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Application of an Enhanced Genetic Algorithm to Radar System

Hatem Elgothamy M.S[1], Mohamed A. Zohdy Ph.D[2], Hoda S. Abdel-Aty-Zohdy Ph.D[3]*

Department of Electrical & Computer Engineering, Oakland University, Rochester, Michigan, USA[1-3]

*Microelectronics & Bio-Inspired Systems Design Lab

Abstract: This paper introduces an enhanced Genetic Algorithm (GA) that is faster and less computationally expensive than the standard GA. Four enhancements are introduced here (multiple weighted roulettes, multiple cross over points, multiple mates and utilizing the D4 wavelets). Then the new enhanced system was applied on a dynamic large optimization problem that consists of an array of sixteen radar sensors to predict the Angle of Arrival (AoA) for an approaching object. Results was obtained using the enhanced GA as well as the standard GA. The enhanced GA is able to find the AoA using the least possible number of calculations, which, means it was less expensive computationally and is robust to parameter selections. Special software was developed using Java for this purpose; also, MS-Excel was used to represent the data map as charts.

Keywords: Genetic Algorithm; bio inspired system; evolutionary algorithm; weighted roulette wheel; Daubechies wavelets.

I. INTRODUCTION

In the past few decades, various computational methods have been developed which have their working inspired from the nature. One such computational method is Evolutionary algorithms which are generic, optimization algorithms that are biology-inspired mechanisms.

One of the most worrying problems in Artificial Intelligence (AI) and Data Mining (DM) is that of high dimensionality in data which refers to the situation where the number of attributes is large (nominally 15 or more). A highly dimensional data set creates problems in terms of increasing the size of the search space which makes the process very expensive computationally.

In addition, the growth in the search space as more features are added increases the number of training samples required to generate reliable results. In order to develop effective Data Mining algorithms, the problem of dimensionality must be overcome.

GA is an intelligent method for solving combinatorial, NP hard optimization problems in n-dimensions. GA theory is based on Charles Darwin's theory of evolution that describes the principle of natural selection "Survival of Fittest". GA imitates the process of evolution and follows the process of natural selection. Natural selection is probabilistic but favors the fittest individual in the generation. We propose enhancements that give a new variant of the Standard GA. Selection is the first genetic operation in the reproductive phase of GA. It helps the GA by directing the genetic search towards promising regions in the search space.

The objective of selection is to choose the fitter individuals in the population that will create offspring for the next generation, commonly known as mating pool. The selected mating pool takes part in advancing the population to the next generation and hopefully close to the optimal solution. Selection pressure is a crucial factor that determines the efficiency of the algorithm and it is desirable that the mating pool should have good individuals to offer a better chance for a better offspring. The worthiness or the value of each individual depends on its fitness. Fitness value is determined by an objective function. The process of selection of individuals can be done using different algorithms. The convergence velocity of the algorithm is also improved thereby reducing the time taken for the algorithm to reach the sought solution.

II. ENHAMCEMENTS

A basic part of the selection process is to stochastically select from one generation to another in order to create the basis of the next generation. The underlining requirement is that the set of fittest individuals would have a greater chance of survival than the set of weaker ones. This inheritance nature in that fitter individuals will tend to have a better probability of survival and will go on forward to form updated mating pool for the next generation. Weaker individuals are not left without a chance though. In nature those individuals may have genetic coding that may also prove useful to future generations.

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The first enhancement proposed is to use multiple weighted roulettes, each designed to complement the others, example shown in Fig. 1. This will further distribute the selection pressure for one generation to another. The roulettes can be operated in series or in parallel depending on the application at hand. The job that GAs have in this case is to mate sets of individuals and then replicate this selection process. The usual implementation is by crossover. There are no fixed methods associated with crossover, but the only general requirement is that the offspring carry forward the important genetic material from the parents, whilst introducing enough variation that they survive. The crossover method emulates this process by exchanging chromosome patterns between individuals to create offspring for the next generation

