Evolution of RF-Signal Cognition for Wheeled Mobile Robots using Pareto Multi-objective Optimization

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Abstract

This article describes a simulation model in which a multi-objective approach is utilized for evolving an artificial neural networks (ANNs) controller for an autonomous mobile robot. A mobile robot is simulated in a 3D, physics-based environment for the RF-localization behavior. The elitist Pareto-frontier Differential Evolution (PDE) algorithm is used to generate the Pareto optimal set of ANNs that could optimize two objectives in a single run; (1) maximize the mobile robot homing behavior whilst (2) minimize the hidden neurons involved in the feed-forward ANN. The generated controllers are evaluated on its performances based on Pareto analysis. Furthermore, the generated controllers are tested with four different environments particularly for robustness assessment. The testing environments are different from the environment in which evolution was conducted. Interestingly however, the testing results showed some of the mobile robots are still robust to the testing environments. The controllers allowed the robots to home in towards the signal source with different movements' behaviors. This study has thus revealed that the PDE-EMO algorithm can be practically used to automatically generate robust controllers for RF-localization behavior in autonomous mobile robots.

1. Introduction

This article describes a set of simulation in which an Evolutionary Robotics (ER) method is used to automatically design the robot controller through the artificial evolution for a minimalist mobile robot; so called Khepera for the RF-localization homing behavior.

A numerous studies have been carried out in the ER optimization technique in generating complex robot controllers for the required behavioral, such as phototaxis, phonotaxis and obstacle avoidance task [2, 5, 8-10, 21, 23, 31, 35, 36]. However, most of the hybridized evolutionary algorithm and artificial neural network (ANN) used in the ER studies are still suffer from its limitation compared to the hybridized Pareto-frontier Differential Evolution Multi-objective Optimization (PDE-EMO) algorithm and feed-forward ANN used in this studies.

With respect to the other ANN studies [1, 2, 5, 8-13, 16, 20-23, 31, 35, 36], the PDE-EMO application is advantageous compared to some of the conventional algorithms, such as backpropagation, conventional GAs, and Khonen SOM network. As literature reviewed, the number of hidden neurons used in multi layer perceptrons and number of cluster centers in Kohonen's SOM network need to be determined before training. Meanwhile, the traditional learning methods for ANNs such as backpropagation usually suffer from the inability to escape from local minima due to their used of gradient information. In additional, a set of unpredictable size of huge normalized input and output data samples are preliminary requested before the training. In such reasons, the PDE-EMO application is more advantages compared to the discussed ANNs studies. Furthermore, EMOs are able to solve two or more conflict objectives in a single evolutionary process compared to the conventional GAs [3, 4].

The research of radio frequency (RF) signal localization has yet to be studied in ER. It is a term that refers to an alternating current that having characteristics such that, if the current is an input to an antenna, an electromagnetic field is generated suitable for wireless broadcasting and/or communications used [19, 27, 30]. The RF signal source has provided the capability for improvement in tracking, search and rescue efforts. As such, the robots that are evolved with RF-localization behaviors may potentially serve as an ideal SAR assistant.

In this study, the elitism Pareto Differential Evolution (PDE) is used as the primary evolutionary optimization algorithm. There are two distinct objectives to be optimized: (1) maximize the robot's RF signal source localization behavior, and (2) minimize the complexity of the neural network in term of number of hidden neurons used. In our previous studies [25], it was clearly shown that elitism helps in producing better controller behavioral and the elitist PDE-EMO algorithm used has been successfully generated the required robot controller behavior. However, robustness was not the primary focus in that study. Therefore, further experiments were conducted in order to test the robustness of this approach and the experimentation results are presented next in this study.

The PDE-EMO used was presented during 2001 and 2002 [17, 18]. In some researchers mind, it might be a pitfall in discussing the PDE-EMO application when we are in 2008 with ignored recent proposals EMO techniques such as GDE3, NSGA-II, and SPEA2 [14, 15, 24]. However, a presented research work showed the PDE-EMO was successfully generated the required abstract legged robot controllers [20-22]. Thus, it might be an advantageous in reducing our research risks since other EMOs techniques have never been applied and discussed in ER study. In addition, we attempt to investigate the comparison of generated controllers' performances in an ER viewpoint, instead of multi-objective metaheuristics and quality indicators such as generational distance, hypervolume, etc. since these have already been analyzed thoroughly in other EMO studies [14, 15, 24].

