IMAGE ENHANCEMENT INCORPORATING FUZZY FITNESS FUNCTION IN GENETIC ALGORITHMS

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Abstract : *Genetic algorithms represent a class of highly parallel adaptive search processes for solving a wide range of optimization and machine learning problems. The present work is an attempt to demonstrate their adaptivity and effectiveness of searching global optimal solution in selecting an appropriate image enhancement operator automatically.*

Key words : *Image Enhancement, Genetic Algorithms, Ambiguity Measures.*

I. INTRODUCTION

Genetic Algorithms (GAs) [1,2] are search algorithms based on the mechanics of natural selection and natural genetic system. GAs find out the global near optimal solution employing three basic operations over a limited number of strings(chromosomes). The operators are *reproduction/selection, crossover and mutation.*

Reproduction is a process in which individual strings are copied according to their objective function values, f, called the fitness function. These strings are then entered into a mating pool, a tentative new population, for further genetic operator action.

The crossover generates offsprings for the new generation using the highly fitted strings (parents) selected randomly from the mating pool. Each pair of strings (selected randomly) undergoes crossing over as follows : an integer position k is selected uniformly at random between 1 and $l - 1$, where, l is the string length greater than 1. Two new strings are created by swapping all characters from position $k + 1$ to l.

Mutation is the occasional (with small probability) random alteration of the value of a string position. The mutation operator plays a secondary role in the simple GA. Note that, the frequency of mutation to obtain good results in the empirical genetic algorithm studies is on the order of one per thousand bit (position).

There are many problems in the area of pattern recognition and image processing [3,4,5] where we need to have efficient search in complex spaces in order to achieve optimal solution. Let us consider the problem of contrast enhancement of an image by gray level modification. Given an image it is difficult to select a functional form which will be best suited without prior knowledge of image statistics. Even if we are given the image statistics it is possible only to estimate approximately the function required for enhancement, and the selection of the exact functional form still needs human interaction in an iterative process.

The present article attempts to demonstrate the suitability of GAs in the automatic selection of image enhancement operator for an unknown image. The problem is to select automatically an optimum set of 12 parameters values of a generalized enhancement function, that maximizes some fitness function. The algorithm used both spatial and grayness ambiguity measures as the fitness value. Multiple point genetic cross-over operation has been used for better convergence.

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II. IMAGE ENHANCEMENT OPERATOR SELECTION

The purpose of image enhancement is to improve the picture quality for visual judgment and machine understanding. One of the most popular approaches is contrast enhancement by gray-level modification. Usually, a suitable nonlinear functional mapping is used to perform this task. The simplest form of the functional mapping may be expressed as

$$x'_{mn} = x_{max} \cdot f(x_{mn}) \tag{1}$$

where, x_{mn} = gray value of the (m, n)th pixel in the input image; x'_{mn} = transformed value of the (m, n)th pixel (enhanced); $f(x)$ is prescribed transformation function defined in equation (7) and x_{max} (x_{min}) = maximum (minimum) value of gray level dynamic range.

The most commonly used transformation functions [6,7] are shown in figure 1(a-d). The mapping function (f_1) depicted in figure 1(a) increases the contrast within the darker area of the image while, the application of a function (f_3) like figure 1(c) will produce effects exactly opposite to that of figure 1(a). The functions (f_2) shown in figure 1(b) will result in stretching of the middle range gray levels and the function (f_4) in figure 1(d) will compress drastically the middle range values, and at the same time it will stretch the gray levels of the upper and lower ends. The mathematical forms of the above mentioned mapping functions are given below.

