

BLURRED IMAGE RESTORATION USING GENETIC ALGORITHM⁺

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Abstract

The Genetic Algorithm models are becoming very attractive in image processing where high computational performance is required. This paper describes a genetic algorithm for blurred image, which is designed and estimated using Matrix $R_{3 \times 3}$. The genetic algorithm takes random strings as an input in binary code and uses one point crossover between two random strings and uses mutation after many generations. The output is restored matrix $R_{3 \times 3}$ according to mask size, The computer test shows that the restored images have better visual properties compared with inverse filter

المستخلص

بدأت نماذج الخوارزميات الجينية تصبح مرغوبة أكثر في مجال معالجة الصور إذ تظهر الحاجة لأداء عمليات حسابية مطلوبة. هذا البحث يصف استخدام الخوارزميات الجينية لمعالجة الصور المشوشة و المصممة بتقريب مصفوفة قياس 3×3 . وتستعمل الخوارزميات الجينية متغيرات رمزية عشوائية كمدخلات. بعدد من الأجيال و الأخراج يكون مصفوفة مثبتة قياس 3×3 حسب حجم مصفوفة القلب. أظهر اختبار البرنامج باستخدام الحاسوب خواص مرئية وصورية أفضل من استخدام Inverse Filter في الوضوح و الدقة.

1. Introduction

Restoration of high-quality images from a degraded recording is an important problem in early vision processing. Here *image* refers to a two - dimensional lights intensity function $x(a, b)$. Since lights intensity is a real positive number and the $x(a, b)$ is a finite, real, and nonnegative function [1]:

$$0 \leq x(a, b) \leq 255$$

Digital image restoration system containing three sub systems: an imaging system, image digitizer, and image restoration system. The imaging system which consists of an optical system and recoding devices is a major source of degradation [1, 2]. To enable processing by computer, images are sampled and quantized by the image digitizer. This also introduces some degradation because of quantization error. The image restoration system uses some techniques to remove (1) blur due to optical system aberrations and (2) noise due to electronic imaging sensors. Hence the digital image restoration system gives an estimate of the original image in some sense. Over the last 20 years, various methods such as the inverse filter, Wiener filter, Kalman filter, and many other models - based approaches have been proposed for image restoration [3, 4]. A major drawback of most image restoration algorithm

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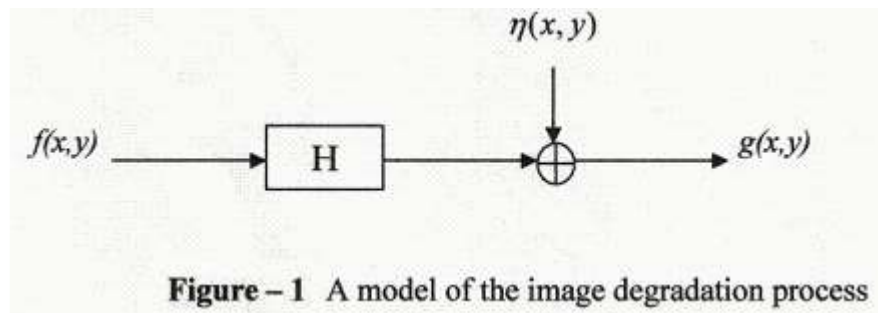
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is their computational complexity, so much so that many simplifying assumptions have been made, such as wide-sense stationary and availability of second order image statistics, to obtain computationally, feasible algorithms. The inverse filter method works only for extremely high signal-to-noise-ratio images [5].

A genetic algorithm that can perform extremely rapid computations seems to be very attractive for image restoration. In this paper we present a genetic algorithm for restoration of gray level images degraded by a known blur function.. The image gray level is represented binary number in genetic algorithm, that mean each matrix 3×3 represents sting 72-bit. The restoration procedure consists of two stages (1) estimated the coding of the genetic algorithm model (2) codes are estimated by comparing the energy function (Fitness Value)of genetic algorithm with the constrained error function, then iterative genetic algorithm is used to minimize the function

2. Image Degradation Model

As shown in Figure -1 the degradation process will be modeled in this paper as an operator "H", which together with an additive noise " $\eta(x, y)$ " operator on an input image " $f(x,y)$ " to produce a degraded image " $g(x,y)$ ".The digital image restoration problem may be viewed as that of obtaining an approximation to " $f(x,y)$ ", given " $g(x,y)$ " and a knowledge of degradation in the form of the operator "H". It is assumed that our knowledge about " $\eta(x, y)$ " is limited [1, 2].



