

A Genetic Algorithm for the Detection of 2D Geometric Primitives in Images

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Abstract

We investigate the use of genetic algorithms (GAs) for image primitives extraction (such as segments, circles, ellipses or quadrilaterals). This approach completes the well-known Hough Transform, in the sense that GAs are efficient when the Hough approach becomes too expensive in memory, i.e. when we search for complex primitives having more than 3 or 4 parameters. A GA is a stochastic technique, relatively slow, but which provides with an efficient tool to search in a high dimensional space. The philosophy of the method is very similar to the Hough Transform, which is to search an optimum in a parameter space. However, we will see that the implementation is different.

Keywords : Genetic Algorithms, Image Primitive extraction, Sharing, Hough Transform.

1 Introduction

Geometric Primitives extraction is an important task in image analysis. It is important especially in the case of indoor vision, where most of the objects to be analysed are manufactured. Their description with the help of bidimensional or tridimensional geometric primitives is well adapted. Our aim is to present an alternative to the Hough Transform (HT). HT is a very efficient method for lines or simple primitives detection, but reaches its limits for complex primitives. HT consists in the searching of maxima in the space of parameters which describe the primitive. It constructs explicitly the function to optimize, represented by an "accumulator", i.e. a sampling of the parameter space. The effective detection of primitives is thus done by a rough sequential search on the accumulator. It becomes rapidly untractable to store an accumulator and detect optima on it when the number of parameters to estimate (and thus the dimension of the search space) increases. This is why we have to think about efficient optimization techniques to solve the problem for complex geometric primitives. As we have seen, it is an optimization problem : optimizing the position and size of a geometric primitive (or equivalently the values of parameters), knowing the edges detected on an image. The function optimized in the HT is the total number of contour points which coincide with the trace of the primitive defined by the parameters. When the dimension of the space

to search is large, this function can be very irregular. When a function has a certain type of regularity, a number of optimization methods exists, mostly based on gradient or generalized gradient computations. For very irregular functions, different methods have to be used. Most of them are based on stochastic schemes, as for exemple simulated annealing.

In this work, we investigate the use of another stochastic optimization method, namely Genetic Algorithms (GAs) [2]. Roth and Levine [5] have proposed a GA-based method for 2D and 3D primitives detection in 1992. For the detection of 2D primitives, we have improved that method mainly in three ways (detailed in [4]) :

- by using distance images instead of directly using contour images, which tends to smoothen the function to optimize,
- by using a GA-sharing technique, to detect several image primitives in the same step,
- by applying some recent theoretical results on GAs (about mutation probabilities) to reduce convergence time.

2 Genetic algorithms

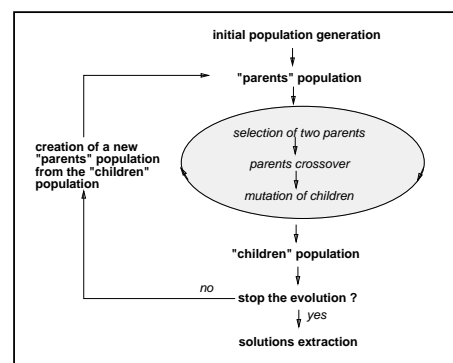


Figure 1: *General Organigram of a Genetic Algorithm*

The benefit of using GAs to optimize irregular functions is that they perform a stochastic search over a large search space, by making a set of solutions (called *population*) evolve together, instead of using a single solution as in the Simulated Annealing. The solutions

of the population (also called individuals, and represented by chromosomes: most of the time, binary codes) go through a process of evolution. Some solutions are better than others, in the sense that the function (also called fitness) is better; they are more likely to survive and propagate their genetic material. The convergence of a GA leads to a concentration of the population into regions of the search space where the fitness function presents a global optimum. The creation of the “children” population is done in three steps : *selection* of two parents (random shot which probability proportional to the relative fitness of the solution in the population), *crossover* of their chromosomes to create two offsprings, then *mutation* of the offsprings (see figure 2). The crossover and mutation operators are randomly applied. Mutation is applied with a very low probability (reversely proportional to the chromosome length) so that few chromosomes are altered.

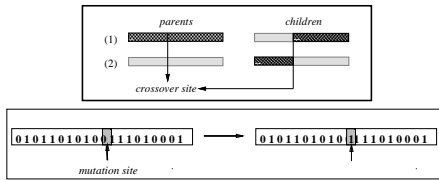


Figure 2: *Genetic operators: Crossover and Mutation*

Selection and Crossover favor the concentration of solutions having good fitness, thus attracting the population in local optima. On the contrary, Mutation maintains the diversity of the genetic materials. The simultaneous action of these three operators allows to converge into a global optimum (Schema Theory, see [2], and Markov Chain approaches [1]). Davis in 1991 [1] has proposed a Simulated Annealing - like convergence proof for the simple GA, and derived a decreasing formula (very slow) for the mutation probability that guarantees the convergence towards a global optimum. In our implementation, we have experimented a faster decreasing rate: it improves the convergence speed, in comparison with the classical scheme where the mutation probability stays constant.