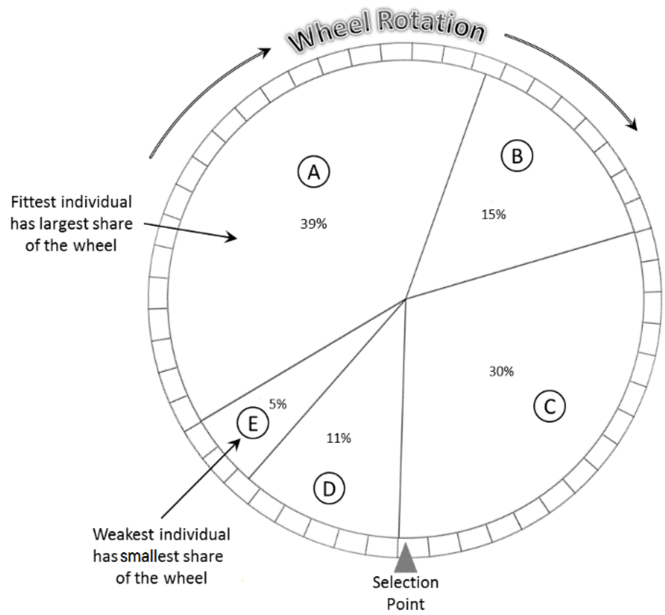

Fig. 1. Weighted Roulette Example

The second and third enhancements are to use multiple cross over points as well as using multiple mates as a function of results of mating individual parents creating some offspring. Those offspring will have of the genetic material of both parents. There are three options regarding the fitness of the offspring, they can be weaker, the same or fitter than their parents. If they are weaker they will tend to die out – if they are stronger their chances of survival are better. It is of general note that the stronger the parents are in terms of fitness then the fitter the offspring will be. The variation caused by this process allows the offspring to search out different available niches, i.e. find better fitness values and subsequently better solutions. Example shown in Fig. 2.

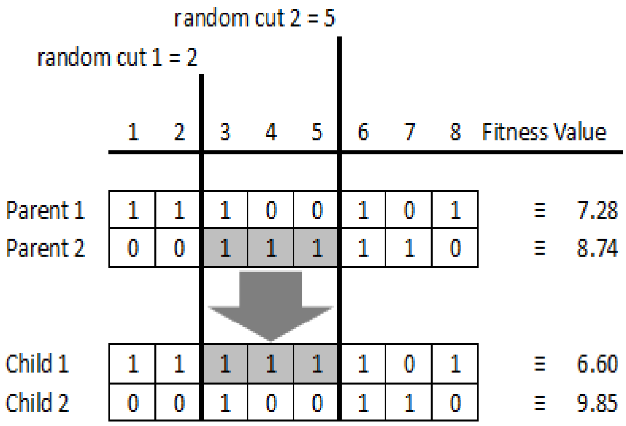

Fig. 2. Mating selected genes to produce new generation.

The fourth enhancement proposed is to utilize the Daubechies wavelets, which is named after its discoverer the mathematician Ingrid Daubechies, as a preprocessing step. There are multiple types of Daubechies wavelets. The easiest way to understand these transforms is just to treat them as simple generalizations of the Daubechies D4 transform. The most obvious difference between them is the length of the supports of their scaling signals. The most common Daubechies wavelets are shown in Fig.3.

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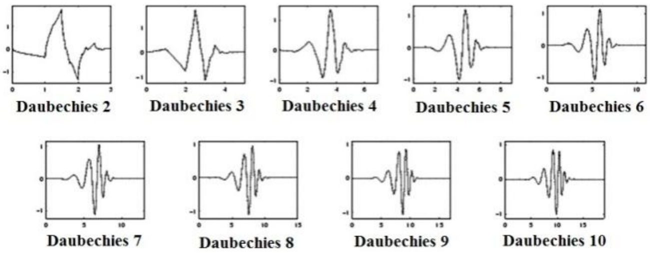

Fig. 3. Daubechies wavelets.

