

# An Importance Driven Genetic Algorithm for the Halftoning Process

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## Abstract

Most evolutionary approaches to halftoning techniques have been concerned with the paramount goal of halftoning: achieving an accurate reproduction of local grayscale intensities while avoiding the introduction of artifacts. A secondary concern in halftoning has been the preservation of edges in the halftoned image. In this paper, we will introduce a new evolutionary approach through the use of an importance function. This approach has at least two main characteristics. First, it can produce results similar to many other halftoning techniques. Second, if the chosen importance function is accordingly changed, areas of the image with high variance can be highlighted.

**Keywords:** Halftoning, Importance function, Genetic Algorithms, Limited resource rendering, Segmentation methods.

# 1 Introduction

Evolutionary computation (EC) is a multidisciplinary growing field that simulates evolution for problem solving[2, 11]. Global search abilities, adaptation to the task in hand, and robust performance are favorable characteristics of evolutionary algorithms that have made them successful to solve various kinds of complex optimization problems. In particular, Genetic Algorithms (GAs) have vigorously been developed and analyzed since Holland's and Goldberg's contributions, and employed in different kind of applications domains[5, 7] like signal processing.

In the signal processing area, a number of application methods using GA are also being increasingly developed. Existing methods[17, 10, 6, 19, 4] use a GA to generate a bi-level halftone image with quality higher than conventional techniques such as ordered dithering, error diffusion and so on[8, 14, 12, 16, 15, 20].

While many halftoning techniques have achieved reasonable results in the approximation of global gray-scale intensities, without the addition of obvious artifacts, the focus of halftoning research has now shifted to the secondary concern of preserving edges in the halftoned image. Knuth[9] suggested enhancing edges before halftoning to reduce the destruction of the edges throughout this process. Velho et al.[21] and Buchanan et al.[22, 3] have suggested customizing the halftoning technique for approximating regions containing edges either by arranging the clusters around edges or adjusting the cluster size where edges are prominent.

In GA research area, traditional halftone images are generated attaining both, global high gray level and global high spatial resolution but no assumption are made about particular areas in the image or alternative attributes as edges in order to emphasize them.

Our approach enables the user to choose an attribute of the image that is important (e.g., edges) and ensures that this attribute will be preserved throughout the halftoning process.

The usefulness of this approach is illustrated by showing that user importance halftoning is easily achieved as well as intensity based halftoning. The importance based results are achieved through the use of a particular filter according to the areas the user want to preserve. Whereas, the intensity based results are obtained by using a box filter as the importance function.

In the next sections we will describe the basis of conventional genetic approaches used to halftone images, then we will introduce our proposal and finally we will suggest some extensions to make suitable images for Non Photorealistic Rendering.

## 2 Conventional Genetic Halftoning

In most conventional genetic halftoning [17, 10, 6, 19, 4], an input gray scale image is divided into non-overlapped blocks of  $n \times n$  pixels and then the 2-dimensional optimum binary pattern for each image block is searched using a GA. The GA uses a  $n \times n$  2-dimensional binary representation for the chromosomes. Crossover is implemented to interchange either sets of adjacent rows or columns between two chromosomes. Mutation inverts bits with a very small probability per bit and it is applied after crossover similar to canonical GA.

Considering individuals as image blocks, individuals are evaluated for two factors required to

obtain high quality halftone images. One factor deals with the gray level resolution (local mean gray levels close to the original image). The other one measures the spatial resolution (appropriate contrast near edges). The objective function that measures the individuals' error to simultaneously satisfy these conditions could be expressed by

$$e(x_k^{(t)}) = w_m E_m(x_k^{(t)}) + w_c E_c(x_k^{(t)}) \quad (1)$$

where  $x_k^{(t)}$  is the  $k$ -th individual at  $t$ -th generation,  $E_m$  and  $E_c$  are the errors for gray level factor and contrast one, and  $w_m$  and  $w_c$  are their weighting parameters, respectively. Then individuals' fitness is assigned by

$$f(x_k^{(t)}) = e(x_W^{(t)}) - e(x_k^{(t)}) \quad (2)$$

where  $e(x_W^{(t)})$  is the error associated with the worst individual at the  $t$ -th generation. Therefore, the GA is used to find the optimum compromise between  $E_m$  and  $E_c$ .

