

A Multi-Population Genetic Algorithm for Robust and Fast Ellipse Detection

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Abstract

This paper discusses a novel and effective technique for extracting multiple ellipses from an image, using a Genetic Algorithm with Multiple Populations (MPGA). MPGA evolves a number of subpopulations in parallel, each of which is clustered around an actual or perceived ellipse in the target image. The technique utilizes both evolution *and* clustering to direct the search for ellipses – full or partial. MPGA is explained in detail, and compared with both the widely used Randomized Hough Transform (RHT) and the Sharing Genetic Algorithm (SGA). In thorough and fair experimental tests, utilizing both synthetic and real-world images, MPGA exhibits solid advantages over RHT and SGA in terms of accuracy of recognition - even in the presence of noise or/and multiple imperfect ellipses in an image - and speed of computation.

Keywords

Genetic Algorithms, clustering, Sharing GA, Randomized Hough Transform, shape detection, ellipse detection.

1. Introduction

In this paper, we propose a novel Multi-Population Genetic Algorithm (MPGA) for accurate *and* efficient detection of multiple imperfect (e.g. partial) ellipses in noisy images. This capability that the algorithm provides is genuinely useful for many real-world image processing applications, such as: object detection and pattern recognition, scene characterization and event detection.

Rather than evolving a single population, as in traditional Genetic Algorithms, we evolve a number of subpopulations. These subpopulations simultaneously seek all potential optima, resulting in a dramatic increase in the GA's ability to detect multiple ellipses (compared, for example, to the Sharing GA technique SGA) [10]). Indeed, not only is the leading edge of GA-based ellipse detection techniques advanced, but also the MPGA's detection ability *and* computational efficiency are superior to

those of the widely-used Randomized Hough Transform (RHT) [8].

Our MPGA algorithm employs both evolution and clustering to detect ellipses. In addition, the algorithm uses two complementary measures of fitness and specially designed forms of crossover and mutation. This results in a robust algorithm that performs very well on images with multiple ellipses, imperfect ellipses, and in the presence of noise. These are additional advantages that our algorithm has over other techniques such as RHT and SGA, whose performance degrade considerably in the presence of multiple ellipses or/and noise.

Section 2 provides the reader with some necessary background material, and discusses a number of related research articles. In section 3, the new algorithm is explained in detail. Section 4 presents and analyzes the experimental results; it compares the performance of MPGA with both RHT and SGA. Section 5 concludes the paper and summarizes planned future work.

2. Background

In the literature, the Hough Transform (HT) is one of the most widely used techniques for location of various geometric shapes [8]. Basically, the Standard Hough Transform (SHT) represents a geometric shape by a set of appropriate parameters. For example, a circle could be represented by the coordinates of its centre and radius, hence 3 parameters. In an image, each foreground (e.g. black) pixel is mapped onto the space formed by the parameters. However, since we are dealing with digital computers, this parameter space is quantized into a number of bins. Peaks in the bins provide the best indication of where shapes (in the original image) may be. Obviously, since the parameters are quantized into discrete bins, the intervals of the bins directly affect the accuracy of the results and the computational effort required to obtain them. For fine quantization of the space, the algorithm returns more accurate results, while suffering

from large memory loads (for bins), and expensive computation - especially in high-dimensional feature spaces. Hence, the SHT is most commonly used in 2 or 3-dimensional feature spaces and is unsuitable for higher dimensional spaces. Ellipses, for example, are five-dimensional. More efficient HT based methods have been developed [5, 7, 9]. They improve efficiency by (a) exploiting the symmetrical nature of some shapes, and (b) utilizing intelligent means of dimensionality reduction. Nevertheless, both computational complexity and memory load remain a serious problem.

One of the fastest and most widely used variant of the Hough Transform is the Randomized Hough Transform proposed by Xu *et al.* [18]. It improves HT with respect to both memory load and speed. McLaughlin's work [13] shows that RHT produces improvements in accuracy and computational complexity, as well as a reduction in the number of false positives (non-existent

ellipses), when compared with the original SHT and number of its improved variants.

The Genetic Algorithm (GA) is another interesting way for extracting ellipses. As early as 1992, Roth *et al.* [15] proposed a way of extracting geometric shapes using Genetic Algorithms [15]. Since then, a number of GA-based techniques have been developed for the purpose of detecting specific geometric shapes such as straight lines [2], ellipses [10, 11, 12, 14], and polygons [10, 11, 12].

Procter *et al.* [14] made an interesting comparison between GA and RHT. These two techniques have the following features in common:

- Representation of geometric shapes using minimal sets of parameters.
- Random sampling of image data.
- Sequential extraction of multiple shapes.

Their experiments clearly demonstrate that GA-based techniques return superior

results to those produced by RHT methods when a high level of noise is present in the image but RHT methods are more attractive for relatively noise-free images.

Nevertheless, a straightforward implementation of GA-based shape detection methods, gives us a fitness function that lacks the flexibility necessary for the detection of *multiple* ellipses in an image. A fitness function with a single term, which only reflects how well a candidate shape matches an idealized ellipse, will drive the whole population towards a single global optimum. Hence, in the presence of multiple optima (ellipses), the final winner is obtained randomly. Moreover, when there are both perfect *and* imperfect ellipses, the latter, being *locally* optimum, will most likely be replaced with better (more perfect) individuals during evolution, and eventually ignored.

A possible and intuitive solution is to extract shapes *sequentially*, as in [2, 14 and 15]. This entails removing detected shapes

from the image, one at a time, (sequentially), and iterating, until there are no more shapes that the program is able to detect in the image. It is clear that this approach involves a high degree of redundancy and, as such, is computationally inefficient.

Lutton *et al.* [10] improve the simple GA by using a *Sharing* technique, first introduced by Goldberg *et al.* [3] in 1987. This technique aims to maintain the diversity of the population by scaling up the fitnesses of local optima within the population (so that they would stand out).

Unfortunately, sharing is based on the assumption that the neighborhoods of local optima are less crowded (with individuals) than the neighborhood of the global optimum and that, therefore, the fitnesses of local optima will be enhanced by sharing. This assumption is not valid for our application, as imperfect ellipses may attract many neighbors with a high probability, as long as they contain a sufficiently large number of pixels. This will deflect the search from

exploring potentially promising areas, and will, often, result in missed ellipses.

Fig. 1 provides a concrete example. After running the Sharing GA, to convergence, with a population size of 100, the individual (candidate ellipse) at the centre of the densest subpopulation of individuals, is represented in Fig. 1 (b) by an overlaid grey ellipse. Since the left ellipse is larger (in terms of pixels) than the right one, it is natural that the left ellipse will attract more individuals (ellipse candidates) around it. However, the ellipse on the left corresponds to a local optimum (with sub-optimal fitness), while the right perfectly formed ellipse corresponds to the global maximum (with the highest fitness). Hence, if the sharing function is applied: the fitness of the sub-optimal individual, will be shared with the rest of its dense subpopulation, and on the other hand, the fitness of the optimal individual will be shared with the rest of its less dense subpopulation. This will result in a global optimum (right ellipse), which is even more

pronounced relative to the local optimum (right ellipse) than the case was before the sharing function was applied. Therefore, sharing in this example defeats the purpose of the exercise.

