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# *Image Enhancement and Image Restoration for Old Document Image using Genetic Algorithm*

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**Abstract**— This paper presents the use of genetic algorithm in old document image enhancement and restoration. The term of ‘old document’ is document coming from hundreds years ago. The purpose of the study is to preserve the information contained in old documents into a digital form, because the process to rescue the old images using physical approach is too slow. The main contribution of this study is in the development of its fitness function to select new population and the best new enhanced image. The experimental results also show the influence of using the median filter in the image preprocessing. The results show relatively effective image enhancement (92.9% data get more than 90% success rate), and in general the effect of using the median filter preprocessing is not good that makes blurring effect to the images (only 59.5% data get success rate above 90%).

**Keywords**—genetic algorithm; image enhancement; image restoration; old document image

## I. INTRODUCTION

Old documents especially a state’s administrative documents contains valuable information that mostly haven’t been identified well. These documents, coming from hundred years ago, have degraded throughout the time because of its media age. Lots of among other things that contributes to old document degradation include humidity, insects, nematodes, bad storing mechanism, tint, and even because the document has been buried under the surface or washed by water or mud. All these degrading factors make old document’s condition deteriorate. The physical documents’ condition may get worse as its age adding up so that we can’t preserve those documents in its physical form. But what is important is the information it contains. An effort should be done to preserve this valuable information when it’s possible, that is when the documents are still available. The document needs to be converted to a digital image form, enhanced and stored. The need to recover the condition of old document image to its better condition is the purpose of this study.

Image enhancement and image restoration are processes in digital image processing which attempt on giving results which have a better quality compared to the original image input. In image enhancement, an effort is done to increase the image’s dynamic range by improving its contrast. In image restoration, the process is trying to restore a degraded image to its original condition by making an approximation

given by the degradation model [1]. The difficulty of enhancing or restoring an old document image is that the background, the object, and the noises tampering the image have similar gray value. A simple threshold technique will not suffice to solve this problem. One of the best ways to deal with this problem is contrast stretching. Genetic algorithm (GA) is one of evolutionary algorithms that have been successfully applied to image enhancement or image restoration problem. For example, there are GA implementations for electronic consumer image [2], neutron penumbral imaging [4], and binary image [5]. In [2], GA method is used to perform contrast stretching to the input image and stated that the proposed method has been done successfully to enhance electronic consumer image’s quality. Based on the previous success in using GA for contrast stretching, this study has adopted several steps used in [2] to solve the problem in restoring old documents.

This paper proposed a method for enhancing and restoring an old document image using GA. Besides being a contrast stretching technique as in [2], the proposed method can also be included into an image restoration method because the degradation model of an old document can be measured. A degradation model is a degradation function that, together with an additive noise term, operates on an input image to produce a degraded image. In general, the more we know about this degradation function and additive noise term, the better we restore the image [1]. In the domain problem of old documents, the degradation model is implied in the number of edges containing 1 pixel, or in other words, number of edges with length 1. The degradation model of the old document images is being estimated and then the process makes an attempt to recover the input image, i.e. trying to make approximation about the original image before being degraded.

This paper is organized as follows. Section 2 explains the proposed image enhancement and restoration using GA and Section 3 discusses the experimental result. This paper is closed by a concluding remark and further development in Section 4.

## II. GENETIC ALGORITHM IMPLEMENTATION

The proposed implementation of the genetic algorithm for image enhancement and image restoration is presented in this section. The flow diagram is shown in Fig. 1 and each

important step in this GA is explained in details in the next sub-sections.

#### A. Chromosome Structure

This implementation of genetic method uses chromosome structure proposed in [2]. The structure uses sorted array of random integer numbers from 0 to 255 that represents gray level range in an 8-bit grayscale image. Size of each chromosome is equal to  $n$ , which represents the number of gray levels in input image. This means that each image will have different length of chromosome representation according to its existing gray levels. An example of chromosome representation is shown in Fig. 2.