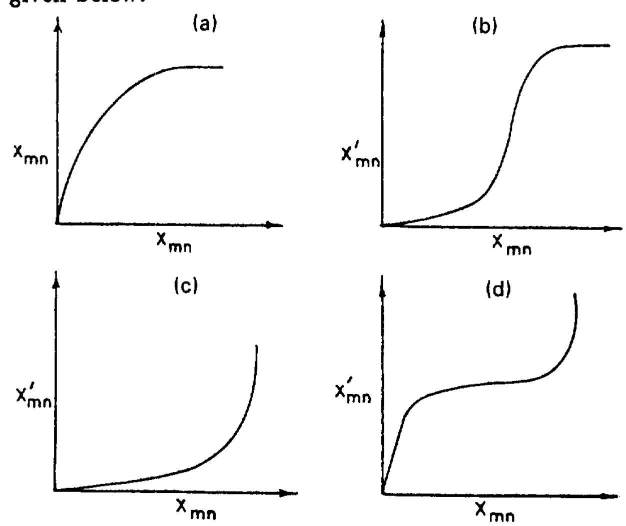

Figure 1. Mapping functions commonly used for contrast enhancement

$$f_1(x) = \frac{x^2}{par_1 + x^2} \text{ or } = par_1 log(x) \tag{2}$$

where, par_1 and a are positive constants.

$$\begin{aligned} f_3(x) &= par_2[F(x)]^2 + par_3 x + par_4 \\ & 0 < par_2, par_3, par_4 < 1 \end{aligned} \tag{3}$$

where

$$\begin{aligned} F(x) &= x - par_5 \quad for \quad x > par_5 \in (x_{min}, x_{max}), \\ &= 0 \qquad\qquad\qquad otherwise, \end{aligned} \tag{4}$$

The functions in figure 1(b) and 1(d) are represented respectively by

$$f_2(x) = [1 + (\frac{x_{max} - x_{min}}{par_6})^{par_7}]^{-1} \tag{5}$$

and

$$f_4(x) = \frac{1}{x_{max}}[x_{max} - par_6\{(\frac{x_{max}}{x} + par_8) - 1\}^{-par_7}] \tag{6}$$

where par_6 and par_7 are positive constants and par_8 is the value of $f(x)$ for $x = 0$.

All these functions make contrast enhancement of an image. Note that, not all non-linear function will produce desired (meaningful) enhanced version [6] only for a particular image. Since we do not know the exact function which will be suited for a given image, it seems appealing and convenient to use one general functional form which will yield the aforesaid four functions as special cases and others, if necessary. As an illustration one may consider a convex combination of these four functions e.g.,

$$\begin{aligned} f(.) &= par_9 f_1(.) + par_{10} f_2(.) + par_{11} f_3(.) + par_{12} f_4(.) \\ & par_9 + par_{10} + par_{11} + par_{12} = 1. \end{aligned} \tag{7}$$

Here, the multipliers (par_9 – par_{12}) are to be chosen according to the importance (suitability) of a function for a given image, on the other hand, parameters (par_1 – par_8) of the respective functions, are to be defined according to the quality of enhancement desired. It may be noted that this combination will enable one to stretch/compress any region of an image one may desire. Therefore, the problem now boils down to determining an optimum set of values of these 12 parameters in order to achieve a desired enhancement.

In the following section we will be explaining the role of GAs in determining the optimum parameter set (i.e., the exact functional form) for enhancement of an image.

III. GA FOR IMAGE ENHANCEMENT

The main features to solve a problem using GAs are

1. Chromosomal representation of solution (parameter set) to the problem.
2. Creation of initial population of solution.
3. An evaluation (fitness) function that plays the role of the environment, rating solution in terms of their "fitness".
4. Genetic operators that alter the composition of children during reproduction.
5. Values for the parameters that the genetic algorithm uses.

In the following subsections we shall explain the way of formulating these five components in the context of automatic image enhancement.

A. Representation of Parameters : Let $f(.)$ be a transformation function having p parameters par_1, par_2, ..., par_p. These parameters may have different domains of definitions. A binary string of length $p.q$ can be considered as a chromosomal representation of the parameter set. Here each substring of length q is assumed to be the representative of each parameter. For example, let us consider the equation (7). There are 12 parameters including 8 (par_1 – par_8) for 4 basic functions and 4 (par_9 – par_{12}) for multipliers. A binary string of length 10 is used for each parameter. So a chromosome for 12 parameters will be of length 120 such as

1100010101	0100011010	.....	0111110001
par_1	par_2	.....	par_{12}.

