3].

The following parameters can be altered in order to change the GA search to a different printing system:

```
ADD = 600;          % Printer addressability
Na = 50;            % Analysis image size
Rk = .05;           % Reflectance of ink
Rg = .85;           % Reflectance of paper
kp = .3;            % Paper spread constant
a = 20;             % Printer TTF
b = .3;             % Printer TTF
sigmap = .8;        % Printer PSF width
p = 3;              % Printer PSF shape
sigmas = .1;        % Printer noise
```

D. Crossover Operation

A fundamental property of any evolutionary system is the ability to exchange genetic material between superior individuals in the population. In our case it is necessary in order to pass the good properties of the parent dithers on to their offspring. In our experiments the crossover operation was implemented as follows: for children C_1, C_2 and parents P_1, P_2, $C_1(i,j) = C_2(i,j) = P_1(i,j)$ in case $P_1(i,j) = P_2(i,j)$ there will be an even number of cases there $P_1(i,j)$ not equals $P_2(i,j)$ for those cases set half of $C_1(i,j) = 1$ and the other half set to $C_1(i,j) = 0$, also set C_2 complementary. The above procedure could be repeated a certain number of times depending on the size of the dither being improved and on the desired amount of genetic code interchange between the parents. This type of crossover clearly preserves the total respective number of ones and zeros and so does not affect overall gray-level of the dither.

E. Mutation Operation

Occasional genetic mutations are necessary to provide genetic diversity to otherwise stagnating population and allows for the exploration of search space to take place. Since in the case of dithers it is important to preserve the overall gray-level of the pattern, simply randomly flipping zeros to ones and wise versa is not a feasibly way of introducing genetic diversity. An alternative approach is for a set of values at two different randomly selected locations within the binary array to get interchanged. Since only two different values are present in the dither half the time such mutation produces no novel genetic material. But just as in the case of the crossover operation we are at liberty to control the amount of total mutation taking place. So by repeating the mutation operation a certain number of times possible proportioned to the total size of the dither we can achieve any degree of genetic mutation we desire.

III. Experiments

Our experiments concentrated on finding optimal parameters for the control of the genetic search, including optimal rates of crossover, mutation and population size.

A significant amount of testing was done to determine how the properties of the initial population affect the eventual outcome of the genetic search and if superior dithers from different initial populations tend to evolve towards a common type of dither.

The following types of dithers were seeded in the initial populations:

1) Randomly generated 2-dimensional binary array with gray-level value of $.25$.
2) Checkerboard pattern, cluster dot of size 1×1.
3) Checkerboard pattern, cluster dot of size 2×2.
4) Checkerboard pattern, cluster dot of size 3×3.
5) Checkerboard pattern, cluster dot of size 4×4.
6) Checkerboard pattern, cluster dot of size 5×5.
7) Checkerboard pattern, cluster dot of size 25×25.
8) Dithers containing high degree of Blue noise with gray-level value of $.25$.

IV. **Results**

In terms of the optimization of the genetic search, parameters, we used are population size $N = 10$, crossover probability $p_c = 0.8$ and mutation rate $p_m = 0.3$.

Figure 1 shows preliminary dither improvements achieved by our genetic search algorithm based on different initial populations. Theoretical properties of our model suggest an eventual convergence to the same dither type regardless of the type of the initial population.

Figures 2, 3, 4, 5, 6 , 7 show consistent, although slow, improvements produced by our genetic search for different sizes of cluster dots or for Blue noise in the initial population. Typically, larger size of cluster dots in the initial population produces a relatively low initial fitness value and so allows for a much more significant overall improvement by the genetic search of such dithers.

V. **Conclusions**

Genetic algorithms are useful tool in designing dither masks. By automating the process of such design it is possible to develop well performing dithers for specific printing hardware systems. Our ongoing work focuses on optimization of the search process in order to reduce the time required for each dither improvement.