The D4 transform has four scaling function coefficients and can be extended to multiple levels as many times as the signal length can be divided by 2. The scaling function coefficients are:

$$\alpha_1 = \frac{1+\sqrt{3}}{4\sqrt{2}}, \quad \alpha_2 = \frac{3+\sqrt{3}}{4\sqrt{2}}, \quad \alpha_3 = \frac{3-\sqrt{3}}{4\sqrt{2}}, \quad \alpha_4 = \frac{1-\sqrt{3}}{4\sqrt{2}}.$$

Using these scaling numbers, the 1-level Daub4 scaling signals are:

$$\begin{aligned}
\mathbf{V}_1^1 &= (\alpha_1, \alpha_2, \alpha_3, \alpha_4, 0, 0, \ldots, 0)\\
\mathbf{V}_2^1 &= (0, 0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, 0, 0, \ldots, 0)\\
\mathbf{V}_3^1 &= (0, 0, 0, 0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, 0, 0, \ldots, 0)\\
&\vdots\\
\mathbf{V}_{N/2-1}^1 &= (0, 0, \ldots, 0, \alpha_1, \alpha_2, \alpha_3, \alpha_4)\\
\mathbf{V}_{N/2}^1 &= (\alpha_3, \alpha_4, 0, 0, \ldots, 0, \alpha_1, \alpha_2).
\end{aligned}$$

An important property of these scaling signals is that they all have energy 1. This is because of the Euclidean norm of the α vector

$$\|\underline{\alpha}\|2=1$$

$$\alpha_1^2 + \alpha_2^2 + \alpha_3^2 + \alpha_4^2 = 1.$$

$$\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = \sqrt{2}.$$

III. APPLICATION AND RESULTS

The enhanced GA will be implemented in a sensor array application. The array consists of sixteen radars. Each one of these radars receives readings using three carrier waves, shown in Fig.4, to help detecting the angle of arrival (AoA) for an approaching object. There are seven different angles of arrival (-60, -30, -15, 0, 15, 30, 60).

Data for known AoA was obtained. Each radar has 32,668 readings for each of the seven angles. That gives the system about 3.66 million cells of data to dig into. The 32,668 records of data were split into separate files, the first part consists of 31,644 records and is used as the training set for the system. The remaining 1,024 records are used to test the system by selecting a random sample from them and giving it to the system to see if it will detect the right AoA.

Fig. 4 - 10 show a small sample of the radar data read by each radar for each AoA. Each one of these figures represent one angle readings. Each line represents one radar readings, the X-axis represents one point in time for the radar readings & the Y-axis represents the value of the radar readings.

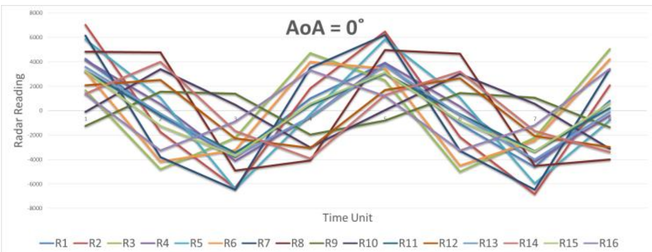

Fig. 4. Small sample of the radar data read by each radar for AoA = 0

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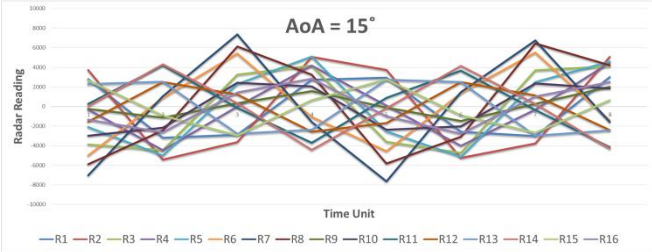