### 3 Importance Driven Halftoning

Most halftoning techniques assume that a good local approximation implies a good global approximation. If the measure of the approximation is the average intensity then this is not a bad assumption. However, other factors may be considered when halftoning an image. Importance may be placed on alternate attributes depending on perceptual information or the type of the original image. One possible important attribute may be regions containing plenty of details. In this case, we may wish to use less ink in areas of the image that have low variance (less detail) and more ink in areas of high variance or regions with many edges in order to emphasize some detail. In our work the goal is provide a new way of halftoning based on the preservation of some user defined set of important image attributes enhancing different features of the image such as edges.

The human visual system acts like a Fourier analyzer in the spatial domain as stated by Snyder[18]. Due to this behavior the human visual system can be thought of as initially assessing the image on a global level and then focusing at varying resolutions on certain attributes or areas of the image. This allows us to identify important image attributes from a global level down to a local scale allowing distributing drawing primitives accordingly.

When trying to extract visual information from a medium we must rely on the analysis of the semantic content of the medium, or in other words, its subdivision into the semantic objects that compose it. Computationally, single pixel values in a digital image do not constitute a semantic object by itself but the spatial combination of them. The cornerstone of any such content-based application is the segmentation algorithm. Segmentation methods for 2D images can be primarily divided into region-based and boundary-based methods[1]. Region-based approaches rely on the homogeneity of spatially localized features such as intensity and texture, whereas boundary-based methods use primarily gradient information to locate object boundaries. As a first attempt, in this paper a boundary-based approach is adopted.

## 4 The New Objective Function for the GA

Importance halftoning involves the construction of a user-defined importance function. The importance function identifies the presence of important image attributes over a segment of the image. Consequently, the function will be a filter that enables the recognition of the attributes. Our new objective function is similar to that in Equation 1, except that the term  $E_m$  is changed accordingly<sup>1</sup>.

For the calculus of  $E_m$  our approach is based on the proposal made by Saito & Kobayashi[17]

$$E_m(x) = \sum_B \frac{1}{n^2} |g(i, j) - b_G(x, i, j)| \quad (3)$$

where  $B$  represents the image region associated to  $x$ ,  $n^2$  is the number of pixels in the image block,  $g(i, j)$  is the gray-tone of the pixel  $(i, j)$  in the original image with  $(0 \leq g(i, j) \leq M)$ . The importance function,  $b_G(x, i, j)$ , represents the local mean gray level of the halftone image block  $x$  at position  $(i, j)$  which is calculated by convolution with a 2D Gaussian function. Thus,  $b_G(x, i, j)$  assures the preservation of the average intensity.

Since our intended goal is to look for other attributes, it should be necessary to change the objective function of the GA. Specifically, it should be necessary to control the treatment of the local pixel  $g(i, j)$  in order to decide if it is a critical one. A pixel is considered to be critical when it belongs to a significant image region, hence it must be preserved.

Analyzing Equation 3, it can be seen that the above mentioned decision will be based on  $b_G(x, i, j)$ . This term involves the application of a filter that returns a representative intensity value of the image region under evaluation. This value will help to determine the critical level of the analyzed pixel  $g(i, j)$ .

In view of the Saito & Kobayashi proposal, the importance function  $b_G$  assures the preservation of the average intensity. Generalizing this concept, an according layout of  $b_G$  will subservient the preservation of a specific attribute. As an example, changing the Saito & Kobayashi's 2D Gaussian function by any existing filter for boundary detection (e.g., Sobel or Laplace)[13] will assure the preservation of edges. As a test, in this work we used a Sobel filter as an importance function.

## 5 Experiments and Results

In this section we present the used source images and those obtained by applying the method described in the previous section. We also describe some aspects of the method that have to be taken under consideration.

