Utilizing Genetic Evolution to Enhance Cellular Automata for Accurate Image Edge Detection

Farhana Akter Tumpa, Md Saydur Rahman and Md Shazid Islam

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Farhana Akter Tumpa[1], Md Saydur Rahman[2], Md Shazid Islam[2]

Department of Computer Science and Engineering[1]

Department of Electrical and Computer Engineering[2],

University of California, Riverside, CA, USA

ftump001@ucr.edu , mrahm054@ucr.edu , misla048@ucr.edu

***Abstract*—Cellular Automata (CA) is a dynamic system with discrete time and spatial neighborhood structure which, if tuned properly, can automate image processing to a great extent and tune the CA ruleset, a Genetic Algorithm (GA) has been used. In this paper, we have worked on a GA model, trying different types of setups to come up with a better GA that should have the capability to handle any kind of 2D image. Our proposed GA shows an improvement of 21.53% and 13.7% on two different images.**

***Index Terms*— Cellular arrays and automata, Edge and feature detection, Evolutionary computing and genetic algorithms, Image Processing and Computer Vision.**

I. INTRODUCTION

Abstraction provides researchers and engineers to be able to use a single methodology that has been developed in a definite scenario to implement that in various other fields of research. Genetic Algorithm (GA) is an abstract methodology that can be used for solving complex problems of various fields. Although in the modern world, GA is being used for optimization, scheduling, planning, and design problems mainly [1]. GAs is a probabilistic search theorem that works on a set of chromosomes inside a population to come up with a probable solution to the problem. Cellular Automata (CA)s are discrete mathematical models organized on a lattice structure where the next state of the cell is dependent on the current state of the neighbors, and this is being done by a transition function. Once a transition function is defined, it can run parallel to reach the goal [2]. This paper discusses the implementation of GAs to come up with a rule set for CA, which will be much closer to the objective of detecting edges of any 2D image [3],[8].

This paper uses the binary state of any image and uses their pixel to compare within the search space. CAs element is being used to find the matches which resemble the two-dimensional neighborhood theorem of Moore. A matrix of 3x3 cells is being used where each cell state represents a pixel shade -either black (1) or white (0). This matrix is basically a pixel's neighborhood which resembles the ruleset of the CA where if the rule is '0', then the pixel in focus would be converted to '0', and if the rule is '1', then that one would be turned to '1' in next generation.

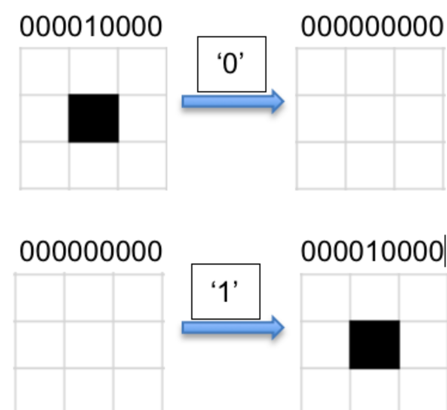

Fig. 1. Ruleset in CA

To obtain a cellular automaton using GA our approach is mentioned below:

1. Using tuning parameters such as mutation probability crossover probability (section 3.3 & 3.4)
2. Random number points for mutation in a child from 512x512 search space. (Section 3.4)
3. To achieve diversity, we have considered half of the total population for crossover (section 3.2)
4. We have tested the GA with different types of crossovers. Inversion of full 3x3 matrix set in mutation stage using mutation probability and randomly selected mutation points.

5. Randomization in parent and child selection

There are four following sections in this paper. Sections 2 and 3 deal with Cellular Automata and the demonstration of the proposed GA model along with various components, respectively. Next, in the section, you have the full experimental setup with results. Finally, in section 5, the GA model's worth is validated by results and different images.