VI. **Acknowledgments**

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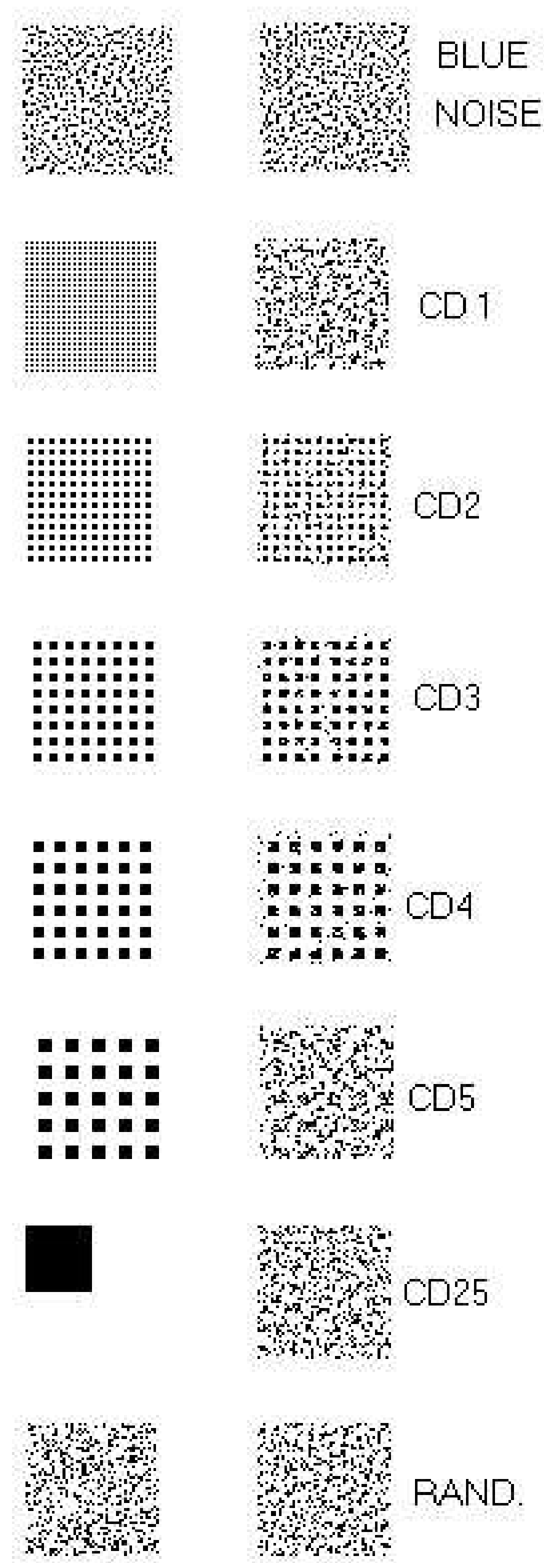

Fig. 1. Left: Sample from the initial population, Right: Improved dither. Blue noise, Cluster Dots 1-5 and 25, Random Noise

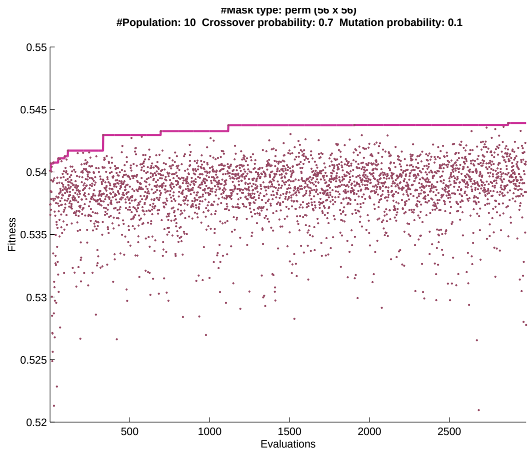

Fig. 2. Progress of the GA search starting with the Blue noise dithers.

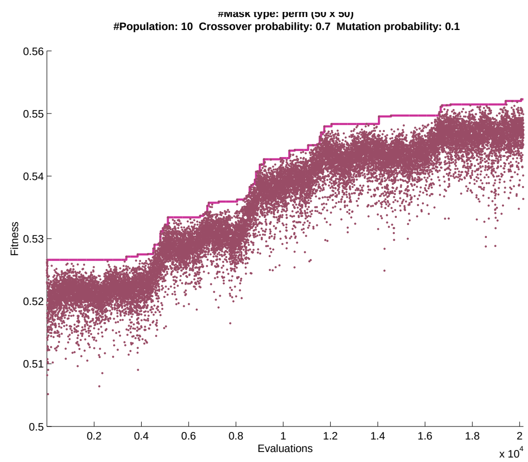

Fig. 3. Progress of the GA search starting with Cluster Dot 1×1.