After applying the genetic operators the resulting substrings of length q are decoded into a real number in $[0,1]$. These parameter values are then multiplied by appropriate factor to make them lie into their respective domains in order to be used for computing the enhanced version. In our application the domains of parameters are as follows : $par_1 - par_4$ & $par_8 - par_{12} \in [0,1]$; $par_5 - par_6 \in (x_{min}, x_{max})$ and $par_7 \in [0,3]$.

B. Creation of Initial Population : GAs search for the global, near optimal solution under the complete lack of knowledge about the search spaces. Usually in GAs, the initial population consists of entirely random strings. However, random binary strings each of length pq can be considered as chromosomes for the initial population.

C. Evaluation Function : In GA objective/fitness function is the final arbiter of the string creators. Again, we need an evaluation function for quantifying the desired enhanced output i.e., to make the task subjective evaluation objective. Here we have used entropy, compactness [7], index of area coverage (IOAC) [8] and their combinations as the quantitative index for evaluating picture quality, as they have been successfully used as grayness and spatial ambiguity measures for image enhancement and segmentation problems [8].

Entropy of an image (X) considers the global information and provides an average amount of fuzziness in grayness of X. Compactness and IOAC on the other hand, take into account the local information and reflect the amount of fuzziness in shape and geometry (spatial domain of an image). Therefore one may use a composite measure (e.g., product of both grayness and spatial ambiguity measures [7]) as the basis of the fitness function.

D. Genetic Operators : Since the size of the parameter set for this problem is not small it is intuitive that, the single point cross-over operation (described in section 2) may not be useful for fast convergence. Therefore, instead of applying cross-over at a single point over the entire string we applied this (multiple point cross-over) operation on each substring. The proposed operation has been demonstrated below when the substring length $q = 10$. Let, a = 1100010101 0100011010 ... 0111110001 and b = 1000101110 1110110001 ... 0011010100 be two strings selected for crossing over. Let the random number generated by the operation be 7, 5, ..., 4 then, the newly produced offsprings will be a' = 1100010110 0100010001 ... 0111010100 and b' = 1000101101 1110111010 ... 0011110001.

E. Domains of Parameters : In our experiment we considered Size of the population = 100; Number of Generations = 30 and Probability of mutation = 0.001.

IV. IMPLEMENTATION AND RESULTS

Two images (blurred chromosome in figure (2a) and A. Lincoln in figure (3a)) have been considered here to implement the proposed algorithm. The function $f(.)$ (equation(7)) having 12 parameters is taken here as the transformation or mapping function for gray level rescaling. The composition (product) of the measures entropy and compactness of the image is used as the evaluation function. The reciprocal of the evaluation function is considered to be the fitness function.

The intermediate and the final configurations of the transformation functions (e.g., functional forms after 15, 20, 25 and 30th generations) for the image and the final enhanced outputs are shown in figures 2(b-c). This shows how the GAs make the enhancement function gradually converge to the optimal state. Figure 2(d) shows the monotonic nondecreasing behavior of the fitness function value in this respect.

Similar observation is also found for the Lincoln image (figures 3(b-d)). Note that, one can use IOAC, instead of Compactness, in computing fitness value when the object is elongated (non-compact) [8].

The algorithm does not need iterative visual interaction and prior knowledge of image statistics in order to select the appropriate enhancement function. Convergence of the algorithm is experimentally verified. The algorithm determines the optimum parameter set not the individual parameters in selecting appropriate enhancement function. Although it considers a large search space, it requires, in practice, only a smaller number of points to achieve the result (e.g., the algorithm considered 3000 points out of 2^{120}). Note that, the domains of the parameters here are continuous. Therefore, to obtain a more accurate solution one needs to increase the length of the strings, though it will increase the computational time.