Furthermore, Smith *et al.* [16] highlighted the fact that the computation of the distance of an individual to any/all other individuals in a population has a time complexity of $O(N^2)$, where N is the size of the population [16].

To overcome the various problems discussed above, with both RHT and SGA, we developed and tested a new multiple-population GA, with the following key features:

- Parallel evolution of multiple subpopulations each focused on a potential elliptical pattern in the image;
- Clustering is used to effectively create and maintain the multiple subpopulations;

- Use of two fitness terms to enhance the overall fitness of local optima in an effective manner;
- Customized crossover and mutation operators to take advantage of specialized domain-knowledge;

Experiments show that this algorithm works well for multiple ellipses, imperfect ellipses, and high noise.

3. The Multi-Population Genetic Algorithm

The overall operation of the multi-population GA is presented graphically in Fig. 2.

Initially, a single population is created by creating a number of chromosomes whose genes (see section 3.2) are randomly selected from the set of foreground pixels in the image. The population is then ranked in terms of both *similarity* and *distance* and searched for good candidates- if any. If, by chance, all the ellipses in the image are included in the first generation, the program

terminates. Otherwise, a clustering technique is used to divide the chromosomes into a number of clusters (or subpopulations). From that moment on, all the subpopulations are evolved, in parallel. If one of the subpopulations converges on an optimal or a suboptimal chromosome, then that whole subpopulation and the corresponding ellipse (in the image) are removed. This has the positive side effect of accelerating the search process, since the rest of the subpopulations will have one less ellipse to search for. The program, as a whole, terminates when all (full and partial) ellipses are found, or when a pre-set maximum number of generations is reached.

The following sections (3.1 - 3.6) detail the key steps of the MPGA algorithm, starting with an introduction to elliptic geometry and concluding with clustering.

3.1 Ellipse Geometry

Chromosomes, in the MPGA, are no more than candidate ellipses, and hence

understanding the geometry of ellipses is essential to understanding chromosomal representation, within the MPGA. The ellipse equation can be written as:

$$ax^2 + 2hxy + by^2 + 2gx + 2fy + 1 = 0 \quad (1)$$

Assuming we have five distinct points belonging to the perimeter of an ellipse, we can solve 5 linear equations, simultaneously, for a , h , b , g and f . Hence, the geometric parameters (the long and short radii of an ellipse, the coordinates of the center; and the angle the long axis makes with the X-axis - or the rotation angle) for an ellipse are computed, by substituting the values of a , h , b , g and f , into a set of five equations, listed in [14].

3.2 Representation and Initialization

We represent chromosomes (using Roth *et al.* approach [15]) with a minimal set of points on the shape's perimeters. Since we need 5 points, each chromosome contains 5

genes. And, since each gene (point) has both horizontal and vertical coordinates, the total number of numbers in a chromosome comes to 10.

There are, in the literature, alternative ways of chromosomal representation of ellipses. For example, Mainzer [11, 12] represents an ellipse using a set of five geometric parameters (see Fig. 3): a and b , which are the dimensions of the long and short axes of an ellipse, respectively; x_0 and y_0 , which are the X and Y coordinates of the center; and finally θ , the rotation angle.

In contrast, Lutton *et al.* [10] encode an ellipse using the center O ; a point on its perimeter P ; and rotation angle a . Lutton *et al.* (and so could Mainzer) claim that their representation is preferable to Roth's representation of ellipses, since Roth's chromosomes allow for redundancy, and their chromosomes do not. This is so, since many of Roth's chromosomes (which are 5-tuples of points) could belong to the same ellipse.

Nevertheless, the encoding of ellipses *via* their geometric parameters is also problematic. These techniques provide no guarantee that the resulting candidate ellipses will actually contain any point from any of the actual ellipses in the target image. Using these techniques amounts to blindly placing ellipses at randomly selected locations within the image, in the hope that some of them will partially overlap some actual ellipses in the image. Hence, such algorithms spend a long (if not most of their) time evaluating the fitnesses of many chromosomes representing useless candidate ellipses.

Therefore, we choose to encode a chromosome with a set of 5 points, as Roth *et al.* did [15]. The redundancy problems identified by Lutton *et al.* can be avoided by disallowing *identical* chromosomes in the population. Two chromosomes are identical if their phenotypes (geometric parameters), and not genotypes (sets of points), are identical.

The MPGA algorithm creates an initial population of between 30 and 100 chromosomes, depending on the complexity of the target image. The five points comprising each new chromosome are selected, at random, from the set of foreground (or black) pixels in the target image.

3.3 Fitness Evaluation

Most of the reported work in this area, such as [10, 11, and 12], evaluates the fitness of a candidate ellipse (chromosome) by, essentially, counting the number of black pixels in the target image which coincide with the perimeter of the candidate ellipse. These black pixels may or may not belong to actual ellipses in the image. However, if many pixels in the actual image match a candidate ellipse then it is highly probable that these pixels form part of an actual ellipse in the image.

To enhance the robustness of the matching function, Mainzer [11, 12]

distinguishes pixels lying near the perimeter of a candidate (ideal) ellipse from those far from it, and assigns a penalty to the latter. Mainzer defines fitness S of a given candidate ellipse as:

$$S = \sum_{x,y} \left(\text{MAX}_{\forall i,j} \left(E(x+i, y+j) - \frac{1}{d}(|i|+|j|) \right) \right) \quad (2)$$

$E(x+i, y+j)$ is a function that returns 1 if there exists a foreground pixel $(x+i, y+j)$ coincident with, or close to a pixel (x, y) on the candidate ellipse. Otherwise the function returns 0. i and j are the horizontal and vertical displacements, respectively, between the two pixels. Finally, d is a constant (determined by the nature of the image). If there exists points in the image that exactly (i.e. $i = 0$ and $j = 0$) match every point in the candidate ellipse then this candidate ellipse will receive the maximum fitness of 1.

In [10] Lutton *et al.* use a grey-level “distance image”, where each pixel’s grey value indicates its distance to the nearest contour point. This distance image is

computed from the original image using two morphological masks. Like Mainzer, they also punish points not exactly on the perimeter of a candidate ellipse, using a displacement factor. However, the construction of the distance image requires serious extra storage. And the manual tuning of the two distance parameters in the mask requires extra preparatory work, before the algorithm can be used.