Fig. 5. Small sample of the radar data read by each radar for AoA = 15

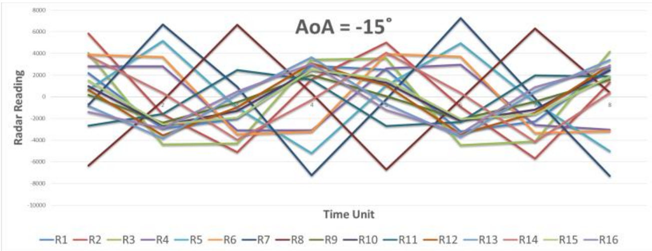

Fig. 6. Small sample of the radar data read by each radar for AoA = -15

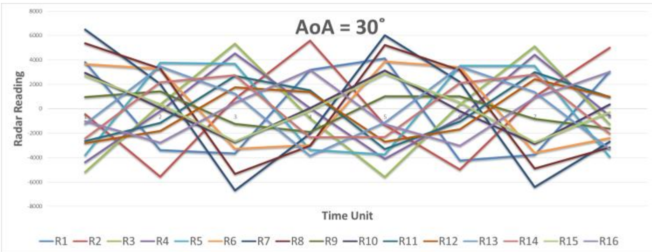

Fig. 7. Small sample of the radar data read by each radar for AoA = 30

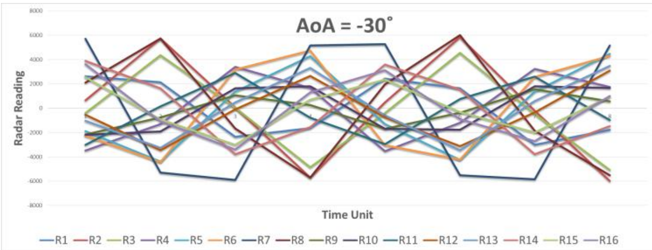

Fig. 8. Small sample of the radar data read by each radar for AoA = -30

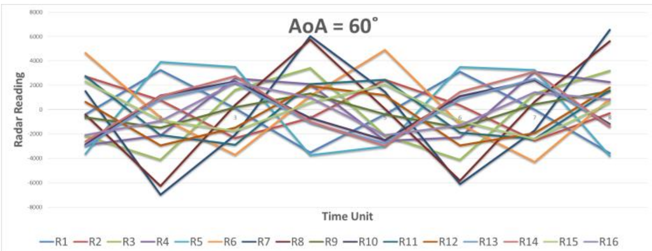

Fig. 9. Small sample of the radar data read by each radar for AoA = 60

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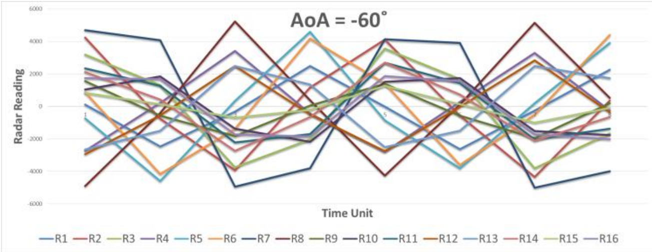

Fig. 10. Small sample of the radar data read by each radar for AoA = -60

Java was selected since it is an excellent language for developing cross-platform desktop applications, which enables the system to be migrated on any operating system that supports Java. All results obtained in this paper are from running the program on the same computer without changing anything in its configuration or software.

The following tables show the results of obtaining the AoA using the two mentioned approaches. Each cell in any of the tables below represents the average of 100 tests. For instance in Table 1, the number of iterations for the AoA (-60) using the enhanced GA is 396.5. This number is obtained by calculating the average of running the same test 100 times. The first row in the table shows the number of iterations done when using the enhanced GA. The second row shows the results while using the standard GA. The number of iterations needed in the standard GA to reach a result is almost double any of the first row which means that the enhanced GA was able to outperform the standard GA and immensely reduce the amount of calculations.

TABLE I. NUMBER OF ITERATIONS

	Number of Iterations							AVERAGE
AoA	-60	-30	-15	0	15	30	60	All
Enhanced GA	397	389	394	398	397	403	389	395.4
Standard GA	770	771	771	770	770	771	772	770.6

Fig. 11 depicts an alternative way to display the data obtained from Table 1. Fig. 11 shows a comparison between the first two rows, which are the enhanced GA and the standard GA.

