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A SURVEY OF GENETIC ALGORITHMS APPLICATIONS FOR IMAGE ENHANCEMENT AND SEGMENTATION

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Abstract. It was proved that genetic algorithms are the most powerful unbiased optimization techniques for sampling a large solution space. Because of unbiased stochastic sampling, they were quickly adapted in image processing. They were applied for the image enhancement, segmentation, feature extraction and classification as well as the image generation. This article gives a brief overview of the canonical genetic algorithm and it also reviews the tasks of image pre-processing. The survey of publications of this topic leads to the conclusion that the field of genetic algorithms applications is growing fast. The constant improvement of genetic algorithms will definitely help to solve various complex image processing tasks in the future.

1. Introduction

Genetic algorithms (GAs) [19] are a relatively new paradigm for a search, based on principles of natural selection. For the first time they have been introduced by John Holland in 1960s [29, 18].

GAs were proven to be the most powerful optimization technique in a large solution space [43]. This explains the increasing popularity of GAs applications in image processing [19] and other fields [36, 28]. They are used where exhaustive search for solution is expensive in terms of computation time. Applications of GAs for image processing extend from evolving filters or detecting edges to making complex decisions or classifying detected features.

The aim of this article is to review GA applications for the most fundamental image processing tasks – image enhancement and image segmentation. The article surveys recent and older approaches which solve optimization problems using GA as a primary optimization tool. The main ideas of such approaches are explained as well. Brief descriptions of problems are given.

2. Genetic algorithm

Genetic algorithms are based on natural selection discovered by Charles Darwin [40]. They employ natural selection of fittest individuals as optimization problem solver. Optimization is performed through natural exchange of genetic material between parents. Offsprings are formed from parent genes. Fitness of offsprings is evaluated. The fittest individuals are allowed to breed only.

In computer world, genetic material is replaced by strings of bits and natural selection replaced by fitness function. Matting of parents is represented by cross-over and mutation operations.

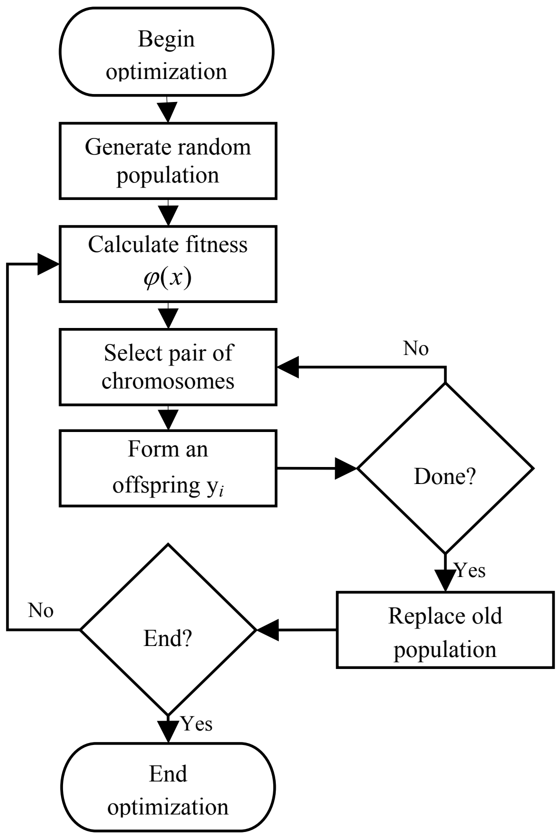

Figure. 1. Flowchart of genetic algorithm

A simple GA (Figure 1) consists of five steps [29]:

1. Start with a randomly generated population of N chromosomes, where N is the size of population, l – length of chromosome x.
2. Calculate the fitness value of function $\phi(x)$ of each chromosome x in the population.
3. Repeat until N offsprings are created:
   3.1. Probabilistically select a pair of chromosomes from current population using value of fitness function.
   3.2. Produce an offspring y_i using crossover and mutation operators, where $i = 1, 2, \ldots, N$.
4. Replace current population with newly created one.
5. Go to step 2.

In case of simple GA, the whole population is formed of strings having the same length. These strings contain encoded information.