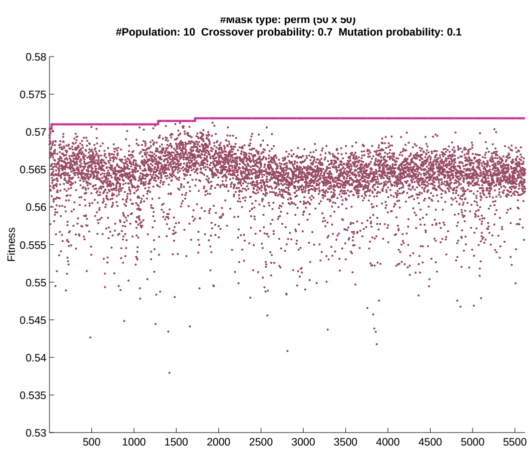

Fig. 4. Progress of the GA search starting with Cluster Dot 3×3.

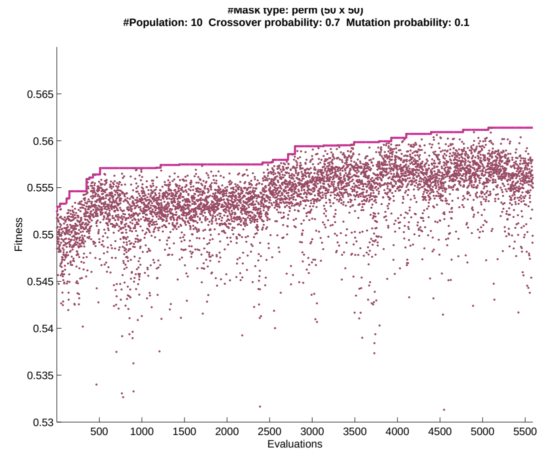

Fig. 5. Progress of the GA search starting with Cluster Dot 4×4.

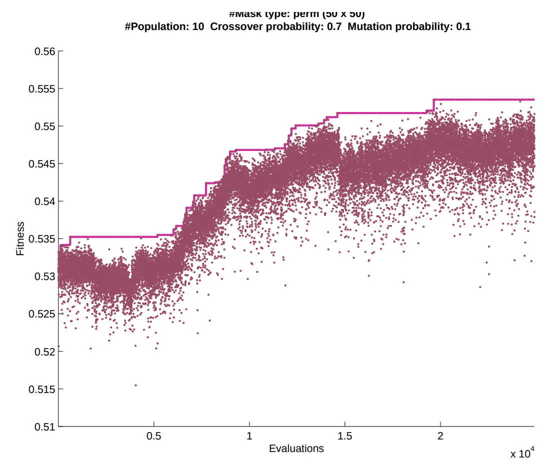

Fig. 6. Progress of the GA search starting with Cluster Dot 5×5.

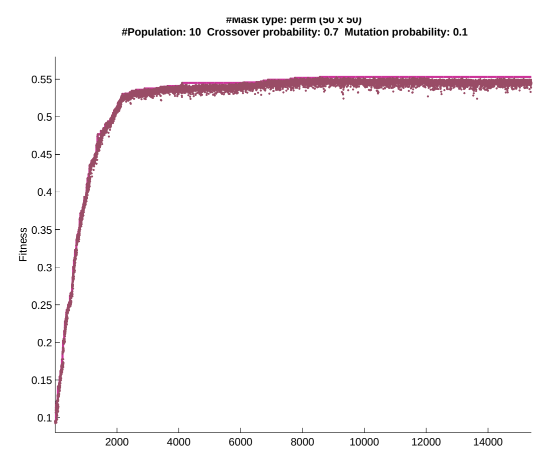

Fig. 7. Progress of the GA search starting with Cluster Dot 25×25.