### 5.1 Original Images used for Illustration

We will use three images throughout this paper to illustrate various results (see Figures 1(a), 1(b), and 1(c)). The images have sizes of  $600 \times 600$  pixels with 256 grey levels (0 - 255). They were selected

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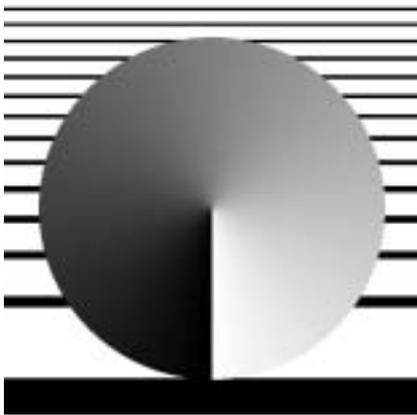
<sup>1</sup> $E_c$  is defined as in Saito & Kobayashi[17]

from a huge set of images taking into account the originating sources and different aspects that have to be preserved by the proposed method.

The first image (Figure 1(a)) is a computer generated continuous tone grey-scale circular ramp with black and white bands in the background. This is a regular image used to verify how accurate is the halftone process reproducing the whole ramp.

The second image (Figure 1(b)) is a gray-scale photograph of the ubiquitous Lena. This image records cuasi-real combinations of pixels generating different shade tones and edges.

Finally, the last image (Figure 1(c)) is a synthetic one generated by rendering a flower vase object. This image has a white background in order to produce a defined representation of the rendered object without disturbing scene pixels. Figures 1(b) and 1(c) involve different combinations of pixel tones that will help to evaluate how the process approximate grey-scale intensities and preserve existing edges in the original images.



(a) Continuous tone gray-scale image.



(b) Lena, the ubiquitous image.



(c) Synthetic image of a flower vase object.

Figure 1: Original images.

## 5.2 Preliminaries

By generating the approximation in a top-down manner, we can retain the global approximation and yet control local placement of ink by adjusting the drawing primitive according to the importance attribute.

Global approximation (Equation 1) allows us to easily approximate relative intensity (halftoning) and local approximation (Equation 3) allows us to have control over the decision criteria and introduction of artifacts.

During processing of an image block, every pixel evaluation at Equation 3 is made using a representative value obtained through the convolution of an image region with a filter. For the convolution calculus, pixel's neighboring information will be need.

Although the input image is divided into non-overlapped blocks of  $n \times n$  pixels, the evaluation

of image boundary pixels will include not existing information. This will lead to wrong decisions and the introduction of artifacts in the resulting image. Under this consideration it is necessary to include more information for the treatment of the image block's boundary pixels. Thus, considering a  $3 \times 3$  filter size, while keeping the  $n \times n$  image block size for processing, a greater block size with original neighboring information (e.g.,  $n + 2 \times n + 2$ ) is used to get a more accurate  $E_m$  value.

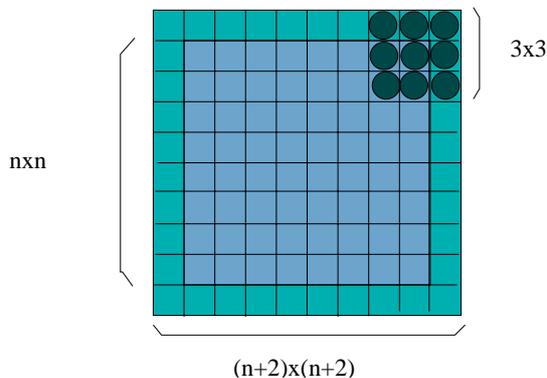


Figure 2: Block under processing (grey) and surrounding pixels (dark gray)

Figure 2 shows the relationship between these blocks. A third block (marked with dark circles) represents the involved pixels when processing an  $n \times n$  block boundary pixel by using any particular filter (e.g., Gaussian convolution). Pixels outside the  $n \times n$  block belong to the original image. Likewise, during the processing of the next  $n \times n$  block, the algorithm will take the surrounding pixels of the original image (see Figure 3).