For example, GA is used to enhance image contrast [39]. It is done by mapping intensity of image values according to the predefined table. Each intensity value I is mapped to a new value B. In this case, each chromosome x is represented by a byte string, where each byte (gene) encodes the difference $b(j-1)$ between values of transformed curve $B(j)$ and $B(j-1)$ (Figure 2), where j is a byte position in chromosome. The value of curve $B(j)$ is represented by

$$B(j) = \begin{cases} 0 & j = 0, \\ B(j-1) + b(j-1) & 1 \le j \le I_{\max} - I_{\min}, \end{cases} \quad (1)$$

where $I_{\max}$ and $I_{\min}$ represent maximum and minimum intensity values.

The fitness of each individual is measured by calculating the sum of edge intensities, which are produced by Prewitt transform of enhanced image [39]. The most fit individual is considered to be the one, which creates most intense edges. The least fit individuals are extinguished and their place is taken by newly created offsprings.

Offsprings are created during crossover and mutation. The crossover is an operation when new chromosomes – offsprings are produced by fusing parts of other chromosomes – parents. The mutation is random replacement of chromosome bits [29]. Thus offsprings form a new generation which replaces the old one.

Such evolution process can be terminated using various conditions. In [39] termination takes place after fitness stability over 10 generations. There are other ways to terminate algorithm. For example, when fitness reaches predefined threshold, evolution takes certain number of generations or fitness converges to a specific value [29].

3. Applications for image enhancement

The first task of machine vision is to enhance image quality in order to obtain a required image perception. It is done by removing noise, amplifying image contrast and amplifying the level of a detail [15]. A huge amount of techniques for such operations exist there. The GAs were adopted to achieve better results, faster processing times and more specialized applications.

Evolutionary algorithms have been applied to image enhancement by several authors [32, 21, 33].

GAs are used to construct new filters, to optimize parameters of existing filters, and to look for optimal sequence of existing filters.

For filtering and enhancement of a colour image, there is a useful class of weighted vector directional filters (WVDF) [22]. Optimization of their coefficients using mathematical approaches was mentioned in [22]. It was proved that they can't converge to globally optimal coefficient weight vector [33].

WVDF filter can be described as follows. Let us consider a two-dimensional matrix of three-component samples (pixels) $\mathbf{x}_i = (x_{i1}, x_{i2}, x_{i3}) \in Z^2$ [23], which represents $K_1 \times K_2$ colour image $\mathbf{x}(i): Z^2 \to Z^3$; and a sliding window $W = \{\mathbf{x}_i \in Z^2;\ i = 1,2,\ldots,N\}$ of finite odd size N [21]. Window usually affects one image pixel at the centre of the window. WVDF filters utilize a non-negative real weight coefficients vector $\mathbf{w} = (w_1, w_2, \ldots, w_N)$ associated with image sample vectors $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N$. Each weight vector element corresponds to one image pixel. Weight coefficients' vector is similar to the feature vector used in [17]. The output of filter $\mathbf{y} = \mathbf{x}_i \in W$ minimizes the sum of aggregated angular distances to other image samples inside the window W [24]:

$$\min_{\mathbf{x}_i \in W} \arg \sum_{j=1}^{N} w_j A(\mathbf{x}_i, \mathbf{x}_j) \quad \text{for } i = 1,2,\ldots,N, \quad (2)$$

where $A(\mathbf{x}_i, \mathbf{x}_j)$ represents the angle between the two colour vectors $\mathbf{x}_i = (x_{i1}, x_{i2}, x_{i3})$ and $\mathbf{x}_j = (x_{j1}, x_{j2}, x_{j3})$.

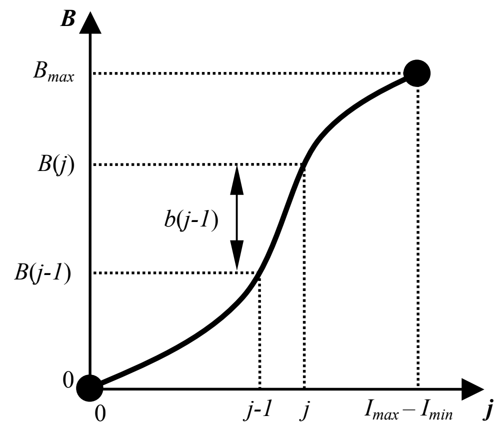

Figure 2. Brightness mapping curve

Each set of weight coefficients represents a different filter. Optimization procedure must be adopted to obtain an optimal filter. A GA optimization is employed to solve such a task [22]. Candidate solutions (WVDF weight vectors) are represented by real coded chromosomes [22]. This means that each gene corresponds to one weighting coefficient $w_j \in \mathbf{w}$, for $j = 1,2,\ldots,N$. In this case one chromosome contains all weights of a filter.