Lutton *et al.* [10] also introduced another fitness term that counts effective contour pixels “to favor bigger primitives [or shapes]”. However, bigger shapes are not necessarily better ones; and the extent to which an actual pattern matches a candidate shape has nothing to do with the patterns absolute length or size.

Neither of the measures of fitness discussed above satisfy our requirements. Our aim is to detect full as well as partial multiple ellipses with varying types and degrees of imperfections. Fig. 4 provides

concrete examples of such shapes, where ellipse no. 3 shows a partial ellipse, and ellipse no. 2 is an ellipse with an irregular outline. These two measures of fitness are defined formally below. Therefore, we propose that the fitness of a given candidate ellipse is measured in terms of both (a) *Similarity*: how well the candidate’s perimeter matches (or not) the perimeter of an ideal complete ellipse; and (b) *Distance*: how close or far is the perimeter (or part of it) to the perimeter of an ideal ellipse (or part of it).

A. Similarity (S) is defined as:

$$S = \frac{\sum_{(x,y)} \frac{E(x+i,y+j)}{d_{i,j}}}{\#total} \quad (3)$$

The value of S belongs to $[0, 1]$, with 1 indicating a perfect match and 0 no match at all. For a given point (x,y) on a candidate ellipse, the term $E(x+i,y+j)$ returns 1 if there is a point in the target image that coincides with, or is close to (x,y) ; otherwise $E(x+i,y+j)$ returns 0.

The terms i and j represent the horizontal and vertical displacements, respectively, between a point on the ideal ellipse and the corresponding actual point in the image. Fig. 5 shows how an actual point (Q) is determined and how the distance between this point and the corresponding point (P) on the candidate ellipse is computed.

In Fig. 5, the dashed arc belongs to an ideal template with centre C. The solid arcs belong to actual (full or partial) ellipses in the image. If P does not coincide with any point in the image (in which case, P=Q), then a line is extended from C passing through P, and radiating outward. A fast search, based on Bresenham's algorithm [6], is initiated along this line until a point (Q) on some pattern is found. This point is the corresponding actual point, and the horizontal and vertical displacements between it (Q) and P represent the i and j terms, respectively, used in the computation of distance $d_{i,j}$.

$$d_{i,j} = e^{\frac{|i|+|j|}{4}} \quad (4)$$

$\#total$ is the total number of pixels on the candidate ellipse's perimeter.

To compute S efficiently, we further assume that the ideal template is centered at the origin of coordinates with a horizontally aligned long axis (see Fig. 6).

A classic midpoint ellipse algorithm [6] is then used to traverse the perimeter of this candidate ellipse. This algorithm uses favours integer computation, and it only computes a quarter of the ellipse's perimeter. All the other points in the remaining 3 quadrants are obtained from symmetry. Each computed pixel is matched to its "actual" ideal position using:

$$\begin{bmatrix} x^T \\ y^T \\ 1 \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta & x_0 \\ \sin \theta & \cos \theta & y_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad (5)$$

(x, y) are the original coordinates and (x^T, y^T) are the transformed coordinates. Finally, the term $E(x+i, y+j)$ is replaced

by $E^T(x+i, y+j)$, giving us the final form of the similarity equation:

$$S = \frac{\sum_{(x,y)} \frac{E^T(x+i, y+j)}{d_{i,j}}}{\#total} \quad (6)$$

B. Distance (D) is defined as:

$$D(x, y) = \frac{\sum_{(x,y)} d_{i,j}}{\#eff} \quad (7)$$

D ranges from $[0, \infty)$ The term $d_{i,j}$ is defined in (9) above. $\#eff$ is the total number of points on the actual ellipse that were successfully matched with points on the ideal ellipse. One reason for using $\#eff$ here instead of $\#total$ is that actual ellipses may be missing parts of their perimeter, i.e. there may be partial or highly irregular ellipses in an image.

Similarity is the main measure, since it is directly observable by the human eye. However, distance is particularly important for cases where multiple ellipses are present in the image, and especially when complete ellipses (with high similarity) as well as

imperfect ellipses (with relatively low similarity) exist. We aim to seek those candidates with good similarity *and* small distance, or those with acceptable similarity *but* excellent distance. Obviously if, for a given candidate ellipse, both of these measures return bad values, then this candidate can be reasonably ignored as noise.

Again, Fig. 4 shows an example of an image with perfect and imperfect ellipses. Table 1 lists the fitness values (in terms of both similarity and distance) for the best three candidate ellipses produced by an MPGA run. There will exist in the population many other candidate ellipses, but all the fit ones will eventually cluster around these three highly fit candidates.

Without distance, it is highly possible that the population will converge towards ellipse 1, while ignoring the other two (very real) ellipses in the rest of the image. However, with distance included, candidate ellipses converging on ellipses 2 and 3 will be ranked highly in terms of distance. Since the ellipses

converging towards these two ellipses will have acceptable similarity *but* excellent distance, this will result in a reasonable clustering (and hence subdivision) of the population, instead of complete domination by ellipse 1 candidates.

In MPGA, fitness is computed in the following manner: the 10 numbers of each chromosome are substituted in 5 simultaneous ellipse equations. If the equations fail to produce a solution then this chromosome does not represent any kind of ellipse. Hence, this chromosome is assigned the minimum fitness of 0. If the equations produce a solution, then equations (6 and 7) are used to compute the similarity and distance of this chromosome. These two values together represent the fitness of the evaluated chromosome.

3.4 Termination Conditions

MPGA starts its run with a single population. However, it usually splits it into a number of evolving subpopulations. The termination of

the evolution of any one of these subpopulations occurs independently of the termination of the rest of the subpopulations. A subpopulation terminates if any one of the following conditions is fulfilled:

Condition 1: *Optimal Convergence*. If there exists one (or more) “optimal” chromosomes. An optimal chromosome is one with $S > 0.95$ and $D < 10$;

Condition 2: *Sub-optimal Convergence*. If there exists one (or more) “good” chromosomes and 30 generations have passed without the evolution of an optimal chromosome. A good chromosome is one with $S > 0.7$ and $D < 10$;

Condition 3: *Stagnation*. 500 generations have passed without the fulfillment of either Condition 1 or 2.

Also, a subpopulation is effectively terminated when it is *merged* with another subpopulation (see section 3.5).

3.5 Clustering: Migration, Splitting and Merging

A subpopulation is called a *cluster*. The centre of a cluster is the chromosome with the greatest similarity. If more than one exists then the one with the least distance is declared the centre.

In the MPGA algorithm, the algorithm starts with a single population (or cluster) in which individuals are ranked in terms of both *similarity* and *distance*. The initial single population, and later subpopulations, are manipulated through a clustering process. This process involves Migration, Splitting and Merger (explained below).