3 Application to primitive detection

• Primitives Coding

We propose a different coding as in Roth and Levine [5], to limit the redundancy of the primitives representation :

- ◊ Segment : 2 points of the image I , with integer coordinates, for the vertices of the segment,
- ◊ Circle : 1 point of I for the center of the circle, and a positive integer for its radius,
- ◊ Ellipse : 2 point of I , the center O and the point P , a positive real $a \in [0, \frac{\pi}{2}]$, representing the rotation angle of the ellipse (see figure 3),

- ◊ Rectangle : 2 points of I , coordinates of the top-left and bottom-right vertices. This rectangle is parallel to the axes of the image. For different orientations, we add a positive real of $[0, \frac{\pi}{2}]$, for the rotation angle.
- ◊ Quadrilateral : 4 points of I , for the 4 vertices.

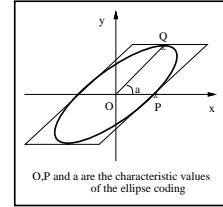


Figure 3: *Graphical coding of an ellipse*

• Computation of the fitness function

If we directly use contour images, the fitness function is a counting of image contour points in coincidence with the trace of the primitive. To tolerate small errors, it is often necessary to make a computation on a strip centered on the primitive, which increases the computational time of fitness evaluation. Moreover, the form of that fitness function is very irregular and the convergence of a GA can be slow, especially when the contours are sparse in the image. We use a well-known tool of mathematical morphology, to obtain distance images, i.e. grey-level images computed from contour images, where each pixels grey-level represents the distance to the nearest contour point. The fitness function takes into account the mean intensity of the pixels of the distances image in coincidence with the trace of the primitive (to position the primitive), plus a counting term of effective contour pixels on the trace (to favor bigger primitives). The benefit of using such distances images is double : the fitness function is more rapid to compute (scanning the trace of the primitive is largely sufficient), and the tolerance to small errors is improved.

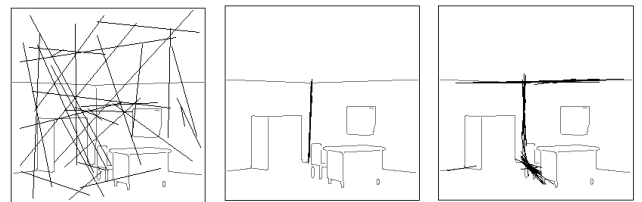


Figure 4: *Left, initial random population of segments (black) on a contour image (grey). Middle, final classical convergence of the population (after 80 generations). Right, convergence with sharing*

• Use of a sharing technique

The interest of detecting several primitives in the same GA-run is evident. For that purpose, we propose

to use a sharing technique, followed by a simple clustering. The sharing scheme is copied from the natural phenomena of “niching” of populations: individuals of a same subpopulation have to share the local resources. Due to overcrowding, the local resources decrease, and individuals tend to search other places. In GAs several solutions have been proposed, based on explicit or implicit creation of niches. We use a technique which modifies the fitness function to simulate the sharing of local resources in the population. This is a way of imposing niche and speciation on chromosomes, based on some measure of their distance to each other. Our technique is a modification of [3], see [4].

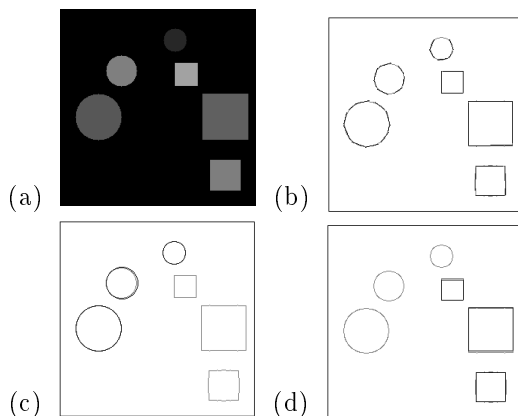


Figure 5: (a) synthetic image, (b) segments detected (black) and contours (grey), (c) circles detected (black) and contours (grey), (d) rectangles detected (black) and contours (grey)



Figure 6: Left, real image. Right, segments detected (black) and contours (grey)

4 Results and Conclusion

We present here results (figures 5 to 7), on synthetic and real images, for four primitives : **segments**, a GA run (wich furnish 4 to 12 segments at the same time) takes 10 to 15 seconds on a Sparc II station, **circles** it takes 70 to 80 seconds, **ellipses** and **rectangles**.

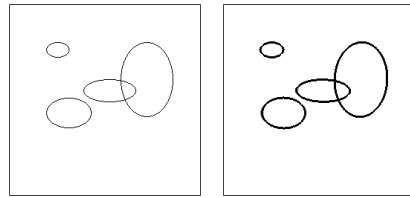


Figure 7: Left, synthetic contours. Right, ellipses detected

The extension of our application to detecting new types of primitives is easily done by updating the fitness and the distance functions. Applications similar to the Generalized Hough Transform (on non-parameterized searched primitives) are also possible with GAs. The particular formulation of GA approach permits to easily use tools as distance images, which smoothen the function to optimize, and decreases the convergence time. We have also exploited the sharing scheme to improve the efficiency of the search on multi modal fitness functions.

The main problem of such an approach remains the parameters tuning, because it severely influences the convergence speed, and the quality of results. Except for the mutation probability where we could use some theoretical results, this tuning is now experimentally done, and varies for each type of primitives. A lot of theoretical researches on GAs are directed towards the problem of judicious choice of parameters.

We hope to have pointed out in this paper the interest of considering GA approaches for complex optimization problems involved in image processing and robot vision tasks. We do not claim that GA can replace some well-known techniques, but we think that they can be considered as a complementary approach for some problems which are untractable with classical techniques.

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