II. CELLULAR AUTOMATA

Cellular Automata (CA)s were introduced by Ulam and Von Neuman to find models for biological self-reproduction [4][5][6]. CAs got much more attention due to diversity and effectiveness in different processes in the field of information, physics, biology, chemistry, and so on. CA is being deployed in the field of image processing sector, which to be precise, are the processes like image enhancement, restoration, pattern recognition, feature extraction, and compression. CAs are dynamic in nature with discrete space and time property and also with a finite number of states. The computation of a new state depends on its neighbors, and values are updated synchronously in discrete time steps on all cells [7]. Moore Neighborhood in a range r is deduced by equation (1)

$$N_{xo,yo}=\{(x,y): |x-x_o| \leq r,\ |y-y_o| \leq r\} \tag{1}$$

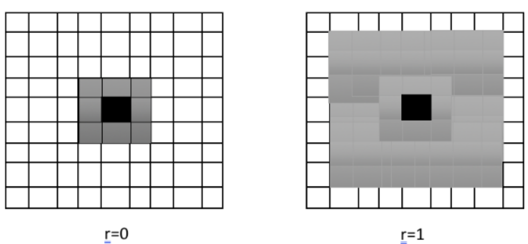

Fig. 2. Moore Neighborhood using range (r) value 0 and 1

The system we are dealing with here is a digital image that is of two dimensions. So, CA model is also a two-dimensional uniform grid that has states and rules. Actually, it's a binary lookup table in the local interaction neighborhood where active cell remains in the middle and neighbors are in square spatial structure and CA rule table allows the active cell to be updated accordingly until it finishes comparing active member neighborhood with all the rules available in lookup tables and updates asynchronously.

III. PROPOSED GA MODEL

GAs consists of population and evolutionary algorithms. Our population consists of a rule table of 512x512 where we have states and rules. The evolutionary algorithm goes through the below-mentioned processes to obtain an objective solution.

- Select an active member(pixel) from a given image and choose a neighborhood of a 3x3 matrix.
- Iterate thorough CA rule table of 512 x 512 matrix and look for a match and change accordingly.
- After iterating through all pixels of the image, determine the fitness of the rule table.
- Select the lowest half of the population for mating using the tournament method.
- Implemented crossover probability to obtain child.
- Randomized mutation point, mutation probability
- Randomized survivor selection and get rid of half of the highest values population.

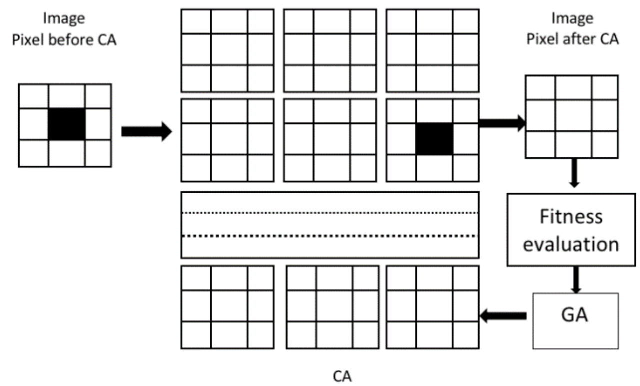

Fig. 3. Workflow of the model where an image pixel is changed by using CA and to get better CA over generations GA is being used.

3.1 FITNESS EVALUATION

Fitness is evaluated by using hamming distance, and our fitness value increases every time there is a mismatch in the same index values between our current image, which we achieve after implementing CA and our final image. The lower the value of the fitness function, the better the GA is in our system.

3.2 PARENT SELECTION

The tournament method is used for selecting parents and to make it diverse, half of the population is participating in the mating process as we are selecting half of the population as parents by sorting the lowest half of the population.

3.3 CROSSOVER

Crossover is the process of using selected parents to breed a child, and in this process, characteristics of both parents are inherited by the child. Two types of crossovers have been tested inside the GA to get the optimum fitness, and they are single-point crossover and multipoint crossover. For tuning purposes, crossover probabilities have also been tuned to minimize fitness and increase diversity.