In this paper, the testing environment used is more complex compared to our previous study. There are four different environments used to test the generated robot controller's robustness, namely Maze O, Maze T, Maze 8 and Maze -S-. The environment complexity is increased according to the number of the obstacles used in the mazes. Maze O involved only one obstacle, followed by two obstacles in Maze T. There are three obstacles involved in Maze 8 and five obstacles involved in Maze -S-. In our experiment, the robot must successfully find another way to track the signal source and home in towards the signal source as fast as possible even the testing and evolution environments are different. Furthermore, the PDE-EMO algorithm used also must able to minimize the number of hidden neurons used in evolving the robot controllers.

This paper is organized as follows. The first section explains the methodology used during evolution. Second section describes the evaluation functions used during optimization. Third section discusses the experimental setup used. Fourth section depicts the evolution results. The fifth section presents the conducted testing results. Conclusions and future trends are lastly presented.

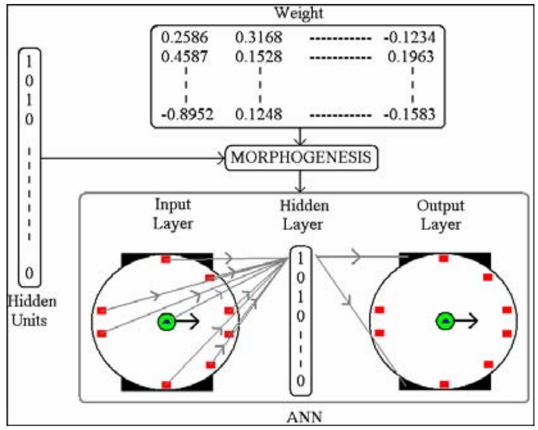
2. Methodology

2.1. ANN Representation

Traditionally, the term neural network is referred to a network or circuit of biological neurons [33]. Modern usage of neural network is referred to Artificial Neural Networks (ANNs). ANNs also named as Simulated Neural Network (SNN) or commonly called as neural network (NN) [33]. The ANNs are made up of interconnection of artificial neurons from a set of constructed executed file through programming language that mimic the properties used in biological neurons [33]. Normally, ANNs used to solve artificial intelligence problem without necessary creating a set of real biological model [21, 25, 33]. Neural networks are widely used for classification, approximation, prediction, and control problems [2, 5, 8, 9, 10, 11, 13, 25, 33]. In more practical, the ANNs are defined as non-linear statistical data modeling and decision making paraphernalia [33]. Based on biological analogies, neural networks try to emulate the human brain's ability to learn from examples, learn from incomplete data and especially to generalize concepts [33].

General NN is composed of a set of nodes connected by weights. The nodes are partitioned into input layer, hidden layer and output layer [20, 21, 22, 33]. The neural network normally learns the behavior that required after optimization processes. A numerous of NN types are available such as feedforward NN, Radial basis function network, Kohonen SOM network, recurrent network, stochastic NN, etc [33]. The feed forward NN was the first and simplest type of ANN devised [33]. In this network, the information moves in one direction, forward from the input nodes through the hidden nodes and to the output nodes. There are no cycles or loops involved in the network. In this research work, the feedforward NN is utilized during the learning processes. The utilization of feedforward NN is more advantageous compared to other NN due to the special features such as easy to construct, less computation time taken, and accurate used during learning processes and more importantly, feedforward NN is the most common used NN for all of the researches especially for the utilization in preliminary experiment [2, 5, 8, 9, 10, 11, 13, 20, 21, 22, 25, 33].

