Blind Deconvolution Based on Genetic Algorithms

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Yen-Wei Chen, Zensho Nakao, Kouichi Arakaki

Abstract

A genetic algorithm is presented for the blind-deconvolution problem of image restoration. The restoration problem is modeled as an optimization problem, whose cost function is to be minimized based on mechanics of natural selection and natural genetics. The applicability of GA for blind-deconvolution problem was demonstrated.

1. INTRODUCTION

Many image processing applications, such as satellite remote sensing, medical and scientific imaging, require a high resolution image. However, currently available image sensors have certain physical limitations, and the image $g(x,y)$ we usually observed is a degraded one by the convolution of the original image $f(x,y)$ and the blurring function (point spread function: PSF) $h(x,y)$ of the imaging system, which can be expressed as

$$g(x,y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x',y')\cdot h(x-x',y-y')dx'\cdot dy'$$
$$= f(x,y) * h(x,y) \qquad (1)$$

where $*$ denotes the convolution operator. The image restoration is to recover the original image $f(x,y)$ from the blurred image $g(x,y)$. If the point spread function (PSF) $h(x,y)$ is known, the $f(x,y)$ can be easily recovered by using some linear deconvolution techniques such as inverse filter and Wiener filter [1]. But in many cases, it is difficult to know the exact $h(x,y)$ because it usually contains unknown aberrations or statistical degradation through the imaging system. The recovery of $f(x,y)$ from the knowledge of $g(x,y)$ alone is known as the blind deconvolution problem[2].

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If the image is blurred by uniform linear camera motion or out-of-focus, the blind deconvolution can be solved by computation of the power cepstrum of the image [3]. In this paper, we proposed an alternative method based on genetic algorithms (GAs) [4] for solution of the blind deconvolution problem. The GAs have been applied for image restoration problem with a known blurring function [5], [6], [7]. In principle, the blind deconvolution problem can be universally solved by GAs only with knowledge of the convolution function (blurred image) alone. The main objective of this paper is to show the applicability of GAs to solving the blind deconvolution problem.

The basis of the genetic algorithm for blind deconvolution is given in section 2. Simulation results are presented in section 3.

2. THE GENETIC ALGORITHM

GA is an iterative random search algorithm for nonlinear problem based on mechanics of natural selection and natural genetics. It uses probabilistic transition rules to guide itself toward optimum solution. It is thus an approach particularly suited to the interpretation of poorly defined data. In GA, the restoration problem is modeled as an optimization problem, whose cost function is to be minimized.

The typical flowchart of genetic algorithm for blind deconvolution of image restoration is shown in Fig.1.

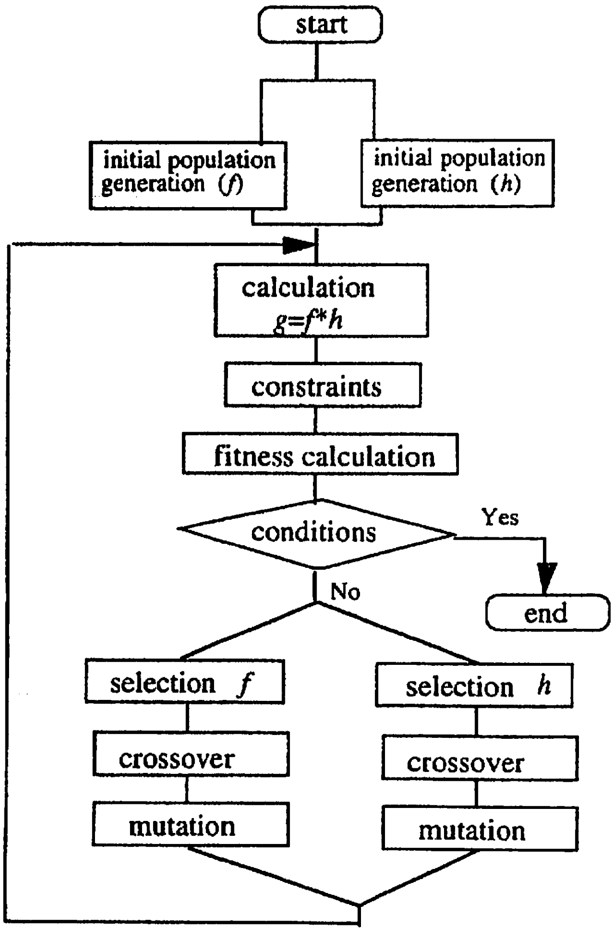


Fig.1 A typical flowchat of genetic algorithms for blind deconvolution.