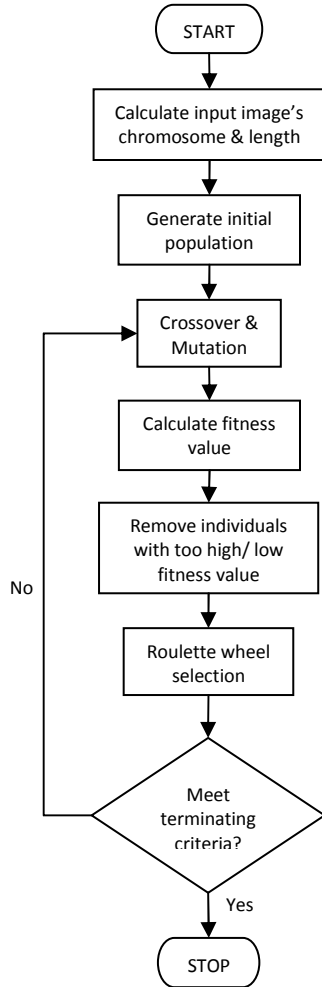


Figure 1. Flow diagram of genetic algorithm implementation

In this structure, indices indicate the order of gray level in an image. For example, in Fig. 2, the first gray level in input image is 1, the second gray level is 12, and so on.

$$\begin{aligned} T(G(k)) &= C_i(k) \\ k &= 1, 2, \dots, n \end{aligned} \quad (1)$$

The remapping of chromosome structure into digital image form follows the transformation in (1) where  $T$  is the function that will change the original image gray levels,  $G$  is the array of input gray levels in ascending order,  $k$  is number of gray levels in the input image and  $G(k)$  is  $k^{\text{th}}$  gray level of them,  $C_i$  is the  $i^{\text{th}}$  chromosome in the population, and  $C_i(k)$  is the value of  $k^{\text{th}}$  cell. This transformation simply means that the first gray level in original image is replaced by the value of the first cell of the enhanced chromosome and so on.

Before creating initial population, firstly, the original image chromosome representation's length should be obtained, that is the number of input image gray levels ( $n$ ). After that, each chromosome is generated using the following steps:

- 1) Create  $m$ , where  $m$  represents population count, empty arrays of length  $n$ .
- 2) Set each element of each empty array with random integers ranging from 0 to 255. Although the length of chromosomes may vary according to number of existing gray values in each image, values to be assigned to new chromosomes don't depend on gray level values on input image. It can be any value, from 0 to 255.
- 3) Sort each array or chromosome in ascending order.
- 4) Set the first element of each chromosome to 0, and the last element of each chromosome to 255.

The number of individuals in the population is constant. This implementation use  $K$ -elitist scheme with  $K = 10$  which means 10 individuals are considered having better fitness values determined by the selection algorithm, and are forwarded to the next generation. These processes are performed until it meets the terminating condition. The terminating criteria used here is a determined number of generations.

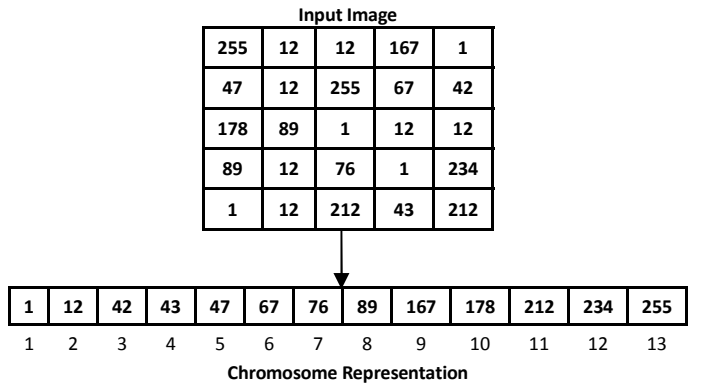


Figure 2. An example of the chromosome structure

#### B. Fitness Function

Reference [2] uses number of edges and their overall intensity as a fitness function, because [6] stated that a gray image with good visual contrast includes many intensive edges. We have applied the fitness function from [2] to this problem, but it didn't describe the characteristic of the wanted solution.

The domain problem of this research is old document image which mostly contained of handwritings. Thus, the

information needed to be preserved is represented by long edges. But it doesn't necessarily say that all short edges are the noises. So, we want to remove those which are considered as noises without losing the information. Based on previous considerations, number of edges detected by Sobel operator, that contain only 1 pixel is used as a fitness function. The best fitness value is the one with the most similarity with the original image chromosome representation's fitness value, because we don't want to lose too much information. For example, in Fig. 3 we have a binary image with 2 edges. The first edge is of length 16, while the other is of length 1. Since the fitness value is number of edge(s) containing only 1 pixel, thus this image's fitness value is 1, although it has 2 edges.