In this research, the experiments are conducted with a Khepera robot [26]. The Khepera robot is integrated with 8 infrared distance sensors, 1 RF receiver and 2 wheels. The infrared distance sensors and RF receiver are presented as input neurons to the ANN while the speed of the robot's wheels represents the output neurons from the ANN. A feed-forward neural network is used as the neural controller for the robot. The chromosome in this experiment is a class that consists of a matrix of real numbers that represents the weights used in the ANN controller. The binary number for the hidden layer represents a switch to turn a hidden neuron on or off. Figure 1 below depicts the morphogenesis of the chromosome into the ANN architecture.



represents robot's infra-red distance sensors
represents robot's left and right wheels
→ represents robot's direction
represents receiver

Figure 1. The morphogenesis's representation. The neural network involved 9 input neurons from 8 infrared distance sensors and a receiver while the output neurons represent the robot's wheels speed.

2.2. The PDE-EMO

The task for finding more than one optimum solutions in an optimization problem is known as multi-objective optimization. It has been well known that EMO is outperformed the conventional GAs or single objective optimizer either in diversity or convergence perspectives [3, 24]. The PDE-EMO is utilized in this study. It is a combination among the Pareto-based selection with differential evolutionary algorithm in EMO approach. In general, DE differs from a conventional GA in a number of ways. The number of vectors used for the crossover operation is the main difference. In DE, three vectors are utilized for the crossover, where one of the selected non-dominated parents serves as the base vector to which the difference between the other two parents' vectors is added to form the trial vector. Then, the new trial vector will replace the randomly selected base vector only if it is better [33]. The vector selection skill used in the algorithm for high behavior's fitness score with less number of hidden neurons used during the optimization processes is able to maximize the robot behavior whilst minimize the neural network complexity in the evolution process.

A multi-objective problem which solves two objectives simultaneously is utilized in this research work with: (1) maximize the RF signal source homing behavior whilst (2) minimize the number of hidden units used in the neural controller. The Pareto-front thus represents a set of networks with different numbers of hidden neurons and different numbers of homing behaviors. A complete set of PDE-EMO algorithm is readily available from our earlier reports [25]. A comparison among elitism and non-elitism has already been carried out in our previous research [25] to verify the argument pointed out in [34] but with regards to an ER perspective. Thus, we observed that, the elitism is encouraged to be use in the ER application and we will not discuss this algorithm again which is used in this paper. Interested readers are encouraged to read the original publication from [17, 18, 32] and further review our extended report [25] for an in-depth description.

3. Evaluation Function

A number of preliminary tests had been carried out in order to obtain a suitable fitness function for the Khepera robot RF-localization behavior. As a result, a combination of several criteria into one fitness function is proposed from the preliminary experimentation results. The fitness function comprises of terms that demonstrate obstacle avoidance behaviors, maximize the average speed of the robot's wheels, maximize the robot wheels speed and lastly maximize the robot RF-localization behavior. The formulation of the fitness function is as follows:

$$F_1 = \frac{1}{T}\sum_{m=0}^{T}(1-i)SVW_L W_R \tag{1}$$

$$0 \le (1-i) \le 1$$

$$S = [1,50]$$

$$0 \le V \le 1$$

$$0 \le W_L, W_R \le 1$$

$$F_2 = \sum_{i=0}^{I} H_i \tag{2}$$

Where F represents the fitness function, T = simulation time, i = highest distance sensor activity, V = average speed of wheels, S = signal source value, W_L = left wheel speed, W_R = right wheel speed and H = hidden neuron used, with $i = 1..15$ representing the number of the corresponding hidden neuron. The F_1 represents the fitness function used for maximizing the robot's behavior in homing towards the signal source whilst F_2 represents the second objective which is minimizing the neural network complexity.

The fitness values from F_1 are accumulated during the life of the simulated robot and then divided by the simulation time. The obstacle avoidance characteristic is one of the most important components in the experiment since the Khepera robot is evolved with the initial orientation of facing away from the signal source. Thus, the controller always has to first evolve a behaviour to avoid crashing into the opposite wall that it starts facing towards before it can home towards the RF signal source. The second important component is the S component in the F_1 function, where the Khepera robot must locate the source properly and attempt to stay in the source area if possible. The other components are used to avoid the robot from evolving to achieve the target but without a spinning movement that uses more time to localize towards the signal source. F_2 represents the numbers of hidden neurons required and are used to reduce the complexity of the neural structure of the robot's controller.