In each subpopulation, all good chromosomes ($S > 0.7$ and $D < 10$) are either kept in their own cluster or placed into a different existing or newly-created cluster. All not-good chromosomes are simply left in their own cluster (and are eventually eliminated by selection- see section 3.6).

The Euclidean distance ED between a good chromosome and the various existing cluster centers determines whether this chromosome remains in its own cluster or moves. ED is computed as follows: given two sets of ellipse parameters $(a_1, b_1, x_1, y_1, \omega_1)$ and $(a_2, b_2, x_2, y_2, \omega_2)$:

$$ED = \frac{\sqrt{(a_1 - a_2)^2 + (b_1 - b_2)^2 + (x_1 - x_2)^2 + (y_1 - y_2)^2 + (\omega_1 - \omega_2)^2}}{5} \quad (8)$$

(a_i, b_i) is the long and short axis, (x_i, y_i) is the center and ω_i is the orientation. When a chromosome migrates from subpopulation A to subpopulation B, it replaces the weakest chromosome in the latter, and the vacancy in the former is filled by the processes of evolution (see section 3.6).

A. *Migration*. If the Euclidean distance between a chromosome and its own cluster centre is lower than a pre-defined threshold tI then this chromosome is moved to another cluster. To determine which one, the ED between this chromosome and every other cluster center is measured. If one or more cluster centers is closer to it than tI then the

chromosome moves (migrates) to the cluster with the closest centre to it.

B. *Splitting*. If the algorithm is unable to find a cluster (with a centre) sufficiently close to a migrating chromosome, then a new cluster is created around this chromosome. This action is called *splitting*.

C. *Mergeing*. An empirically-derived threshold σ_d is used to define the minimum allowable Euclidean distance between any two different cluster centers. As two different clusters may evolve toward a single (local or global optimum), any two clusters with centers closer to each other than σ_d are merged. This is done by taking the fittest 50% (in terms of similarity) of the chromosomes in each cluster and placing them in the new merged cluster. This action is called *merging*.

All clusters are checked periodically (every 30 generations), to see whether some of them could be merged. Merging is barred for the first 50 generations, and (as stated) is

only possible after each periodic check. This is so because early or/and frequent mergers would greatly reduce the diversity of the whole population.

Hence, through the three processes of migration, splitting and merger, clustering works to maintain a number of subpopulations that are independently evolved towards local and global optima. Evolution is explained in the next section.

3.6 Evolution: Selection and Diversification

Evolution proceeds mainly *via* Selection and Diversification. Selection eliminates those chromosomes in the population that are not very fit, focusing the search on promising areas of the fitness surface. On the other hand, diversity is achieved via crossover and mutation, which together serve to direct the search towards new and potentially promising areas. In MPGA, selection is realized using Elitism and Fitness

Proportional Selection. Diversification is realized via Crossover and Mutation.

During evolution of a subpopulation, elitism copies the fittest 15% of the current generation (by similarity) into the next generation, without modification. Following that, two chromosomes are selected from the whole current population. The probability of selecting a chromosome is proportional to its relative fitness (similarity). The two chromosomes are crossed-over, with probability 0.6. The result, whether it is two new chromosomes or the original parent chromosomes, are mutated (on a bit-wise basis) with probability 0.1. This process of selection and crossover-mutation continues until the next generation is complete. As stated, we use constant size subpopulations of between 30 and 100 chromosomes.

Finally, every new chromosome introduced into the next generation is tested to see if it is a good chromosome or not ($S > 0.7$, $D < 10$); if it is not then it is left in the same subpopulation. If however it proves to

be a good chromosome then it is tested for migration-splitting, and is then either kept in its current subpopulation or moved to another existing or new subpopulation (see section 3.5).

In MPGA, Crossover and Mutation are special operations designed specifically for shape detection applications. We describe them in detail below, starting with crossover.

Given the fact that (a) the overall population is divided into a number of subpopulations, each effectively clustering around an ellipse in the image; and (b) each chromosome is defined by a set of points on the perimeter of an ellipse, we can assert that simple single point crossover is an effective method of crossover for our application. A pivot is selected at random, and the parent chromosomes' genes on either side of the pivot are swapped to create the offspring. See Fig. 7.

The effect of the crossover operation, on the actual ellipses represented by the chromosomes, is shown in Fig. 8.

For mutation, we define a new mutation operator, configured specifically for our application. First a gene (or point) is randomly selected from the chromosome that we intend to mutate. As shown in Fig. 8, this point acts as the starting point for a path (r) that traverses the perimeter of a pattern, until a (pre-set) maximum number of points is traversed, or an end- or intersection point is reached. If $r > 10$, the remaining genes (points) are also picked, at random, from this path. As long as the starting point lies on a promising candidate ellipse, it is highly possible that the other points will do so as well. This method of mutation greatly enhances the possibility of mutating a given chromosome into a better one.

Fig. 9 illustrates the mutation process. The original genes are $P_1, P_2, P_3, P_4,$ and P_5 . The starting point, P_1 is selected and path r is traversed. The other new genes, $Q_2, Q_3, Q_4,$ and Q_5 are randomly selected from path r , and copied into the mutated chromosome.

Hence, the new chromosome becomes $(P_1Q_2Q_3Q_4Q_5)$.

Hence, evolution hand-in-hand with clustering (which mainly precedes but also acts during evolution) direct the various subpopulations to local and global optima centered on the various ellipses in the target image.

4. Experimental Results and Analysis

This section compares the performance of the MPGA, SGA and RHT algorithms, using synthetic and real-world images. To carry out a fair comparison between these three different algorithms, we use (a) the same method for computing fitness, in terms of similarity and distance (described in section 3.4), and (b) the same numerical technique for computing the geometric parameters of an ellipse (see section 3.1). This neutralizes any advantages that may be gained via using more efficient methods, which reduce

dimensionality or utilize symmetry [5, 7, 9, 13].

All our experiments were run on an Intel Xeon 2.66 GHz w/ 512 KB of cache, 512 MB DDR RAM and running Red Hat Linux 8.0.3.2-7.

We have two main categories of test data, which are synthetic images and real world images. Accuracy here, is defined as the ratio of correctly detected ellipses, in relation to the total number of ellipses actually present in the target image. If over detection occurs, then that is reflected in the false positive statistics.

4.1 Synthetic Images

The synthetic images are comprised of two sets, set A and set B. Set A is partitioned into 7 collections of 50 images each (totaling 350 images). These collections are used to test the algorithms' performance on images with different numbers of ellipses. Hence, the first collection contains 50 images of single ellipses, the second collection contains

images of two ellipses, and so on. The final collection contains 50 images of 7 ellipses.

Set B, on the other hand, is used to test the algorithms' performance on noisy images. Hence, this set is made of 5 collections of 50 images each (totaling 250 images). The first, second, third, fourth and fifth collections contain images with 0%, 0.5%, 1%, 3% and 5% salt-and-pepper noise, respectively.