Mean absolute error (MAE) criterion was used to evaluate fitness of individuals [22]. Fitness values φ_j, for $j = 1,2,\ldots,N_P$ are computed by

$$\varphi_j = 1 - \frac{\mathrm{MAE}_j}{\mathrm{MAE}_{\max}}, \tag{3}$$

where $\mathrm{MAE}_{\max}$ is the maximum possible MAE of the image.

Elitism was used to improve the performance. The elitism parameter r_e multiplied by N_P denotes fraction of the best individuals which will appear unchanged in the next generation. Selection of individuals is performed using tournament scheme. Small groups are selected from population and individuals and they compete only in the scope of the selected group. This helps to eliminate premature convergence and domination of one genotype. Premature convergence can be eliminated by using ranking scheme [41]. In such case every chromosome is ranked according to its fitness value.

Optimization of WVDF filter coefficients were performed on the standard set of colour images. They were corrupted by impulsive noise of different noise probabilities P_n [22].

Filter optimization which uses GA significantly improves colour/structural characteristics of the traditional colour filtering scheme. Optimized filters exhibit acceptable noise attenuation capabilities [22]. Elitism scheme greatly improves effectiveness of optimization. While using elitism best individuals are not affected during mutation and they can not obtain worse fitness.

Another important problem in image processing is character recognition. Most difficulties arise while separating characters and background. Backgrounds can have complex variations, images vary in lighting conditions and variety of degradations.

In order to binarize degraded printed documents an intensive investigation was done [42, 35, 20]. At the same time well known filtering techniques including Fourier transform, Gabor filters, and wavelet transforms were used. However, it is difficult for a single filtering technique to deal with a variety of degradations, which occur in natural scene images [20]. To solve similar problems Nagao et al. [27, 3] used GAs to construct an optimal sequence of image processing filters to extract characters from different sources. Kohmura and Wakahara [20] extended Nagao's work to colour space and adapted to a wide variety of degradations. They classified degradations into six categories: clear, background with pattern, character with pattern, character with rims, blurring and non-uniform lighting shown in Figure 3.

(a) (b) (c) (d) (e)

Figure 3. Samples of degraded characters from ICDAR conference (available at http://algoval.essex.ac.uk/icdar/Datasets.html) a) non-uniform lighting b) background with pattern c) and e) character with pattern, d) blurring

Instead of evolving a single filter, a filter bank of 17 well-known filters (mean, min, max, Sobel, erosion, dilation, etc.) was created, and a search for an optimal filtering sequence was performed [20]. Possible random sequence was encoded in chromosomes. Each chromosome consists of 8-bit integers representing filter index. The total length of filtering sequence was limited to 80. The simple GA was employed with a population of 300 individuals. Maximum of 800 generations or fitness threshold of 0.9 was chosen as termination criterion. Selection was performed using simple roulette rule, based on fitness values in each generation. Fitness $\varphi(\mathbf{T},\mathbf{F})$ of individuals was computed, comparing filtered image with the image ideally segmented by a human, according to:

$$\varphi(\mathbf{T},\mathbf{F}) = 1 - \frac{\sum\limits_{k=R,G,B} \sum\limits_{x=1}^{K_x} \sum\limits_{y=1}^{K_y} \left| T_k(x,y) - F_k(x,y) \right|}{3\left(255 K_x K_y\right)}, \tag{4}$$

where K_x and K_y – width and height of the image, $\mathbf{T} = \{T_k(x,y)\}$ and $\mathbf{F} = \{F_k(x,y)\}$ $(k = \mathrm{R,G,B})$ denotes target and filtered image, respectively [20].

This optimization procedure is rather slow. Because of that every fitness evaluation requires comparison of two images. And every generation requires 300 of such comparisons. So, the whole optimization can make up to $2.4 \cdot 10^5$ comparisons of images. Speed up could be obtained using different selection scheme. Elitism, as in [22], would bring down convergence time.

Kohmura and Wakahara [20] conducted experiments on 269 samples of differently degraded characters and obtained interesting results. Some of binarizations are remarkably successful even if training set and tested characters are completely different. Authors [20] have obtained approximately 0.9 normalized cross-correlation between the target and filtered images. However, for a practical algorithm usage, automatic degradation type selection problem exists and it has not been solved yet.