4. Experimental Setup

A physics-based simulator namely WEBOTS is used in the experiment for simulating the Khepera robot behavior. The standardized virtual Khepera robot model is readily available for use in the simulator. The WEBOTS simulator has an advantage in that random noise as occurring in real Khepera robots is included for all the distance sensors and robot wheels [6, 7, 28, 29]. Thus, the robot may have slightly different responses even when the same weights and inputs from the environment are used. This is highly advantageous since the simulation results represent the real-life functioning of a physical robot and more importantly, the evolved controllers are directly transferable to a real physical robot [6, 28, 29].

In the preliminary experiment, a Khepera robot is located in a particular position on a ground with four walls. All of the walls are 30*mm* in height. The area of the ground covered is 1m^2. The Khepera robot is located somewhere on the ground and facing the nearest wall. A receiver is located to the top of the Khepera robot. It acts as a device which can receive any signal that comes from an RF emitter. An emitter is modeled as a device that can send RF signals at every time step. The receiver can *only detect* the signal if it is *within the range* of emitter source; otherwise no signal is detected. The emitter source used is a radio type with buffer size 4096 and byte size 8 with signal range of 0.3*m*. It is located as a static emitter near to the center of one of the walls and to the back of the Khepera robot. The experimental setup for the preliminary evolution is depicted in Figure 2 whilst Table 1 represents the parameters used in simulating the robot controller.

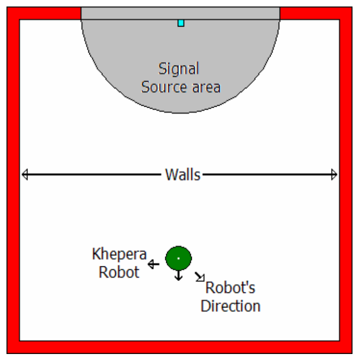


Figure 2. Basic experimental setup.

Table 1. Parameters used for simulation.

Descriptions	Parameters
Number of Generation	100
Population Size	30
Simulation Time Steps	60s
Crossover Rate	70%
Mutation Rate	1%
Number of Hidden Neurons	15
Number of Repeated Simulations	10
Algorithm Used	Elitist without archive PDE-EMO
Random Noise Feature	Activated

Our previous studies have clearly shown that the optimum solutions could be generated with all of the parameters used as shown in Table 1. In this study, the generated controllers were tested for their robustness with four different benchmarked environments. The environments used during testing phases were named as O-Maze, T-Maze, 8-Maze, and S-Maze. A Khepera robot and an emitter with 0.3*m* radius used were utilized during the testing phases. The emitter was positioned statically at the top left corner of the ground in the O-Maze testing environment whilst the Khepera robot was positioned at the bottom right corner of the ground opposite to the emitter and facing 315˚ to the emitter. An obstacle with 0.3*m* length x 0.3*m* width x 0.03*m* height was located statically in the middle of the ground. Two obstacles were included in the T-Maze environment instead of one in the O-Maze environment in order to increase the testing environment's complexity. The obstacles covered 0.6*m* length x 0.7*m* width x 0.03*m* height of the ground. Thus, each of the obstacles was dimensioned with 0.3m length x 0.7m width x 0.03m height. One obstacle was positioned at the bottom left of the ground whilst the other obstacle was located at the bottom right of the ground. The emitter was positioned statically at the top left corner of the ground whilst the robot was positioned at the bottom middle of the ground which was the center between both of the obstacles. Figure 3 below depicts the Maze O and Maze T environments used during testing phases.

Maze O Maze T

Big round shape represents the signal source area, while small circle with an arrow represents robot and it's direction with respectively. Boxes represent obstacles.

Figure 3. Maze O and Maze T environments used during testing phases.

The third testing environment used was named as the 8-Maze. Similar to the O-Maze and T-Maze, an emitter and a Khepera robot were utilized in the test. The emitter was positioned statically at the top left corner of the environment and the Khepera robot was positioned opposite with an angle of 0˚ to the emitter. There were three obstacles involved in the 8-Maze environment. Two obstacles were positioned at the top right corner and bottom left corner of the ground, respectively. The third obstacle was positioned at the middle of the ground, between the emitter and the Khepera robot, particularly to block the most common paths for the robot used to track for the signal source. The S-Maze testing environment covered 2m^2 instead of 1m^2. It provided a larger search space for the robot to home in towards the signal source due to its environmental complexity. Figure 4 below depicts the testing environments used in Maze 8 and Maze –S-.