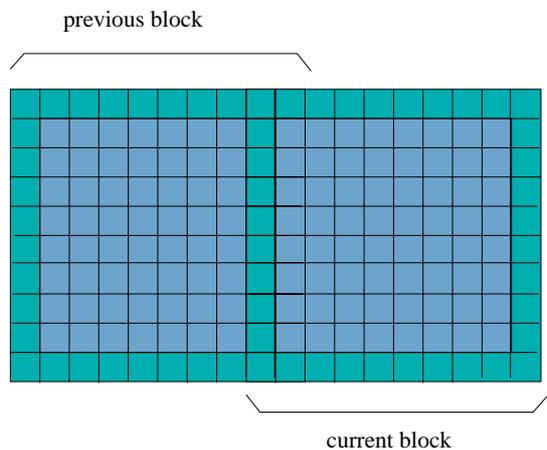


Figure 3: Two contiguous processing blocks

As an example, Figure 4 shows a synthetic image with three semicircles. The shape and distribution of them attempts to give a sort of randomness to the process's test in order to get consistency at the whole algorithm.

The GA used in this work uses a population of binary matrices of size  $n \times n$ , with  $n = 8$ . Crossover is implemented to interchange either sets of adjacent rows or columns between two chromosomes. Mutation inverts bits with a very small probability per bit. The parameter setting for the GA through the all experimental study was as follows: the population size 50, probability of crossover



Figure 4: Original image with three semicircles

0.6, and probability of mutation 0.005. The number of generations was set in a different way for each image. Weights associated to  $E_m$  and  $E_c$  were respectively set as  $w_m = 0.5$  and  $w_c = 0.5$ .

Figures 5(a) and 5(b) display two examples from the application of the GA considering independent sizes in splitting and processing the original image. In both cases we used the same block size for splitting ( $n = 8$ ) and different block size for processing.

For processing, the first example uses the same block size for splitting ( $n = 8$ ). At a low level, the resulting image (Figure 5(a)) reveals that the algorithm fails at the estimation of critical pixels. In spite of our visual system acts filling the missing drawing primitives (points) the algorithm is not robust.

The referred situation is avoided in the second example (Figure 5(b)) by extending the processing block to  $n = 10$ . At this time the algorithm had got more information that helped in assessing important pixels and consequently obtaining a well defined image.

Concluding, as the expected resulting image should be a halftoned edge-enhanced one, is mandatory to guarantee the attribute preservation by using close-black tones in the process. This is achieved by extending the amount of information need for the calculus of  $b_G(x, i, j)$ .

### 5.3 Results

Each image was divided into  $75 \times 75$  blocks of size  $n = 8$  where each block is processed separately by the GA. A relatively small  $n$  will decrease the size of the problem search space which could improve the performance of the GA when processing each image block. However, the resulting (complete) image obtained after processing all blocks could have an increased number of artifacts. This situation is avoided here by taking a bigger block (i.e.,  $10 \times 10$ ) for evaluation as described in section 5.2.

Figures 6(a), 6(b), and 6(c) show respectively the resulting halftone average approximation image by using a box filter as the importance function.

The resulting ramp image (Figure 6(a)) was obtained after 1000 generations. This image, without evident artifacts, shows a good approximation to the original one. Also, it is worth remarking that the existing slide regions of tones arise due to the layout of the Equation 3 which cannot differentiate