3.4 MUTATION

Mutation has been implemented by using random processes.

- Random mutation primality to choose whether mutation should be performed on a child or not.
- Number of mutation points in a child inside 512x512 space has been tuned to 10 to 30%
- Points of mutation in have been selected randomly in every generation into whole search space.
- All the bits in the ruleset have been inverted to create the ruleset of next generation more diverse.

3.5 SURVIVOR SELECTION

Survivor is selected using randomization and elitism as we select child with chromosomes of two lowest fitness value parents and randomly selects another child to replace the highest fitness value population of the previous generation.

IV. EXPERTIMENT

4.1 EXPERIMENT SETUP

The image taken for implementing GA to improve CA is a 2D image with a dimension of (256 x 256). The total number of generations evolved is 15.

4.2 Tuning Parameters

We have performed three types of experiments with the same population to find out the best suited GA, and the experiments are listed below:

- ***Tuning Mutation Points:***
  We have taken 1%,2%, and 3% of total chromosome. To find the one with the least fitness value.

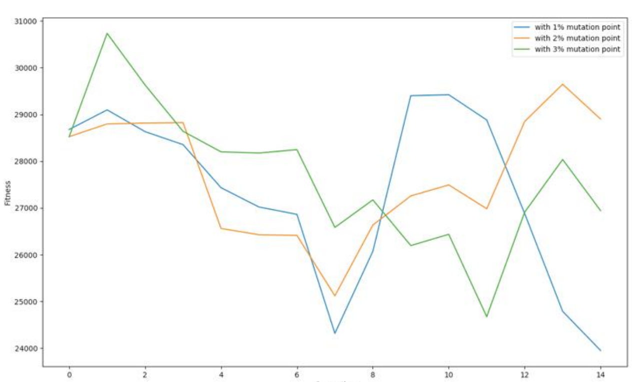

Fig. 4. Variation of mutation points inside chromosome between 1% to 3% of total chromosomes where a lower number of mutation points gives better output

From the figure, we can view that a smaller number of mutation points in the population gives us a lower fitness value with the same mutation probability and same mutation process.

- ***Tuning Mutation parameter***
  We have tuned the mutation probability to 0.2 and 0.3 to see the change keeping every other process the same.

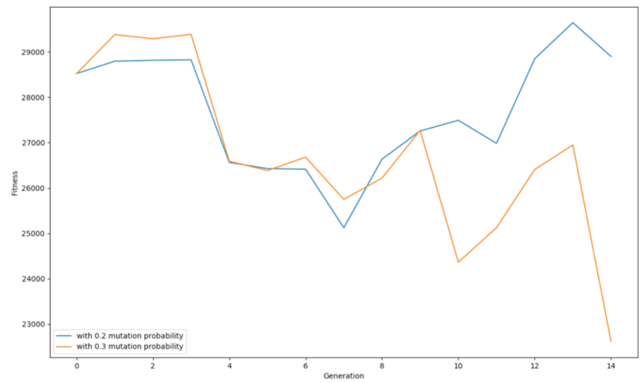

Fig. 5. Variation of mutation probabilities from 0.2 to 0.3 where higher probability gives better output

From the figure, it is evident that 0.3 probability gives out the lowest fitness value over a generation.

- ***Different types of crossover***
  We have tested the GA with single-point crossover, multipoint crossover, and also using the combination of both.