2.1 Image coding

We use a binary matrix as a chromosome to represent the original image and the blurring function. In this paper, we focus our study on restoration of binary images for simplicity. Thus the size ($N \times N$) of the matrix is the same as the pixel size of the image and the allele value (1 or 0) of the chromosome corresponds to the pixel intensity of the image.

2.2 Initial population and fitness measure

We firstly create a population of estimates of the original image (f) and the blurring function (h) as chromosomes randomly in coding and initialization process. And then the degraded image is calculated for each pair of the chromosomes. The fitness for each pair of chromosome is evaluated by comparing the calculated degraded image of the chromosome with the degraded image of the original image. The cost function for evaluation is shown as Eq.(2):

$$E = \left\| g - \hat{f} * \hat{h} \right\|^2 \qquad (2)$$

where $\hat{f}$ and $\hat{h}$ are the estimates (or chromosomes) of f and h, respectively. The lower is the cost, the higher is the fitness. The optimum solution (perfect restoration) can be obtained by minimizing the cost function of Eq.(2). Three genetic operators (selection, crossover and mutation) are applied on the both populations of f and h, respectively, to guide the both chromosomes toward the optimum solutions (minimum cost).

2.3. Genetic operators

Selection: We used an elitist selection scheme [4] for selection process. In this scheme, the best chromosome (estimate) with the lowest cost (the highest fitness) is selected as an elitist, which is copied directly into the new population without any changes. The other chromosomes (estimates) of the new population are selected by using a roulette selection scheme [4]. In this scheme, a roulette wheel with slots size according to fitness is used, where fitness is defined as $Fitness = 1/(1+E)$. We spin the roulette wheel *pop_size*-1 times; each time we select one chromosome for the new population. Obviously, some chromosomes would be selected more than once. This is in accordance with the Schema Theorem [4]: the best chromosomes get more copies, the average ones stay even, and the worst ones die off. Furthermore, some chromosomes of this new population undergo alterations by means of crossover and mutation.

Crossover: Crossover combines the features of two parent chromosomes to form two similar offspring by swapping corresponding segments of the parents. The intention of the crossover operator is information exchange between different potential solutions. Two newly developed crossover operators are used [7], [8]. One is called uniform R/C crossover. Two selected parents (P1 and P2) exchange their row or column information at the same position as shown in Fig.2(a). It performs a local small-scale exchange. Another one is called random R/C crossover. The crossing positions for P1 and P2 are randomly selected. They can exchange their information at the different position as shown in Fig.2(b). Thus it performs a large-scale exchange.

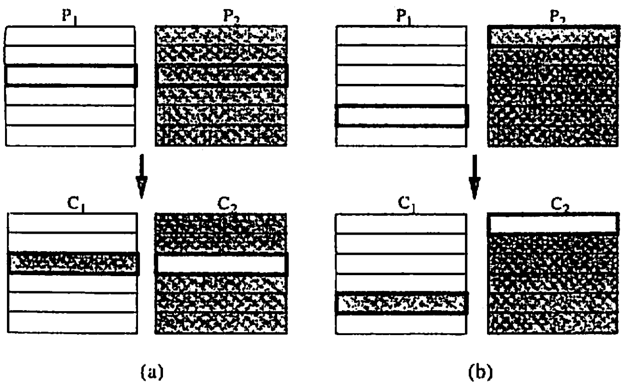


Fig.2 Crossover operators: (a) uniform R/C crossover, (b) Random R/C Crossover.

Mutation: A weighted mutation scheme [8] is also used for generation of offsprings together with the crossover. The intention of the mutation operator is the introduction of some extra variability into the population. The weighted mutation operator is illustrated in Fig.3. The average value *avg* of the surrounding 8 pixels indicates the probability of the selected pixel value=1. It performs a small-scale survey of the area surrounding the pixel selected for mutation and mutates it in the direction that enhances the smoothing of the image.