It is assumed that the image blur can be modeled as a superposition with impulse response " $h(x, y)$ " and output is subjected to an additive noise [4, 5]. In this case, the observed image is modeled by:

$$g(x, y) = \sum_{u=-k}^N \sum_{v=-k}^N f(x-u, y-v) * h(u, v) + \eta(x, y) \quad (1)$$

where the indices x & y take integer number, $(*)$ denotes the convolution operator (multiplication), and $k = (N-1)/2$ [2, 3]. Types of blur masks are shown in Figure (2).

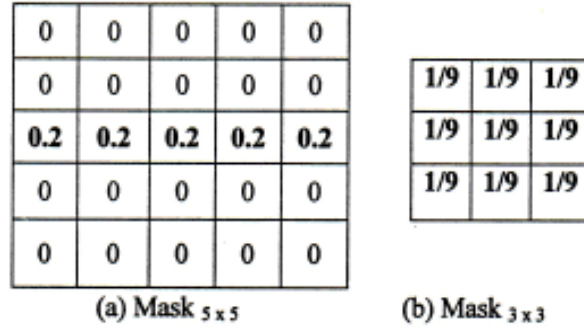


Figure – 2 Type of Blur mask (a) mask with uniform distribution
(b) Mask with mean 1/9

The Point Spread Function (PSF) mask is multiplied with sub-image from original image to get degraded pixel, the convolution of mask can be described as [2, 3]:

Assume the mask size 3x3

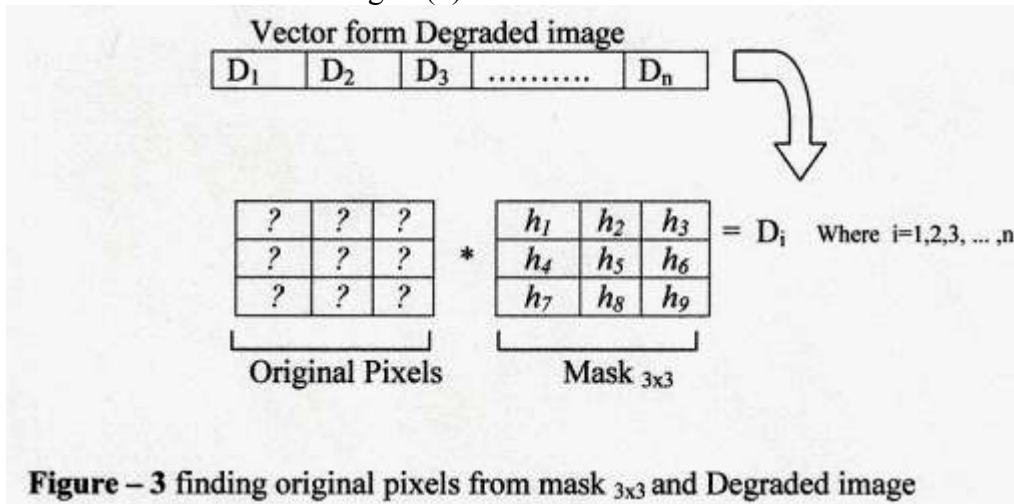
$$\text{Degraded Pixel} = (h_1 * x_1) + (h_2 * x_2) + (h_3 * x_3) + \dots + (h_9 * x_9) \quad (2)$$

$$\text{Degraded Pixel} = \sum_{i=1}^9 (x_i * h_i) \quad (3)$$

x_1	x_2	x_3	*	h_1	h_2	h_3	= Degraded Pixel
x_4	x_5	x_6		h_4	h_5	h_6	
x_7	x_8	x_9		h_7	h_8	h_9	
Sub – Image				Mask 3x3			

3. Image Representation

The degraded image is obtained from convolution operation as given in section 2. In this section we go back to get original pixels depending on degraded pixels and mask convolution as show in Figure(3).