4. Applications for image segmentation

Image segmentation denotes a process by which input image is partitioned into non-overlapping regions [44]. Each region is homogeneous and connected. The union of any two spatially adjacent regions is not homogenous [9].

Each region in a segmented image has to satisfy properties of homogeneity and connectivity [4]. The region is considered to be homogeneous if all region pixels satisfy homogeneity conditions defined per one or more pixel attributes, such as intensity, colour, texture, etc. The region is connected if a connected path between any two pixels within the region exist [9]. If I is a set of all image pixels and $H(\cdot)$ is a homogeneity predicate defined over connected pixel groups, then the image segmentation is partitioning of I into connected subsets $\{S_1, S_2, \ldots, S_n\}$ so that

$$\bigcup_{i=1}^{n} S_i = I \text{ and } S_i \cap S_j = \emptyset,\ i \neq j. \tag{5}$$

The homogeneity predicate is

$$\begin{aligned} &H(S_i) = \mathit{true} \text{ for all } S_i, \\ &H(S_i \cup S_j) = \mathit{false} \text{ for any adjacent } S_i \text{ and } S_j. \end{aligned} \tag{6}$$

Computation of such image partitions has a very high combinatorial complexity. No general solution for all segmentation cases exist [9].

Because of a very big solution space, genetic algorithms were adopted by several researchers. GA's was applied to optimize parameters of various segmentation techniques [4, 10, 5, 30] as well as to develop new techniques [25, 37].

One of modern segmentation techniques is a shape description caused by energy functions and possible shape deformations. In [30], to detect cardiac boundaries in echocardiography images (Figure 4), heart shape is described by an irregular parametric ellipsoid defined by

$$\begin{aligned} x &= x_0 + x_1 \cos\alpha + x_2 \cos(2\alpha + \phi_1) + \ldots, \\ y &= y_0 - y_1 \sin(\alpha + \phi_0) - y_2 \cos(2\alpha + \phi_2) + \ldots. \end{aligned} \tag{7}$$

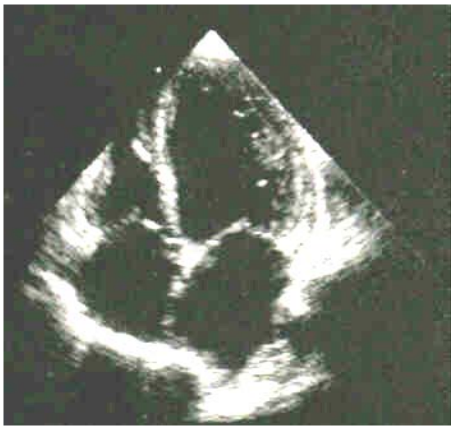

Figure 4. Echocardiography image of human heart

Shape fitting in the image is performed by minimizing energy function adopted from [14]

$$U_{pw}(j) = \begin{cases} [1 - \mathrm{gmax}(j)]^{-1} + \dfrac{255}{1 + I(j)} & \mathrm{gmax}(j) < 0 \\ 1 - \mathrm{gmax}(j) + \dfrac{I(j)}{255} & \mathrm{gmax}(j) \geq 0 \end{cases}, \tag{8}$$
$$U = \sum U_{pw}(j) + \sum U_s(j),$$

where U_{pw} is energy function for posterior wall and U_s – is energy function for septum, gmax(j) is maximum gradient in direction to a normal of ellipsoid boundary.

Each elliptical contour is encoded as a chromosome which genes contain harmonic components of elliptic contour and two position elements. Genetic algorithm tries to minimize energy function U guiding contour to optimal segmentation of echocardiography image and extracting cardiac boundaries. Fine segmentation is achieved through the knowledge of image incorporation into optimization process through adjustable parameter ranges. Such an approach allows segmenting an image with incomplete heart boundaries as well as increases resistance to noise.

Lucia Ballerini [6-8] did an extensive research on snakes' algorithm parameters optimization by using genetic algorithms. Cagnoni et al. [11] use elastic contour model to segment medical images in the search for a particular anatomical structure. They use GA to optimize energy function derived from snakes' algorithm, thus driving contour into an optimal position.

Excellent results are demonstrated in [46], where parallel genetic algorithm [31] is adopted for surface model fitting in three-dimensional space. Parallel genetic algorithm was demonstrated to show that it is a better optimizer than the classical GA [31]. By incorporating migration operation, parallel GA makes itself more natural. Several isolated subpopulations evolve in parallel, periodically exchanging their best individuals [47].