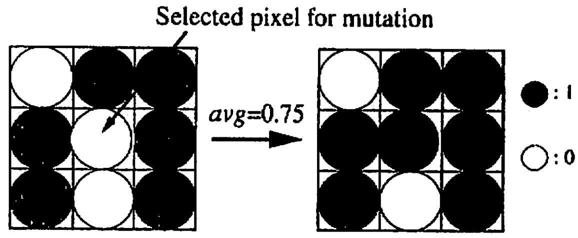


Fig.3 Illustration of the. weighted mutation.

3. SIMULATION RESULTS

We have carried out computer simulations to validate the applicability of GA for blind deconvolution of image restoration. Figure 4(a) shows the original image f used in the simulations. The pixel size of f is 15x15. The simulations are done for two cases. Figures 4(b) and 4(c) show the blurring functions for case 1 and case 2, respectively. Both of the blurring functions are 5x5. The h of case 1 can be considered as a blurring function of out-of-focusing and it can be identified by the power cepstrum of the blurred image [3], while for case 2, it is impossible to be solved by the conventional power cepstrum method.

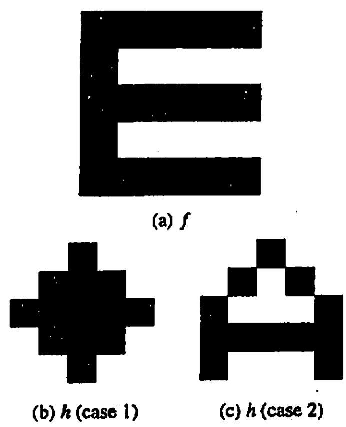


Fig.4 Phantoms used in simulations (unknown images).

The degraded images g used as input images are shown in Fig.5(a) and Fig.6(a) for case 1 and case 2, respectively, which are obtained by the convolution of f (Fig.4(a)) and hs (Fig.4(b), and 4(c)). The purpose of the simulations is to estimate both f and h from g alone.

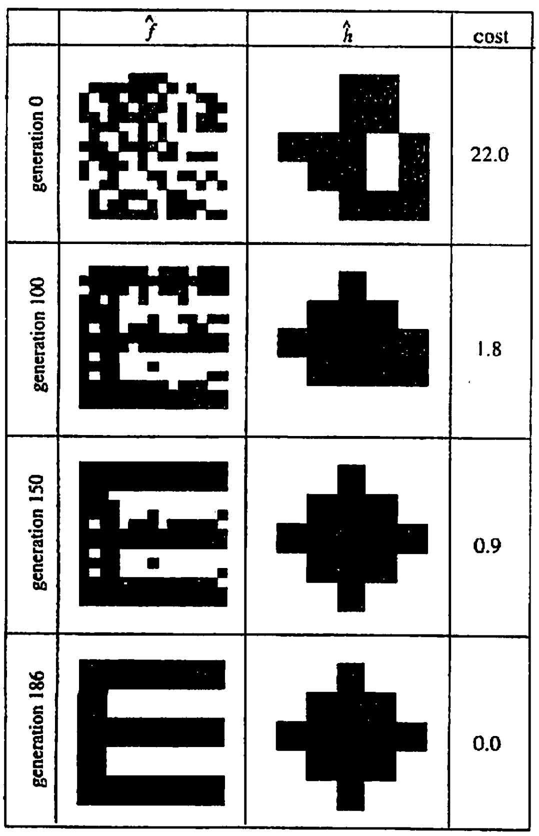
The optimum parameters for the genetic

algorithm, which are obtained through several testing runs, are as follows:

Population size (pop_size)	30
Probability of crossover 1 (*Pc*1)	1.0
Probability of crossover 2 (*Pc*2)	0.45
Probability of mutation (*Pm*)	0.1

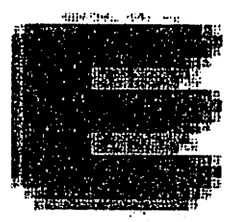
The restoration results for case 1 and case 2 are shown in Fig.5(b) and Fig.6(b), respectively. It can be seen that both f and h are improved as the generation increases. The improvements of the cost function for both cases are shown in Fig.7(a) and 7(b) with a solid line. The costs are minimized by the genetic operators. The cost=0 means the perfect restoration (optimum solution). The convergence toward the optimum solution is dependent on the images to be recovered. The simple image (case 1) shows a fast convergence. In order to make a comparison, we also show the result by a random search (without genetic operators) for the simple case (case 1) in Fig.7(c). It can be seen that if we do not use the genetic operators, there are no any improvements of the cost even after 500 generations.