The ellipses in the synthetic image database are not all full and perfectly formed ellipses; we make sure that some images in both sets have at least 1 partial or deformed ellipse. A typical example is presented in Fig. 10 (with numerical results presented in Table 2). In this figure there are 5 ellipses, 2 of which are malformed. The figure also shows the results, in terms of detected ellipses, of applying MPGA, RHT and SGA to this image.

As seen in Fig. 10 (b), RHT misses the smallest ellipse since the probability of locating it is smaller than the probability of locating the other larger ellipses. The fitness

values shown in Table 2 are those of similarity and not distance (or some combination of the two) because: (a) similarity is the only measure/factor of fitness used by all these three algorithms, and (b) similarity is more intuitive than any combination of measures, since it closely corresponds the human conception of similarity between shapes.

In reference to Table 2, MPGA returns better fitness values than RHT, for ellipses 1, 2 and 3. This is because MPGA, via evolution, executes an iterative and parallel search, focused at different localities of the of the search space, while the RHT carries out a one-shot blind search through the whole space.

Fig. 11 contrasts the performance of the three algorithms in terms of accuracy as well as average CPU running time. Fig. 11(a) shows that the accuracy of SGA decreases dramatically as the number of ellipses increase. Similarly, the accuracy of RHT also decreases gradually from 100% for one

ellipse to approximately 80% for seven ellipses. In contrast, MPGA outperforms the other two algorithms by maintaining an almost perfect level of detection accuracy, and slightly dipping to around 98%, for images with seven ellipses.

Fig. 11(b) demonstrates the clear advantage that MPGA has over both RHT and GAS in regards to speed time. It graphs the amount of CPU time utilized (on average) by the various algorithms for the detection of images with 1-7 ellipses. There is almost no difference in speed for images with 4 or less ellipses. However, for 5 or more ellipses, MPGA realizes a clear and widening gap in speed.

Fig. 12(a) shows a typical image with 5% pepper-and-salt noise. Ellipses detected by MPGA are shown in Fig. 12(b)

Generally, RHT is more liable to false positives (i.e. the detection of non-existing ellipses). Fig. 12(c) demonstrates that. Table 3 presents the exact numerical results.

Fig. 13 shows the performance of these algorithms on noisy images. Again, MPGA shows considerable robustness in the presence of salt-and-pepper noise, while simultaneously operating faster than the other two algorithms.

Many false positives are observed for RHT with high noise, as Fig. 14 shows. This fact further fortifies our claim (in section 1) that RHT searches the space and accumulates votes blindly. Therefore non-existing ellipses may get enough votes in highly noisy images, as is the case in Fig. 14.

4.2 Real World Images

Large, carefully constructed databases of synthetic images (600, in our case) provide the bases for comprehensive tests, which also provide specific feedback about potential problems with detection algorithms. Nevertheless, it is real-world images that determine the difference between a genuinely useful and purely academic novel algorithm. Hence, we have amassed three databases of

intentionally different types of images: hand-written English letters, microscopic cell images and road signs. The databases are of varying size, but contain images that were collected, prior to even the design of MPGA. From each of those databases, 50 images, are selected at random, and then used for the purpose of assessing the real-world performance of MPGA, RHA and SGA. On visual inspection, we noticed that these images contain: all kinds of combinations of perfect and deformed ellipses, noise levels, and other geometric shapes (e.g. lines).

Fig. 15(a) shows a typical handwritten character with elliptical curves detected.

In Table 4 we can see that MPGA is slower than RHT. As discussed in section 1, when the image is relatively simple and noise-free and does not have many overlapping patterns, RHT is expected to run faster than MPGA. However, RHT still suffers from false positives, as Fig. 15(c) shows, and generally, in pattern recognition,

accuracy of detection is of a higher priority than speed of processing.

Fig. 16(a) is a typical microscopic image of cells. Here, MPGA shows its obvious advantage over RHT and SGA in both accuracy and speed. Although RHT approximates all eight cells, it suffers from large misplacement (see cells labeled: a, b, c and d, in Fig. 16(d)) and long running times; SGA fails to detect even a single ellipse. Table 5 contains the exact numerical results.

Fig. 17 is a typical image of a road sign. We can see that neither RHT nor SGA is able to detect partial ellipses, especially when there are also perfect ellipses in the image. They are generally slower than MPGA in this kind of complicated images. Table 6 presents the exact numerical results.

Table 7 gives out the overall performance for real world images. From the table we can see that SGA is almost totally ineffective with complicated real world images; it returns an average accuracy of less than 20%.

RHT suffers from long computation times *and* high false positive rate.

There are some false positives (6.9048%) for MPGA as well, because for some polygons, the algorithm may sometimes approximate them with ellipses. One possible solution is to detect low dimensional shapes first (such as lines), and remove these from the image, before detecting circles and ellipses. This way, the process can be both made more efficient and more accurate.

5. Conclusions and Future Work

This paper presents a new GA, one which uses (a) multiple-populations and an elaborate process of evolution-clustering to (b) efficiently and accurately detect (c) multiple potentially-deformed full and partial ellipses in noisy images. This algorithm, was thoroughly tested on a large number of synthetic and three types of real-world images, and compared to the very widely-used RHT and one of the best-available GA-based ellipse detection technique: SGA.

Despite the conceptual complexity of the MPGA algorithm, the program implementing the new algorithm performed, generally speaking, more efficiently and more accurately than both RHT and SGA. However, this does not mean that there is no room for improvements.

We intend to improve the MPGA by getting to:

1. Detect (and remove) lines and polygons, first, so that any complicated images can be analyzed within a reasonable period of time;
2. Run without the need for prior tuning of GA parameters, such as mutation and crossover probabilities. This can be done by incorporating the ideas of Parameterless GAs, which we have already experimented with, successfully, but only tested using mathematically-defined fitness surfaces.