For finding the original pixels genetic algorithm is used. The genetic algorithm is a parallel search algorithm by using a number of strings and computing fitness value for each string, these strings are shared with each other by crossover and

mutation function until reached to result [6]. In this section we explain how the genetic algorithm reaches the original pixels. The coding in genetic algorithm is shown in Figure(4).

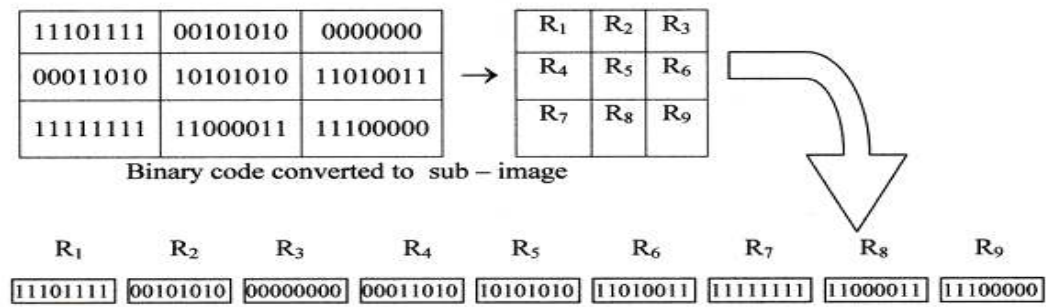


Figure – 4 String length 72-bit according to matrix $R_{3 \times 3}$

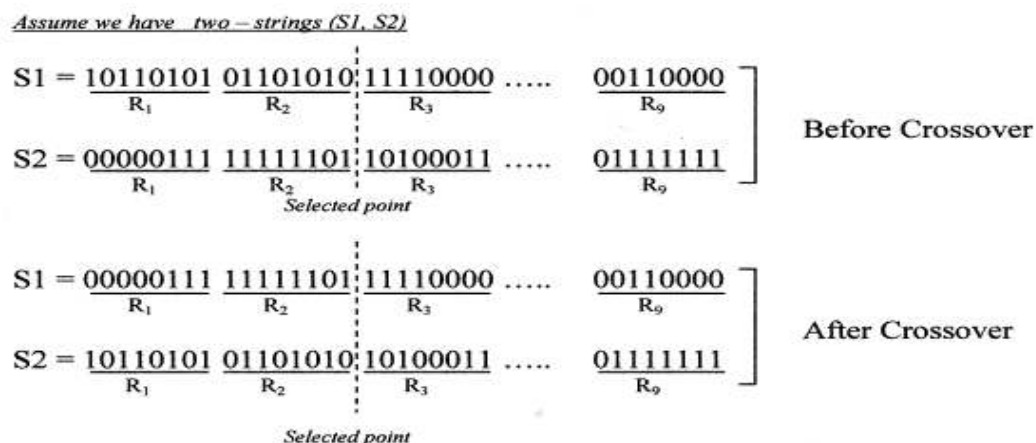
Each number in matrix $R_{3 \times 3}$ (Restorated Matrix) is converted to binary number the interval of these numbers [0,255]. The matrix $R_{3 \times 3}$ input string to genetic algorithm, the length of a string is 72-bit according to the size of mask convolution 3×3 . The number of input strings used in genetic algorithm is 72 strings.

These 72 strings are generated randomly in binary system; this way led the genetic algorithm to find the restorated pixels in fast way and it took less memory, because the array size in turbo C++ language is limited. The genetic algorithm uses four steps to find the optimum solution, they are:

1. Crossover
2. Mutation
3. Fitness function
4. Selection procedure

3.1 Crossover

This operation divides any two strings randomly from selected point, then makes exchange between these strings as shown in the following representation [6]:



3.2 Mutation

Generally, the mutation is performed after many generations[7], in this paper the mutation operation it is done after 10 generations, and this operation selects 3 bits for each string randomly.