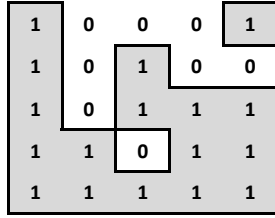


Figure 3. A binary image with fitness value 1

### C. Selection

Roulette wheel rule is used as the selection operator. As mentioned in the previous sub-section, the selection operator will return 10 best individuals based on the fitness criteria. To perform selection operation, the fitness value of all individuals in the population should be calculated first. Furthermore, the selection mechanism is as follows:

- 1) Calculate standard deviation ( $\sigma$ ) of population's fitness value, including fitness value of the original image chromosome representation ( $b$ ).

- 2) Remove all individuals with fitness value  $a$ , where  $a < (b - \sigma)$  or  $a > (b + \sigma)$ . This operation removes outliers, which are images with too high or too low fitness value, because based on the experimental observation, outliers always give bad results.

- 3) Give score for each remaining individuals. Individuals with more similar fitness value to fitness value of input image will have higher score. This score represents the probability a chromosome will be selected and survive to the next generation.

- 4) Generate random number from 0 to the sum of given score for all individuals in step 3. This random number will determine which individual is selected. This is where roulette wheel selection is implemented.

- 5) Repeat step 4 if the number of selected individuals is less than 10.

For example, suppose we have 6 individuals survive from step 2, and each will be given score in step 3. Let's say the score of the 1<sup>st</sup> to the 6<sup>th</sup> individual are 0.5, 0.7, 1.1, 1.2, 0.8, and 0.7, then the sum of given score is 5. From step 4, we will have a random generated number with value ranging from 0 to 5. If the random number value falls between:

- $[0, 0.5]$ , the 1<sup>st</sup> individual is selected.

- $(0.5, 1.2]$ , the 2<sup>nd</sup> individual is selected.
- $(1.2, 2.3]$ , the 3<sup>rd</sup> individual is selected.
- $(2.3, 3.5]$ , the 4<sup>th</sup> individual is selected.
- $(3.5, 4.3]$ , the 5<sup>th</sup> individual is selected.
- $(4.3, 5]$ , the 6<sup>th</sup> individual is selected

This selection process returns 10 best individuals that will be used as initial population for the next generation.

### D. Crossover and Mutation Operator

After comparing the 2 crossover operations presented in [4], Uniform R/C Crossover is selected over Random R/C Crossover, as the crossover operator, with the crossover rate  $P_c = 0.8$ , taken from [3]. In this crossover operation, parent chromosomes will not be guaranteed as the best chromosomes because it is selected at random. After getting 2 parent chromosomes, generate 2 random numbers ranging from 0 to chromosome's length. These numbers will determine the position or index in which elements of both chromosomes are to be substituted. 2 new offspring will be produced after substitution, and each individual will be sorted in ascending order to preserve structure [2].

The mutation operator that is selected is the one presented in [2], with a mutation rate  $P_m = 0.1$ . Individual that will be mutated is selected at random. 5% of the individual chromosome elements are selected randomly for mutation. Those elements will be replaced by randomly generated integer that should be less than or equal to the next element value and more than or equal to the previous element.

## III. EXPERIMENTAL RESULT

There are 2 experimental scenarios that have been conducted, i.e. without and with the use of median filter as a preprocessing method to input images. When median filter is used, the input image for GA method is a resulting image from applying median filter to the original image. For each image in each scenario, 5 experiments will be performed to see the mean of number of good resulting images created by the method.