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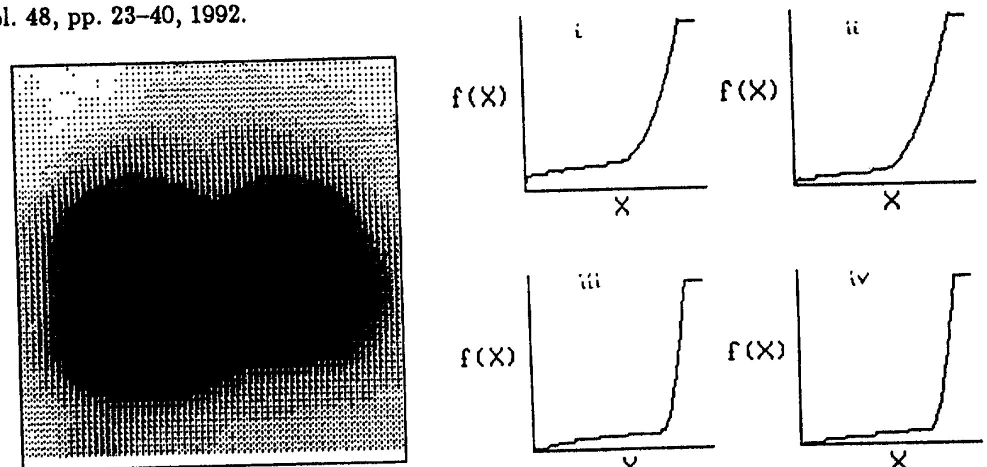
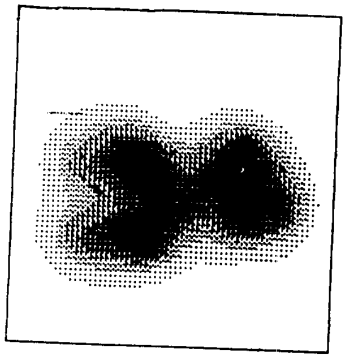


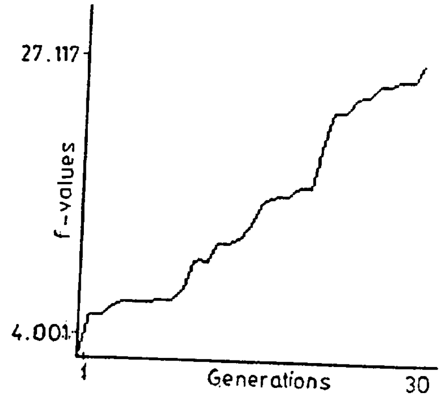
(a) Input

(b) Enhancement functions after i) 15, ii) 20, iii) 25 and iv) 30 th generations

Figure 2. Blurred Chromosome



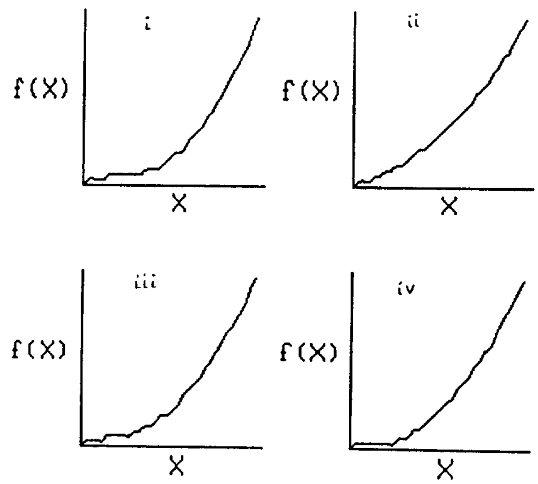
(c) Enhanced output



(d) Fitness values with generations

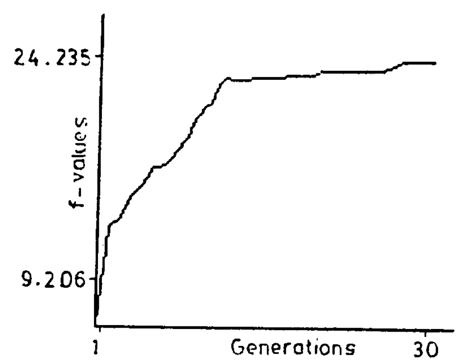
Figure 2. Blurred Chromosome

(a) Input



(b) Enhancement functions after i) 15, ii) 20, iii) 25 and iv) 30 th generations

(c) Enhanced output



(d) Fitness values with generations

Figure 3. Abraham Lincoln