Maze 8 Maze -S-

Big round shape represents the signal source area, while small circle with an arrow represents robot and it's direction with respectively. Boxes represent obstacles.

Figure 4. Maze 8 and maze -S- environments used during testing phases.

Each of the Pareto solutions were utilized during the testing phases and each of the controllers were tested 3 times in the tests. The evolution and testing results were collected and tabulated. The evolution results are further discussed as below.

5. Evolution Results

There were 2 out of 10 failed repeated simulations. The failed results were caused by inconsistent robot movement behaviors in tracking the signal source. The successful simulation results showed the number of hidden neurons used was successfully minimized due to the utilization of PDE-EMO algorithm. Some of the successfully evolved solutions utilized only very few neurons out of the permissible 15 neurons. Thus, the evident has proofed that PDE-EMO algorithm successfully reduced the number of hidden neurons used in evolving the robot controllers, thereby reducing the computational requirements considerably. Furthermore, the optimum solutions were successfully maintained due to the utilization of elitism in the PDE-EMO algorithm. Figure 5 depicts the obtained local Pareto-fronts from the 10 repeated evolutionary runs as well as the overall global Pareto-front whilst Table 2 lists the global Pareto solutions found.

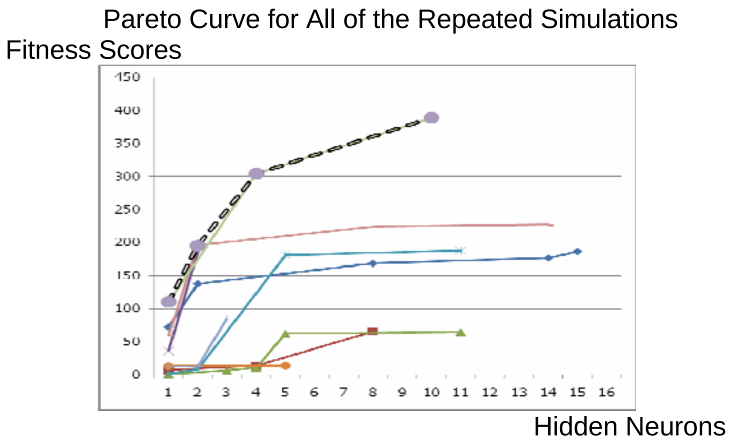


Figure 5. Collected simulation results. The local and global Pareto-frontiers for all of the generated controllers from repeated simulations are illustrated. Dark double dotted-line represents the global Pareto solutions.

Table 2. global pareto obtained

No	Fitness Scores	No. of Hidden Neurons
1	109.9	1
2	195.15	2
3	304.16	4
4	388.95	10

Figure 5 shows the generated controllers were able to be evolved with successfully. Figure 5 also shows the global Pareto-front of solutions found at the last generation utilized very few hidden neurons. The evidence is further proved in Table 2. There were a total number of four global Pareto solutions found. The solutions involved the utilization of 1, 2, 4, and 10 hidden neurons out of permissible 15 hidden neurons. This shows that the ANN complexity was able to be minimized due to the utilization of the PDE-EMO for evolving the robot controllers since fairly successful controllers could be produced using only 1, 2, 4, and 10 hidden neurons only. These controllers allowed the robots to home in towards the signal source area even with least complex controller that utilizes only a single hidden neuron

6. Testing Results

Tests were conducted for all of the generated controllers to verify their ability in tracking the signal source robustly. The testing results showed most of the individuals were able to achieve the target with very few hidden neurons used. There were many different results obtained from the experiments. A comparison of the time taken and success rate was conducted for all of the generated robot’s controllers. Each of the evolved controllers was tested with the same environment setting as that used during evolution for 3 times. The comparison of the tested controllers is depicted as Figure 6 below.