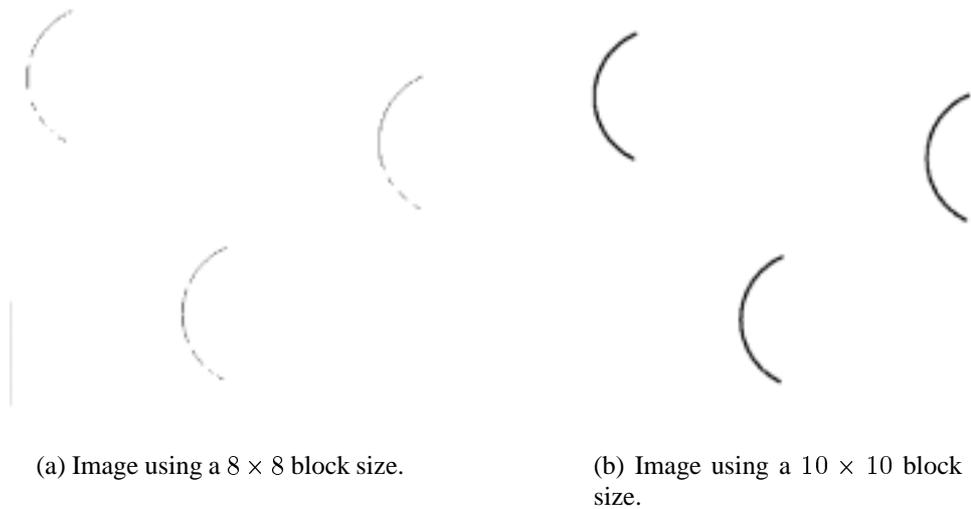


Figure 5: The synthetic image halftoned using different block sizes.

among small tone changes. Then, the GA generates clusters of tones all over the ramp. However, inside of each cluster the GA was able to find different distributions of pixels for the same tone.

The resulting Lena image (Figure 6(b)) was obtained after 5000 generations. It is a very good approximation, better than those obtained by using traditional methods, with a reduced number of artifacts.

The flower vase image (Figure 6(c)) is an interesting example for which the GA after the halftoning process (2500 generations) revealed details not so evident in the original image. The original image looks like a silhouette due to the particular combination of dark tones which diminish the visual information. However, the halftone process augmented the transmitted information since was able to reveal the illumination effects (present in the original image, but not visible).

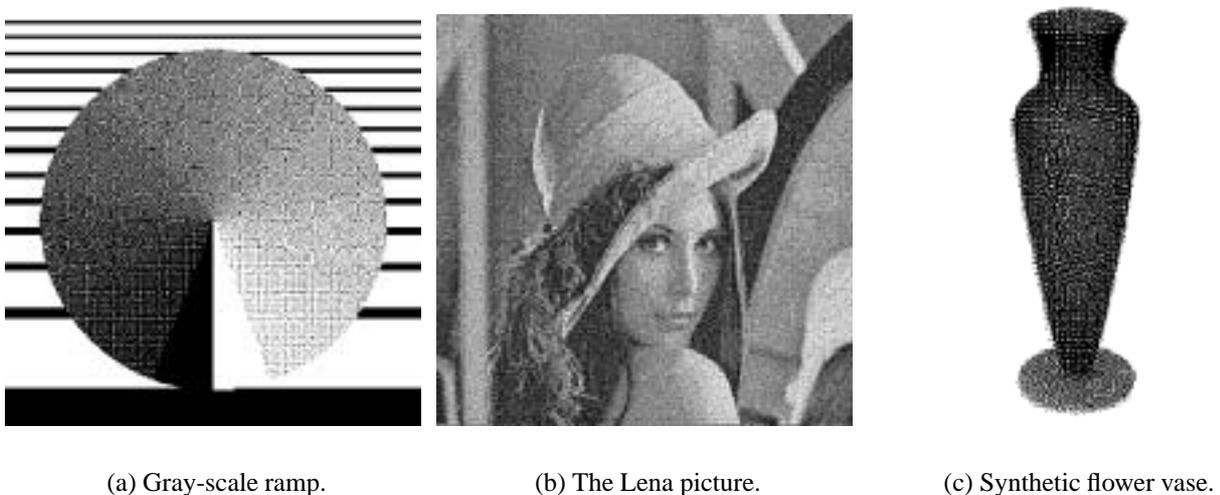


Figure 6: Resulting images after using a box filter as importance function.