(a) g (input image)

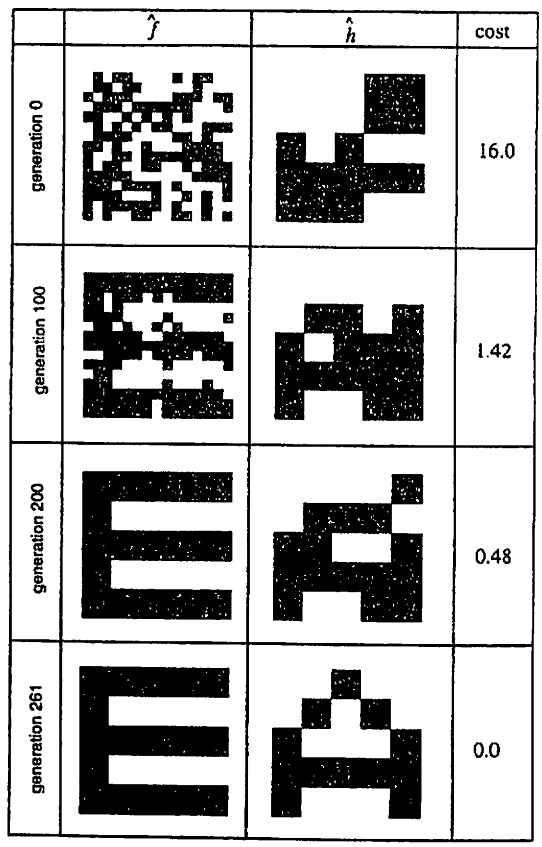


(b)

Fig.5 GA-based blind deconvolution results (case 1).



(a) g (input image)



(b)

Fig.6 GA-based blind deconvolution results (case 2).

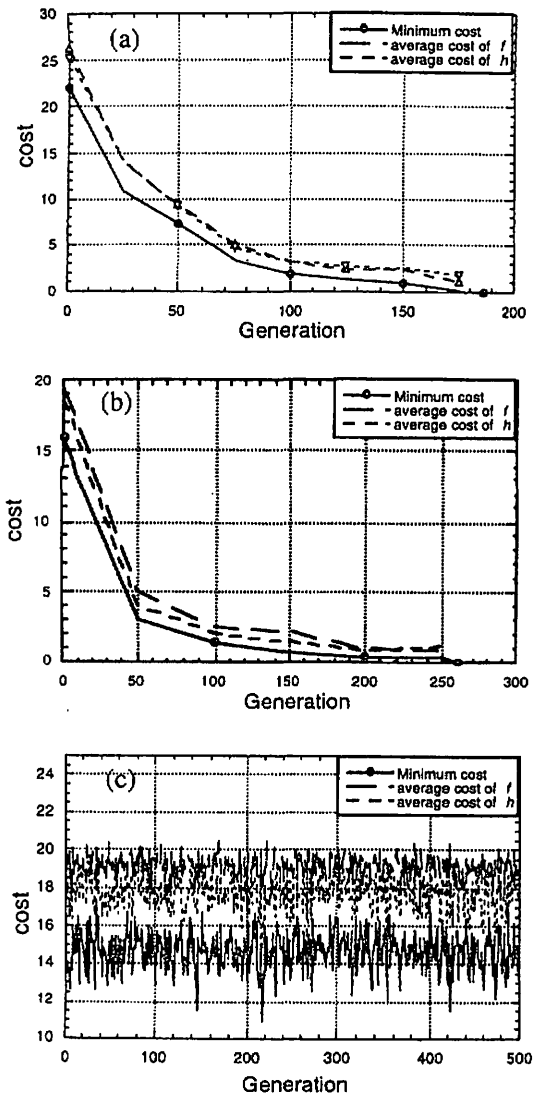


Fig.7 Cost vs. generation. (a) Case 1 by GA, (b) case 2 by GA, and (c) case 1 by random search.

4. SUMMARY

We have applied a genetic algorithm (GA) for blind deconvolution problem of image restoration. The computer simulation results show that it is possible to recover the original image from the degraded image alone. A further investigation is also under way to develop more efficient genetic operator in order to reduce the calculation time.

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