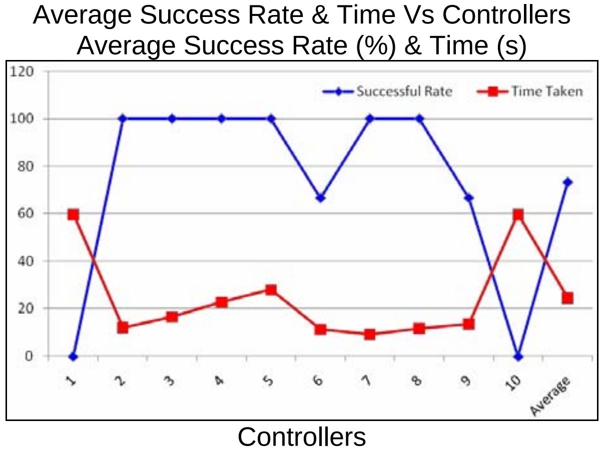


Figure 6. Comparison of average successful rate and time taken for all of the generated controllers from the 10 repeated simulations.

Figure 6 clearly shows some of the controllers were able to home in towards the signal source successfully, although two out of ten evolved controllers failed to display the required behaviors during testing phases. Figure 7 represents the robot movements after the tests performed.

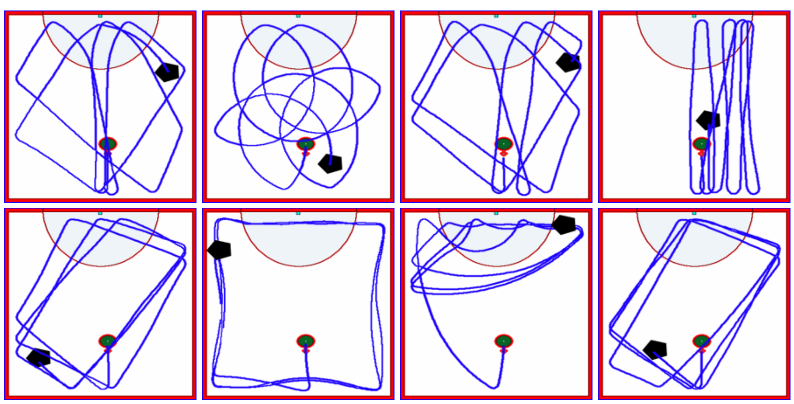


Figure 7. Robot movement obtained from testing results.

The testing results showed the evolved robot controllers learned to home in towards the signal source with straight line movements. Furthermore, each of the best evolved controllers was tested their robustness with the different environmental setting as that mentioned before in the experimental setup section. Table 3 depicts the average time taken and success rate of the comparison testing results.

Table 3. Comparison of testing results during robustness tests.

Testing environment	Success rate (%)	Time Taken (s)
Original/Preserved	67.78	11.668
Maze O	45.67	28.781
Maze T	40.33	30.544
Maze 8	18.67	55.67
Maze -S-	9.79	58.73

The comparison results showed the robots were not as robust as expected to the testing environment when tests were performed in the -S- Maze. The testing result clearly showed that the inclusion of obstacles into the testing environment might affect the generated controller's performance. The robot almost failed to explore and track for the signal source in the most complex environment, which is the -S- Maze. Some failed results showed that the robot failed during the testing phases due to its movement behavior. The robot might fail to home in towards to the signal source if it had learned to navigate using circling movements. It might also only explore in a small corner on the ground during the testing phases. Furthermore, the testing results also showed that it was difficult for the robot to explore for the signal source in an environment with more obstacles, which is different from the results obtained in phototaxis studies. The light intensity is provided in phototaxis studies. Thus, it reduced the environment's complexity during testing phases. Hence, the experiments performed with RF-localization are thus more complex and difficult compared to phototaxis. The robot must firstly do efficient exploration of the ground for the signal source. Otherwise, no signal source will be detected by the receiver. Figures 8 and 9 below show the failed robot movements as well as successful robot movements obtained during testing respectively.