TABLE I. GENETIC ALGORITHM METHOD EXPERIMENTAL RESULT FOR EACH IMAGE & EACH EXPERIMENTAL SCENARIO

Input Image Name	Mean of Number of Good Resulting Images	
	Without median filters	Using median filters
B1-01	9.2	7
B1-02	10	9.2
B1-03	8	5
B1-04	9.8	0
B1-05	10	9.8
B1-06	9.4	10
B1-07	9.8	9.6
B1-08	9.6	10
B1-09	10	0

Input Image Name	Mean of Number of Good Resulting Images	
	Without median filters	Using median filters
B1-10	10	7.6
B1-11	10	10
B1-12	10	10
B1-13	10	8
B1-14	9.6	10
B1-15	10	9.6
B1-16	10	10
B1-17	9.2	8.4
B1-18	9.2	0
B1-19	9.6	9.2
B1-20	10	9.8
B1-21	9.2	10
B1-22	9.8	10
B14-01	9.8	6.6
B14-02	10	9.6
B14-03	9.8	10
B14-04	9.2	5.8
B14-05	10	7.2
B14-06	10	9.4
B14-07	10	8.2
B14-08	10	10
B14-09	9.2	10
B14-10	9.8	9.2
B14-11	10	10
B14-12	10	9.8
B62-01	10	9.8
B62-02	9	5.6
B195-01	10	0
B195-02	10	9.4
B195-03	10	10
G004	7.6	0
G010	9.4	6.6
G012	6.2	2.6

GA parameters for all experiments are defined below:

- Number of individuals in initial population is 10.
- Crossover rate  $P_c = 0.8$ .
- Mutation rate  $P_m = 0.1$ .
- Number of generation is 5, which is used as terminating criteria.

The result of the GA process for each input image and each experimental scenario is 10 new images that will be evaluated visually regarding to the readability of its image's object, which is the writing. Table 1 shows the experimental results using and not using the median filter. Mean of number of good resulting images are represented in scale 0 to 10 with higher score means higher success rate in enhancing and restoring the old document image. Examples of enhanced and restored image are shown in Fig. 5-8.

Table 1 shows that 39 of 42 testing documents (i.e. 92.9% of the data) in the experimental scenario without the median filter has given more than 90% success rate. While in the experimental scenario using the median filter, only 25 out of 42 testing documents has given more than 90% success rate. The comparison of using and not using the median filter is shown in Fig. 4, the curve of without using the median filter is the better. From that graph, it can be concluded that, in general, using median filter will result in worse success score than when median filter is not used. Although the ability of median filter to clean noises from the background is good, but most of the times it will blur the details. For example, see Fig. 8 where the noises are removed but the writings' sharpness can't be preserved. Since in old document image enhancement the goal is to preserve sharpness of the writings, then the median filter is preferred not to be used.

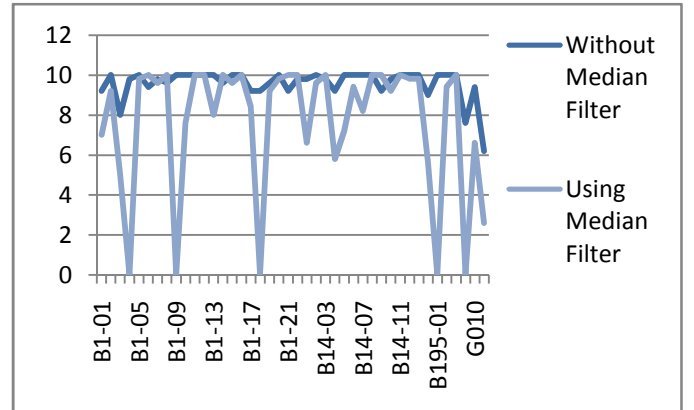


Figure 4. Graph of experimental result without & with using median filter

#### IV. CONCLUSIONS

This paper shows the use of a GA technique for image enhancement and image restoration in the problem domain of old documents. The implementations are mostly based on those proposed in [2]. Experimentally, it is found that the best fitness function is number of edges containing only 1 pixel. Individuals that are likely to be optimal solution are the one having the most similar fitness value to original image's fitness value. In other words, removing noise and retaining information around the original image.

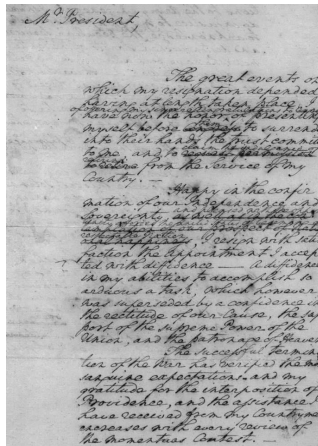
The experimental process also compared the use of median filter and without median filter. In general, the use of median filter will give worse success rate in enhancing and restoring the image. But for some small number of images,

median filter successfully removes noises without decreasing the object's sharpness.