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Tables

Table 1 Fitness of Ellipses in Fig. 4

Ellipse	Similarity	Distance	Center	Major Axis	Minor Axis	Orientation
1	0.975758	0.102167	(282, 236)	88	37	0
2	0.876588	0.255647	(235, 127)	67	67	0
3	0.724566	0.302721	(116, 184)	96	52	90

Table 2 Parameter Values for Ellipses Detected in Fig. 10

Algorithms	Center	Major Axis	Minor Axis	Orientation (°)	Fitness	Time (sec)
MPGA	(71, 54)	29	29	0	0.970238	19.93
	(152, 123)	81	73	0.76	0.955702	
	¹ (259, 80)	47	42	1.03051	0.934348	
	² (196, 176)	78	72	-3.9616	0.822264	
	³ (125, 168)	91	74	0.533168	0.790112	
RHT	(152, 123)	81	73	0.964792	0.976567	31.25
	¹ (260, 79)	48	42	-1.38724	0.810691	
	² (195, 172)	78	78	0	0.680005	
	³ (124, 169)	90	73	4.89973	0.663584	
SGA	(153, 123)	81	73	1.05523	0.968314	172.42
	(126, 169)	91	75	2.18694	0.678744	

Table 3 Parameter Values Ellipses Detected in Fig. 12

Algorithms	Center	Major Axis	Minor Axis	Orientation (°)	Fitness	Time (sec)
MPGA	(103, 104)	78	46	90	0.991525	54.88
	(161, 102)	79	45	89.2954	0.968645	
	(106, 91)	74	43	-0.5067	0.955948	
	(174, 127)	85	53	0.56718	0.847435	
RHT	(161, 103)	79	45	-89.5019	0.933849	2670.24
	(174, 126)	84	53	0	0.82058	
	(117, 95)	60	60	0	0.531464	
	(90, 80)	55	55	0	0.511258	
	(99, 75)	27	27	0	0.417344	
	(126, 151)	22	19	-67.7653	0.338096	
SGA	(103, 104)	79	45	90	0.984774	1267.67
	(161, 102)	79	44	89.3833	0.979715	
	(106, 92)	74	43	0.698993	0.96429	

Table 4 Parameter Values Ellipses Detected in Fig. 15

Algorithms	Center	Major Axis	Minor Axis	Orientation (°)	Fitness	Time (sec)
MPGA	(75, 52)	17	10	-42.8732	0.871649	8.50
	(84, 81)	29	6	31.5684	0.486901	
RHT	(84, 81)	27	6	32.9764	0.493482	1.08
	(72, 55)	22	9	-46.8089	0.466301	
	(61, 73)	38	7	-65.1084	0.25563	
SGA	None Detected					

Table 5 Parameter Values Ellipses Detected in Fig. 16

Algorithms	Center	Major Axis	Minor Axis	Orientation (°)	Fitness	Time (sec)
MPGA	(70, 110)	24	12	78.7455	0.884863	26.71
	(41, 57)	23	18	-26.4053	0.871432	
	(111, 101)	20	14	-19.6434	0.855267	
	(272, 112)	22	16	82.1506	0.844027	
	(48, 133)	27	16	-89.4256	0.841953	
	(242, 63)	27	15	-33.6307	0.837715	
	(144, 23)	20	14	26.6459	0.734521	
	(107, 53)	24	11	22.4682	0.649748	
RHT	(47, 133)	25	17	87.6509	0.747763	1015.98
	(38, 58)	20	20	0	0.644028	
	(70, 112)	25	13	78.18	0.74799	
	(243, 63)	27	16	33.7181	0.805789	
	(89, 48)	44	12	18.0898	0.34089	
	(147, 24)	17	14	34.4332	0.639102	
	(106, 101)	26	14	-14.8053	0.478279	
	(271, 113)	19	16	48.1021	0.627391	
SGA	None Detected					

Table 6 Parameter Values Ellipses Detected in Fig. 17

Algorithms	Center	Major Axis	Minor Axis	Orientation (°)	Fitness	Time (sec)
MPGA	(224, 200)	188	188	0	0.993062	140.68
	(223, 200)	157	157	0	0.908382	
	(255, 160)	39	36	9.34395	0.654582	
	(264, 161)	79	79	0	0.401485	
RHT	(224, 200)	188	188	0	0.993062	335.08
	(223, 201)	158	156	0	0.908279	
SGA	(224, 200)	188	188	0	0.993062	378.74
	(222, 200)	157	157	0	0.886644	

Table 7 Performance of MPGA, SGA, and RHT for Real World Images

Algorithms	Accuracy (%)	Average CPU time (sec)	False positives (%)
MPGA	92.761	134.58	6.9048
SGA	15.113	370.39	0
RHT	64.387	809.73	18.633

Figures

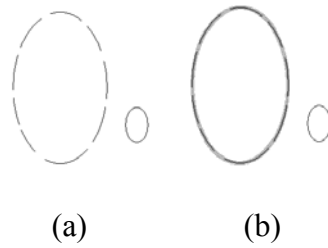


Fig. 1 Global and Local Optima
(a) a Large Imperfect Ellipse (Left) and a much Smaller Perfect Ellipse (Right)
(b) Locally-Optimum Candidate Ellipse Overlaid on top of Left Ellipse

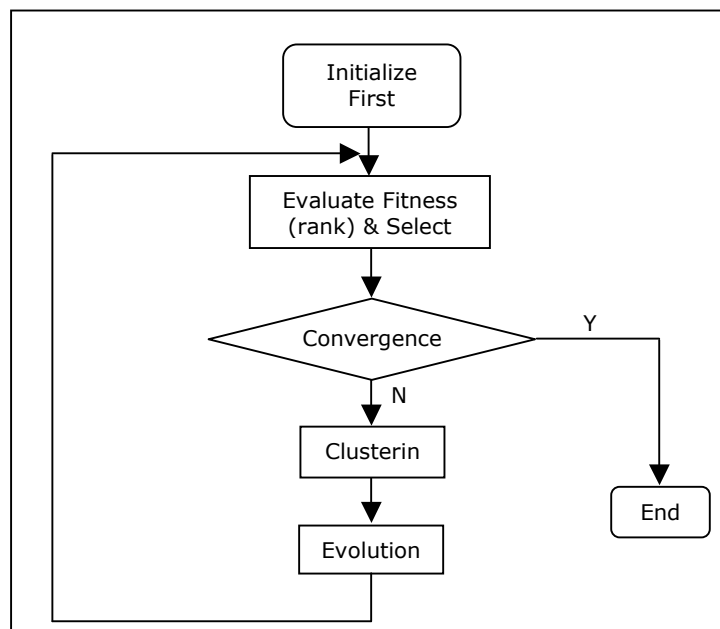


Fig. 2 Summary Flow Chart of MPGA Algorithm

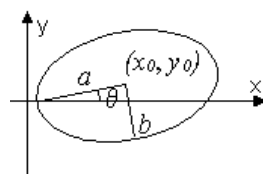


Fig. 3 The Geometric Parameters of an Ellipse

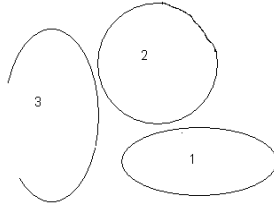


Fig. 4 Perfect and Imperfect Ellipses

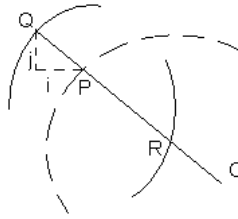


Fig. 5 Matching of a Candidate Ellipse, Point by Point, to Potential Actual Ellipses in an Image