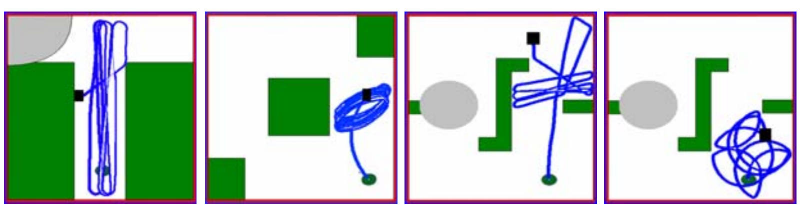
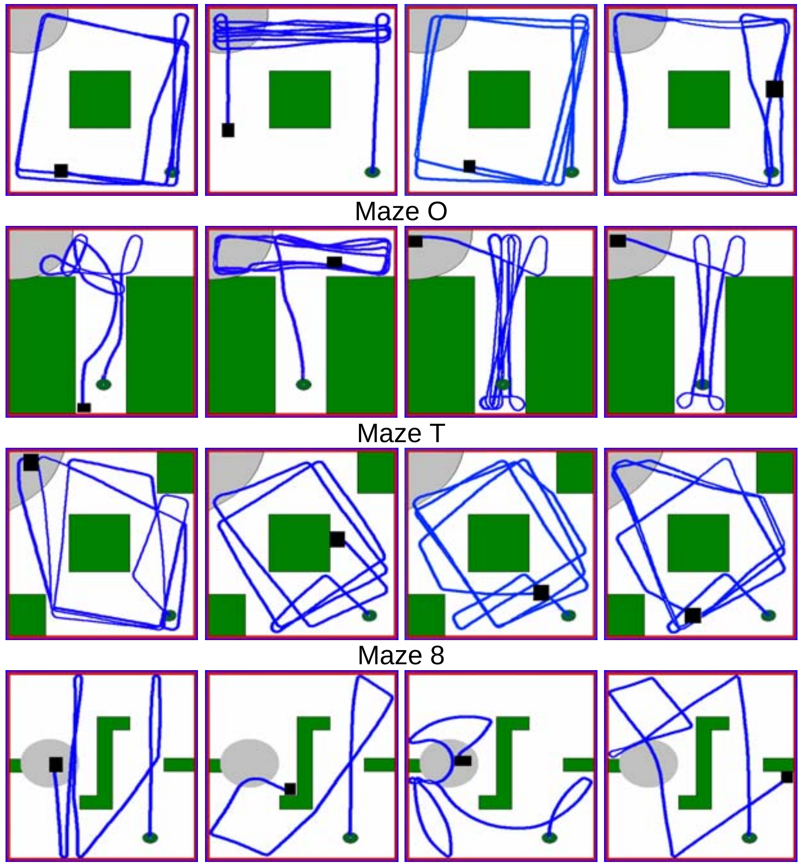


Figure 8. Obtained failed results during testing phases.

Figure 9 shows the robot might robust to the different environments used during testing phases. However, the performance of the generated controllers might reduce due to the complexity of the environment used during testing phases. The robot might home in towards the signal source with successfully if the robot learned to navigate with straight forward at maximum speed in exploring the signal source. Furthermore, the robot must flawlessly learn the obstacle avoidance behavior in order to avoid from bumping to the detected walls during exploration. The success rate could be higher if extra testing time provided for the robot to explore for the signal source.



Maze -S-
Boxes represent obstacles
Big sphere/semi-sphere represents signal source area
Small round object with arrow represents robot and its direction
Figure 9. Testing results obtained during testing phases.

7. Conclusion and Future Research

As a conclusion, this study has shown that the PDE-EMO algorithm used could successfully produce controllers with RF- localization behaviors while minimizing the complexity of the evolved controllers. It was observed that even controllers with only 1, 2, 4 and 10 hidden neurons could perform the task successfully. Nevertheless, the average testing success rate was slightly low when the tests performed with different environments. This happened because some of the controllers were limited to turn to either the left or right side to avoid from bumped to the wall. In additional, the RF-localization behavior is more complex/challenging compared to the other task such as phototaxis and box pushing. Because the robot can only sense the signal source if and only if the robots have successfully track the signal source.

The incremental evolution approach may be considered to be used in the evolution process to start the evolution of robot controllers to perform additional new tasks with best individuals obtained from the previous task evolution. The fitness function used plays an important role in evolving the robot controller, which is not something trivial to design. Hence, a co-evolutionary approach might also be beneficial in more complex environments where a suitably successful fitness function may be hard to identify manually.

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