Figures 7(a), 7(b), and 7(c) show the resulting images obtained by using the Sobel filter as the

importance function. All of them demanded about 5000 generations to get a good approximation. For the computer generated images (the ramp and flower vase) the evident edge discontinuities strongly guided the GA during the driven halftone process. In spite of the Lena image contains a plenty of different edge discontinuities (e.g., ramps, steps, lines, roofs, etc.) the GA succeeded in identifying them.

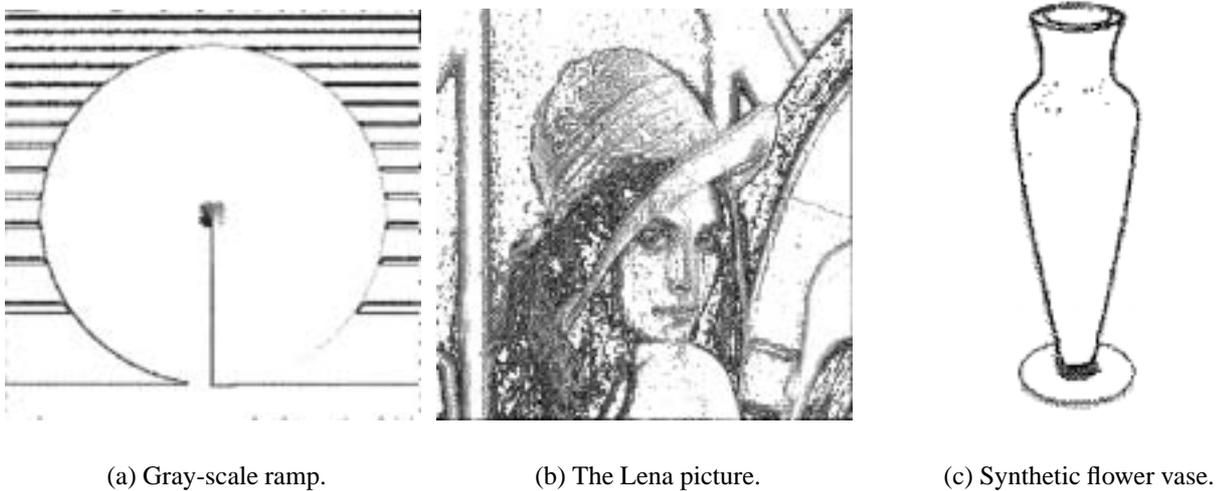


Figure 7: Resulting images after using a Sobel filter as importance function.

## 6 Discussion

In this paper we had presented a tailored GA technique for the halftoning process through the use of an importance function. This technique provides the possibility of easily making global decisions about the halftoning process as well as tailoring local distribution of ink by altering the importance function. This function is a filter used to obtain a single value representation that will be applied for the calculus of  $E_m$  (Equation 3). In particular,  $b_G(x, i, j)$  value could be obtained from other user importance function. Therefore, the user can choose any other regular filter as the importance function as well as construct an importance function that combines several importance functions by weighting them as follows:

$$F(x, i, j) = w_1 \times f_1(x, i, j) + \dots + w_n \times f_n(x, i, j)$$

where  $w_1 + \dots + w_n = 1$  and  $f_1, \dots, f_n$  are different importance functions.

Additionally, we showed in this paper that an special treatment of the block size allowed the GA to reduce the number of artifacts for both, traditional and edge-enhanced halftoning.

As it was stated in the preceding sections, for the semantic analysis of images this work only focused on the boundary-based methods. An interesting challenge involves the use of region-based methods that enable to localize features like textures and colors. Then, further effort can be made changing the spatially bounded pixels by a set of drawing primitives (e.g. lines, brushes) enabling the introduction of NPR effects.

Finally, it is important to note that processing an image by the GA is a very time-consuming task. Hence, one of the future steps concerning our work is related with the reduction of the computational effort. Further work is also required to consider different filter sizes in order to increase the information given by  $b_G(x, i, j)$ , i.e., define a more accurate objective function which could help the GA in distinguishing among tones with low variance. An adequate change of the objective function could avoid the arising features in Figure 6(a).

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