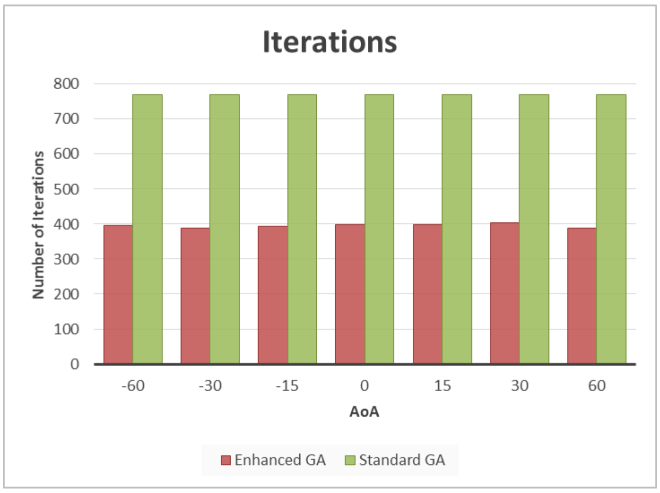

Fig. 11. Comparing The Number Of Iterations Done To Find The AoA Using Standard & Enhanced Genetic Algorithms.

Table 2. Shows the percentage of how many times the system was able to predict the correct AoA. It was found that when using the standard GA the score was a perfect 100%. Fig. 12. Shows a comparison between the two rows of Table 2. In conclusion, the proposed enhanced GA shows a significant improvement in computational cost compared to the standard GA with almost the same accuracy.

TABLE II. COMPARING THE PERCENTAGE OF CORRECT ANSWERS TO FIND THE AOA USING BOTH GENETIC ALGORITHMS

	Correct							AVERAGE
AoA	-60	-30	-15	0	15	30	60	All
Enhanced GA	98	99	99	96	99	99	99	98.4
Standard GA	97	99	99	96	99	99	99	98.3

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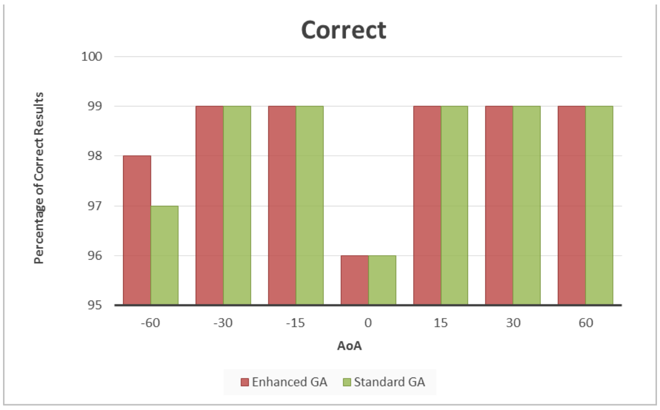

Fig. 12. Comparing The Percentage of Correct Answers To Find The AoA Using Standard & Enhanced Genetic Algorithms.

IV. CONCLUSION

This paper proposed a unique method for enhancing the computational cost of the system by introducing four enhancements to the standard GA which are (multiple weighted roulettes, multiple cross-over points, multiple mates and utilizing the Daubechies D4 wavelets). Significant performance gains were observed utilizing the proposed methods when compared to the standard GA. To obtain significant performance improvement in computational cost over the standard GA, the proposed enhanced GA was developed. Through testing, the proposed enhanced GA is shown to be superior to the standard GA.

The number of iterations needed in the standard GA to reach a result, i.e. AoA, is almost double the enhanced GA which means that the enhanced GA was able to outperform the standard GA and immensely reduce the amount of calculations by almost half. The only slight difference was in processing time which is normal due to the background tasks that the operating system performs and the way it handles the memory usage, and the user do not have any control on these operating system tasks.

The accepted fitness value depends on the problem itself and how much fitness can be sacrificed for the sake of computational cost. In this paper, both GA tests used a default population size of 10 and a maximum number of 100 evolutions. A higher number of allowed evolutions can lead to a higher fitness solution, but the question will be: does it worth the effort? Since enhancing the fitness by 0.1% can take double the time in some cases.

V. FUTURE WORK

Genetic Algorithm (GA) is rapidly growing area of Artificial Intelligence. More enhancements to the GA are currently being researched, like using Gaussian or Chi Square to create the initial random population, islanding of special individual groups and using annealing rate mutation. Another more comprehensive Java/Matlab GUI is being developed and will use the enhanced GA for more complex engineering problems.

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