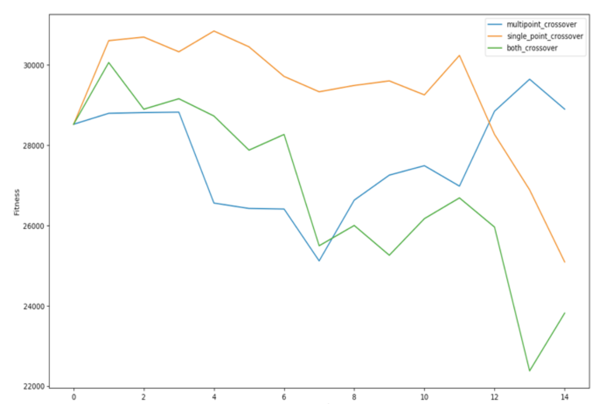

Fig. 6. Variation in crossover process where a combination of single-point crossover and multipoint crossover with crossover probabilities gives the best output.

From the image, it can be concluded that a combination of both single-point crossover and multipoint crossover comes up with the lowest value of fitness.

V. RESULT

If we consider all the scenarios of the experiments, we can see Cleary an improvement of 21.5% over 15 generations. Let us look at table 1 below for all the results to see the actual improvement in CA over generations.

A. TABLE 1

IMPROVEMENT OVER GENERATIONS IN VARIOUS PROCESSES

Process	Starling Fitness	Lowest Fitness	Improvement Over Generations (%)
Combination of crossover	28524	22381	21.53
Single Point Crossover	28524	25094	12.02
Multipoint Crossover	28524	22614	20.71
Mutation Probability (0.3)	28524	22614	20.71
Mutation Probability (0.2)	28524	25121	11.93
Mutation Point (3%)	28524	24674	13.49
Mutation Point (2%)	28524	25121	11.93
Mutation Point (1%)	28524	23951	16.03

After plotting all the scenario in graph, it would be much easier to visualize.

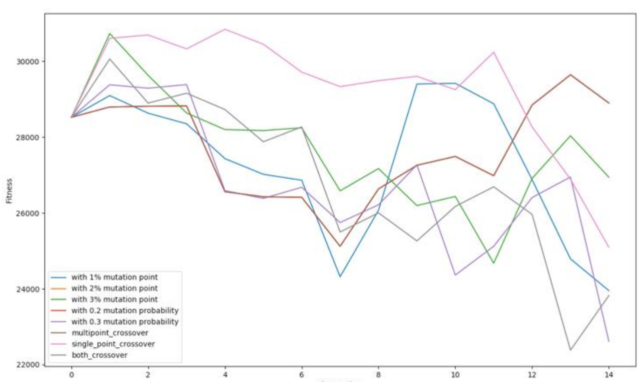

Fig. 7. Various experiment processes showing the combination of both single-point crossover and the multipoint crossover has the best output.

After comparing all the experiment results, we have developed a GA that has a mutation probability of 0.3, mutation points 1%of total chromosomes, combinational crossover, and crossover probability.

We used this model on another image to see whether it improves fitness or not, and, in the picture, we can see 13.7% improvement over generations.

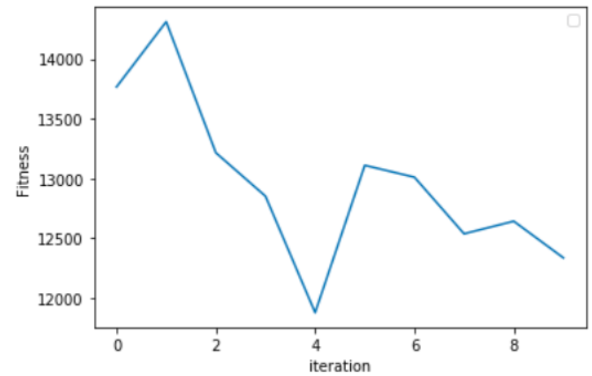

Fig. 8. Improvement of fitness over a generation on different image

7 CONCLUSION

To conclude, we can state that although there are worst values over generation and there, we have not yet achieved convergence, but here we tried to be more diverse, and also, we keep the computation time into consideration as it is a large search space. But after all the experiments developed, GA shows betterment in fitness over generations which proves it can handle any 2D image and provides an automated rule set for CA so that image processing can be done in a more optimized way.

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