3.3 Fitness Function

The fitness value is computed for each string, by converting a 72 bit string to matrix a $R_{3 \times 3}$ which is then convolved with a $h_{3 \times 3}$ mask. Then the fitness value is compared with the degraded pixel as described as followings:-

$$S2 = \underbrace{10000001}_{R_1} \underbrace{00000111}_{R_2} \underbrace{10100000}_{R_3} \dots \underbrace{01111111}_{R_9}$$

$$\text{Where } R_1=129, R_2=7, R_3=160, \dots, R_9=127$$

$$\begin{array}{|c|c|c|} \hline 129 & 7 & 160 \\ \hline 255 & 5 & 0 \\ \hline 100 & 32 & 127 \\ \hline \end{array} * \begin{array}{|c|c|c|} \hline h_1 & h_2 & h_3 \\ \hline h_4 & h_5 & h_6 \\ \hline h_7 & h_8 & h_9 \\ \hline \end{array} = \text{FitnessValue}$$

Restorated matrix_{3x3} Mask _{3x3}

$$\text{FitnessValue} = \sum_{i=1}^9 (R_i * h_i) \quad (4)$$

$$\text{Error Value} = |\text{FitnessValue} - D_i| \quad \text{where } i=1,2,3,\dots,n \quad (5)$$

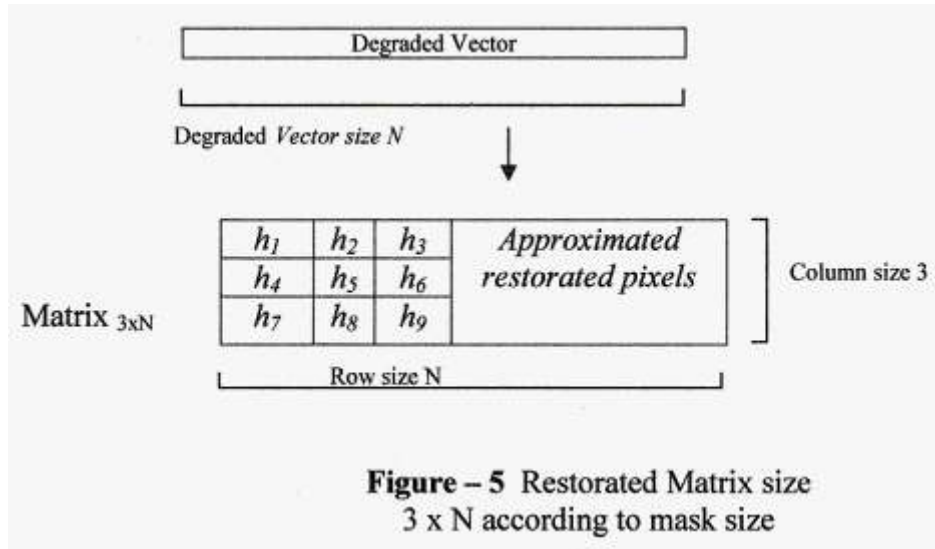
The error value given by (5) for each string in genetic algorithm, is checked if the matrix $R_{3 \times 3}$ has reached optimum solution, then stop the algorithm, otherwise continue in search for the best string. The error value in this problem is "Error Value ≤ 0.001 ". The D_i is represented the degraded pixel in i -th position, that causes to change fitness value according to crossover and mutation.

3.4 Fitness Selection Procedure

After computing the fitness value, a string is selected for the next generation with minimum error value. The selecting procedure is used to find out the numbers of strings required for the next generation [6,7], and the strings with minimum error value are selected. The following points describe this procedure:

1. The string with error values outside the interval [0.001, 1.0] which discarded, and those with error value inside this interval selected. These selected strings are then sorted in an ascending order according to their associated error values, to be used in the next generation.
2. A number of copies for each string is required (not exceeding 7 copies). Therefore, the total number of strings in the next generation will be more than 72 strings.

Finally, after many generations the genetic algorithm finds the optimum solution for matrix the $R_{3 \times 3}$ according to D_i (Degraded pixel). The algorithm of a restoration gets the next degraded pixel D_{i+1} to get next matrix $R_{3 \times 3}$, which means that a degraded vector (size N) is generated as shown in Figure(5).



4. Computer Test and Results

The algorithm that is described perviously, is applied to the image in Figure–6(a) that has a gray level range between 0 and 255 by using *Turbo C++*. The results are summarized in Figur-6.