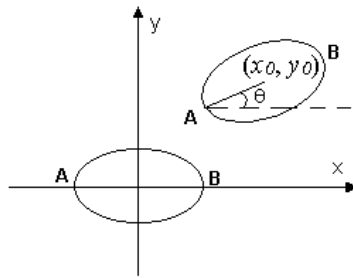


Fig. 6 2D Geometric Transformation of Ellipse

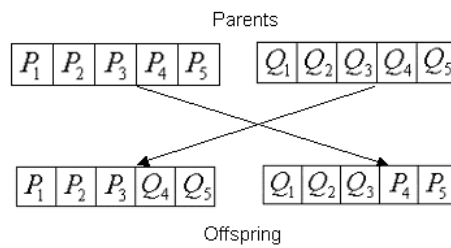


Fig. 7 Result of Crossing-Over Two Chromosomes: Genotypic View

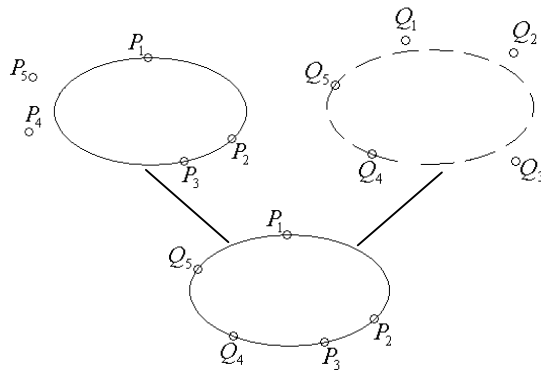


Fig. 8 Result of Crossing-Over Two Chromosomes: Phenotypic View

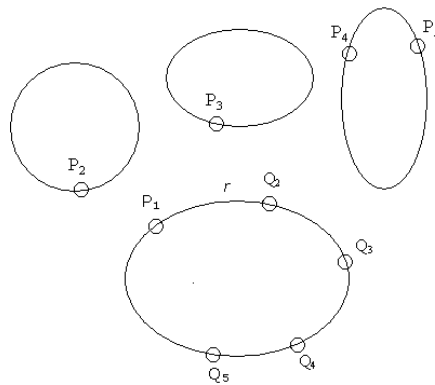


Fig. 9 Mutation Operation

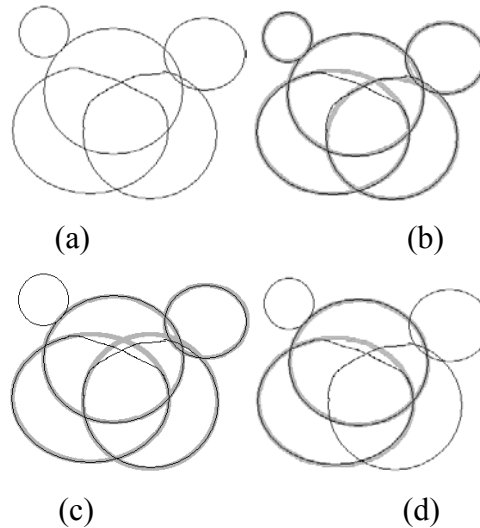


Fig. 10 A Typical Image with Multiple Ellipses: Detected Ellipses Overlaid in Thick Grey Line

(a) Original Image (b) Ellipses Detected by MPG (c) Ellipses Detected by RHT (d) Ellipses Detected by SGA

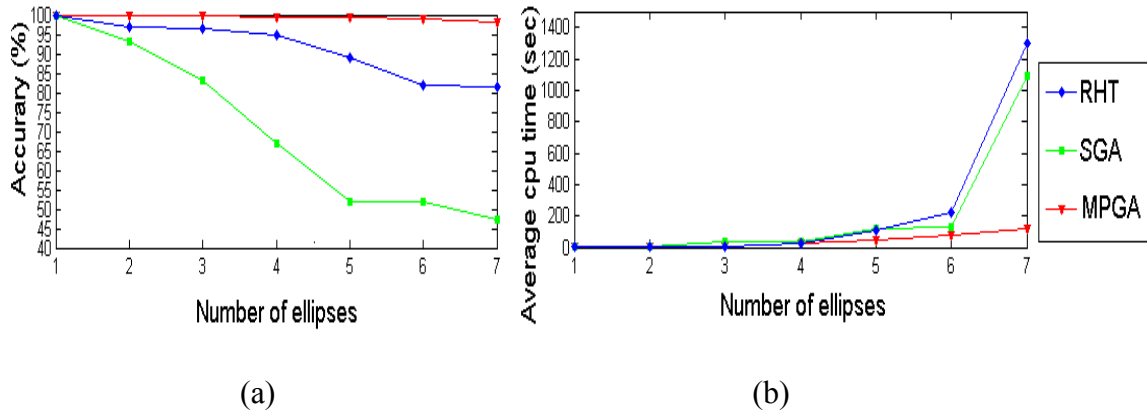


Fig. 11 Comparing the Performance of RHT, SGA and MPGA when Detecting Multiple Ellipses in an Image

(a) Accuracy vs. Number of Ellipses (b) CPU Time vs. Number of Ellipses

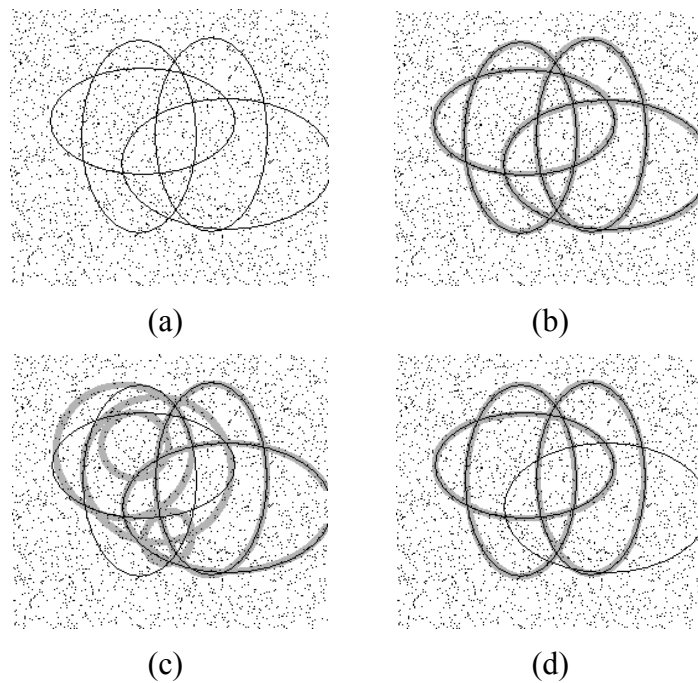


Fig. 12 A Typical Noisy Image with %5 Salt & Pepper Noise: Detected Ellipses Overlaid in Thick Grey Line

(a) Original Image (b) Ellipses Detected by MPGA (c) Ellipses Detected by RHT (d) Ellipses Detected by SGA