One of the most fundamental segmentation techniques is edge detection. It usually involves two stages. The first one is edge enhancement process that requires the evaluation of derivatives of the image and usage of gradient or Laplacian operators (Figure 5). Such methods as threshold or zero-crossing produce an edge map that contains pixels candidates to be labelled as edge points of the image. But these methods provide not enough information on being a good edge. This limits their ability to exploit local edge continuity information in reducing the edge fragmentation due to noise. Furthermore, because of inherent low-pass filtering, they have a tendency to dislocate edges. To solve these problems there were various attempts taken, including different scale kernels [45, 26], fitting models of edges [34], greedy algorithms [46], dynamic programming [2] and finite element method [13].

Figure 5. Detected edges by using Sobel operator

The second stage involves selection and combination of edge map pixels using boundary detection, edge linking and grouping of local edges [38]. This stage can be viewed as a search for optimal configuration of pixels that better approximate edges.

Several approaches [12, 16] applied GA-based search for optimal configuration of edge pixels.

In [12], possible edge configuration S is encoded as chromosome. Each chromosome consists of a K^2 bits string, where K represents the dimension of an image I. Each bit shows the presence of an edge pixel in the image I.

Algorithm evaluates each chromosome by using a cost function. The form of the point cost function is a linear combination of five weighted point factors [12]. It includes fragmentation, thickness, local length, region similarity and curvature. These factors are evaluated for each pixel in its local neighbourhood of $M \times M$ window.

The five factors are defined as follows. Fragmentation describes local edge discontinuities. Penalty for fragmentation is assigned to define the endpoints of the edge. Pixel is considered as an endpoint if it has only one neighbour or is isolated at all.

Edge thinness penalty is assigned to edge pixels that are not thin. A pixel, in configuration S, is considered to be thin, if it is connected with any other pixel, from configuration S, by just one path.

To avoid detection of excessive number of edges, there is length penalty assigned. Each edge pixel receives this penalty. This helps to eliminate pixels appearing because of noise and short and useless edge fragments.

As canny edge operator assigns edge strength value, it is necessary to estimate edge dissimilarity. This penalty is computed by estimating likelihood l, and assigning cost to non edge pixels which is proportional to dissimilarity estimated in likelihood map L.

The last penalty – element smoothness, is assigned according to pixel-to-pixel connection angle. If it is 0, the penalty is also 0, if 45 degrees – 0.5 is assigned, if angle equals or is more than 90 degrees, penalty is 1.

The first population of chromosomes is generated in specific way. Initial edge configurations are generated from the filtered image. This is due to a very large search space. There are 2^{K^2} possible solutions.

Reproduction is performed by copying some portion of one chromosome to another. Mutation, randomly with low probability, replaces members of chromosome. The whole algorithm terminates after the cost function has remained invariant with some tolerance for one generation.

This algorithm was extended by Gudmundsson et al. [16]. In their approach, each chromosome encodes only small portion of image as a 8×8 window. These windows are connected with their neighbouring windows to keep track of edges connectivity at window corners. Also, chromosomes were changed from bit strings to bit arrays. To decrease convergence time they included a special problem-based mutation operator. It selects a mutation strategy from a 24 predefined mutations set.

Image fragmentation into small portions makes the algorithm to be more robust. As small portions of image are evaluated separately, they can converge quicker than others. In such a way, converged portions are not changed by global crossover or mutation. Predefined mutations allow to drive a portion of edge map more directly to the goal than random changes.

5. Conclusions

GA can be used as a very promising unbiased optimization method; it constantly gains popularity in image processing. Various tasks from basic image contrast and level of detail enhancement, to complex filters and deformable models parameters are solved using this paradigm. The algorithm allows to perform robust search without trapping in local extremes.

Different authors adopt GAs to solve a very big variety of simple and difficult tasks. Every approach is unique, with different information encoding types, reproduction and selection schemes.

The success of optimization strongly depends on the chosen chromosome encoding scheme, crossover and mutation strategies as well as fitness function. For each problem, careful analysis must be done and correct approach chosen. As it was shown, one chromosome can contain a whole image or only a small part of it, a whole parameter range or only the most descriptive ones. Crossover can be performed in various manners, for example by exchanging information at one brake point or at several one. Different strategies may be used for genetic information transfer and parallel evolution may be adopted.

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