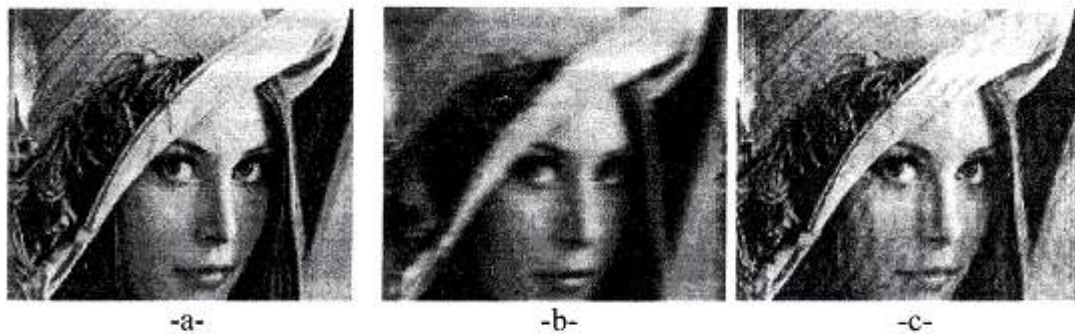


Figure – 6 (a) Original image 150 x 150, (b) Blurred image with mask 7×7 , (c)
Restored image by genetic algorithm

In Figure(6a) the image size is 150 x 150 pixels. This image is blurred by mask $h_{3 \times 3}$ with uniform distribution (See Figure - 2) without noise as shown in Figure – 6(b). The genetic algorithm approach can find an approximation for the original image, as shown in Figure – 6(c). Fifty six (56) different strings are used by the genetic algorithm, and the size of each string is 56 bits. The iteration of the genetic algorithm will stop when the error becomes equal to or less than 0.001. The time required for the used program to achieve this stopping criterion is 1 hours and 30 minutes, executing using a 2GHz P4 processor.

Generally, comparing the performance of different methods needs some quality measures, which are difficult to define owing to the lack of knowledge about the human visual system. The restoration techniques usually refer only to a mathematical concept and are not related to response of human visual system. *Root-Mean - Square - Error* can be used as a reference [3].

Root – Mean – Square – Error :-

$$\text{Rms} = \sqrt{\frac{1}{N^2} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} [I(x, y) - \hat{I}(x, y)]^2} \quad (6)$$

Note Where $I(x, y)$ represented original image and $\hat{I}(x, y)$ represented restored image.

Moreover, the inverse filtering method in frequency domain is applied by using Fast Fourier Transformation (FFT) on degraded image $D(u, v)$ that is given in Figure – 6(b). Then, $D(u, v)$ is divided by the mask $H(u, v)$ in frequency domain, to get restored image $I(u, v)$ in frequency domain also, as follows [7]:

$$I(u, v) = \frac{D(u, v)}{H(u, v)}$$

(7)

Figure – 7 shows the inverse FFT of the restored image $I(u, v)$. The mean-square-error between the original image and restored image is calculated and given in Table 4.1 for the two methods mentioned before.

Table 4.1

Method	Genetic Algorithm	Inverse filter
Root – Mean – Square – Error	1.58	2.966



Figure – 7 Restored image by Inverse Filter

Form the Table(4.1) the performance of genetic algorithm has better visual properties than inverse filter in image restoration system. The error given by (6) for the genetic algorithm is 1.58 which is satisfactorily small when compared to the error of the inverse filter. But from the time of execution point of view, the inverse filter method can find the restored image after 5 seconds, which is a very short time when compared to the execution time of the genetic algorithm.

5. Conclusion

This paper has introduced an approach for blurred image restoration of gray level using genetic algorithm. The restoration algorithm consists of three steps: - generating strings, estimating fitness values by (4) and selecting suitable strings for next generation that satisfies the results. Genetic algorithm compute error values by equation (5) for updating the strings using crossover, mutation operation, and these strings will represent

the restored pixels after many generations. The genetic algorithm approach gives high-quality image; we see from the experimental results conclude that the error function by equation (6) is smaller than inverse filter of image restoration. This is because the genetic algorithm minimizes the error by equation (4). On the other hand the genetic algorithm is very slow to find the restored pixels because the length of each string is very long and number of string becomes very large after much iteration. The number of strings may reach 100; this makes the genetic algorithm slower to find the result.

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