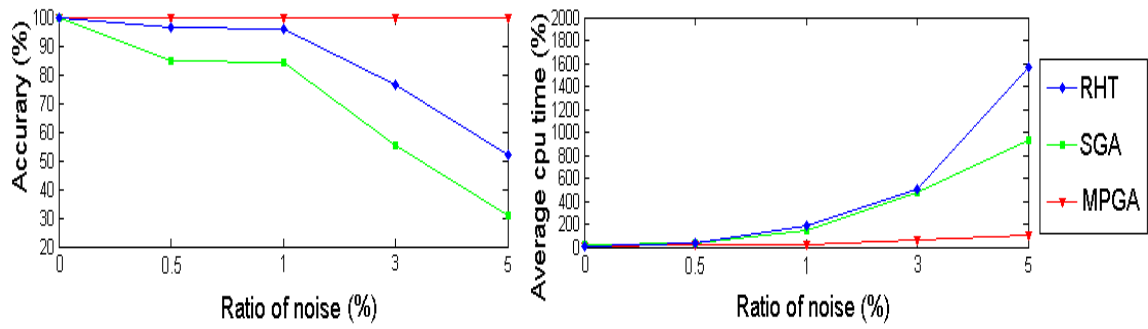


Fig. 13 Comparing the Performance of RHT, SGA and MPGA when Detecting Ellipses in Noisy Images

(a) Accuracy vs. Ratio of Noise in Image (b) CPU Time vs. Ratio of Noise in Image

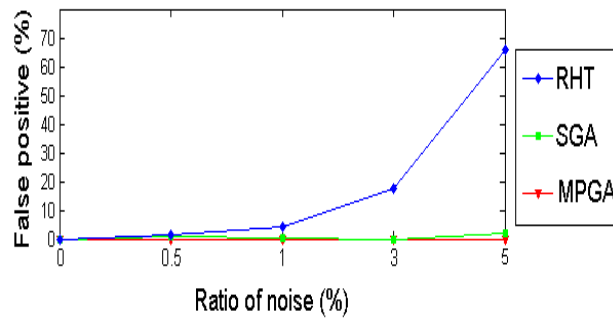


Fig. 14 False positives for different noise level

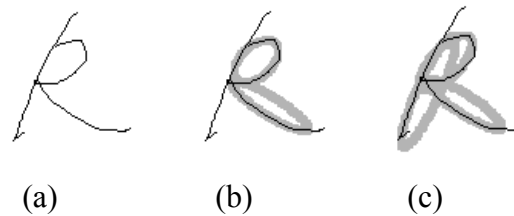


Fig. 15 A Typical Handwritten Character (Capital R): Detected Ellipses Overlaid in Thick Grey Line - SGA Failed to Detect a Single Ellipse

(a) Original Image (b) Ellipses Detected by MPGA (c) Ellipses Detected by RHT

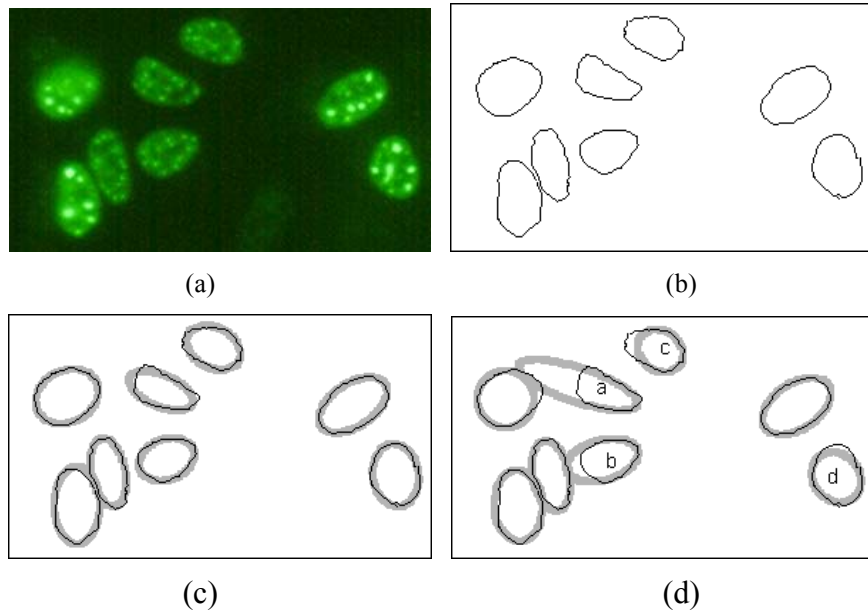


Fig. 16 A Typical Image of Cells taken through a Microscope (at 40x) - SGA Failed to Detect a Single Ellipse
 (a) Original Image (b) Pre-processed Image (c) Ellipses Detected by MPG (d) Ellipses Detected by RHT

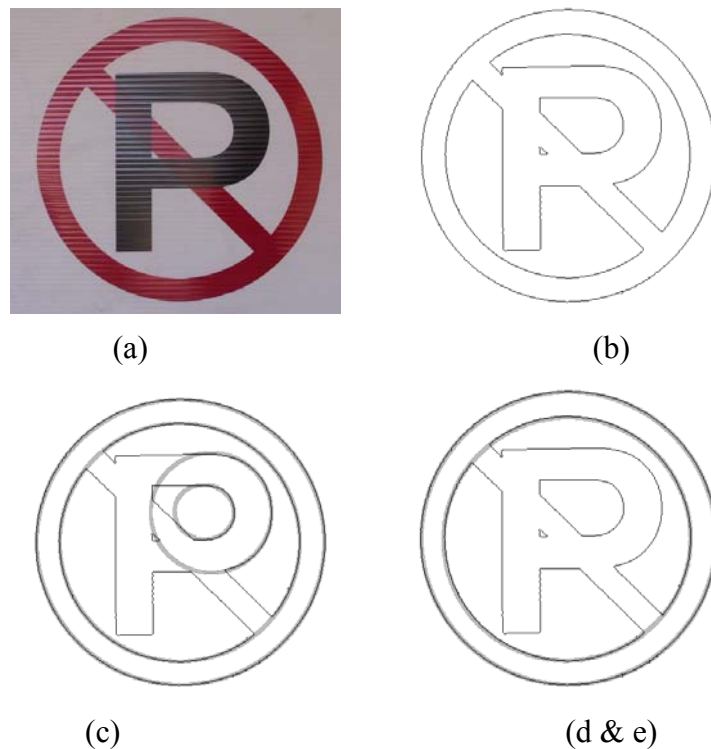


Fig. 17 Typical Road sign Image
 (a) Original Image (b) Pre-processed Image (c) Ellipses Detected by MPG (d) Ellipses Detected by RHT (e) Ellipses Detected by SGA