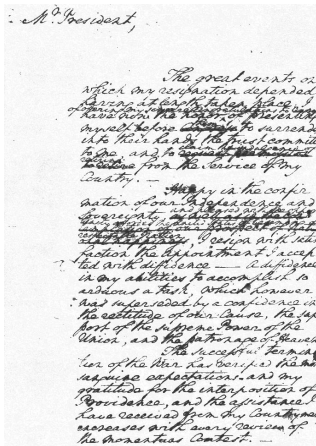
For further work, a pre-processing to normalize the radiometric of the input image and a post-processing to sharpen the writings are carried out.

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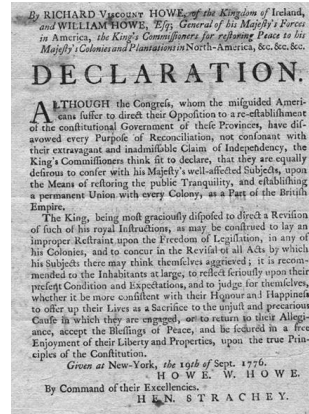


(a)

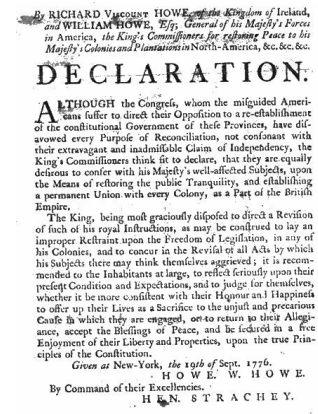


(b)

Figure 5. (a) Original image G012 (b) Enhanced image without using median filter (Source of original image: ROI.us Corporation, <http://www.roi.us/>)

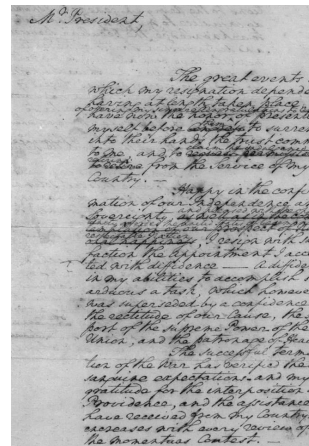


(a)

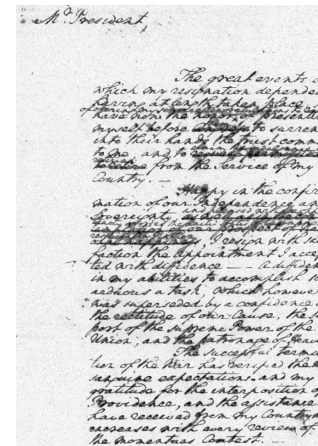


(b)

Figure 6. (a) Original image G004 (b) Enhanced image without using median filter (Source of original image: Chapin Library of Rare Books, <http://chapin.williams.edu/>)

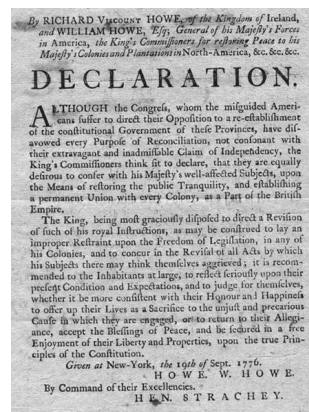


(a)

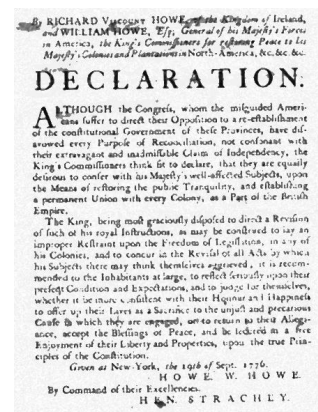


(b)

Figure 7. (a) Original image G012 (b) Enhanced image with using median filter (Source of original image: ROI.us Corporation, <http://www.roi.us/>)



(a)



(b)

Figure 8. (a) Original image G004 (b) Enhanced image with using median filter (Source of original image: Chapin Library of Rare Books, <http://chapin.williams.edu/>)