International Conference on Man-Machine Systems (ICoMMS)
11 – 13 October 2009, Batu Ferringhi, Penang, MALAYSIA

Automatic Generation of Swarm Robotic Behaviors using Multi-objective Evolution

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***Abstract*- This paper investigates the utilization of a multi-objective approach for evolving artificial neural networks (ANNs) that act as controllers for a collective box-pushing task based on radio frequency (RF)-localization of a group of virtual E-puck robots simulated in a 3D, physics-based environment. The elitist Pareto-frontier Differential Evolution (PDE) algorithm is used to generate the Pareto optimal sets of ANN that optimize the conflicting objectives of maximizing the virtual E-puck robots' behaviors for pushing a box towards a wall based on RF-localization as well as minimizing the number of hidden neurons used in its feed-forward ANN controller. A new fitness function which combines two different behaviors (1) RF-localization behavior and (2) box-pushing behavior is also proposed. The experimentation results showed that the virtual E-puck robots were capable of moving towards to the target and thereafter push the box towards the target wall with very small neural network architecture. Hence, the results demonstrated that the utilization of the PDE approach in evolutionary robotics can be practically used to generate neural-based controllers that display intelligent collective behaviors in swarming autonomous mobile robots.**

I. Introduction

Evolutionary techniques hold the potential to solve many difficult problems in robotics which defy simple conventional approaches. Neural controllers have seen to be widely optimized by evolutionary techniques and have been proven to be successful in generating robot controllers for the required tasks [1]-[5]. Formation marching, tandem movement, box pushing, material transport, aircraft engine maintenance, micro surgery, water disposal, planetary exploration, etc are the most common tasks that involved a group of robots in achieving the required objectives [6]-[10]. The listed tasks are unable to be completed without a comprehensive teamwork of more than one robot. Interestingly, there have not been any studies conducted yet in evolving the robot controllers using the evolutionary multi-objectives (EMO) algorithm, especially in group/collective/swarm robotics.

There have been very only been a handful of studies that have been conducted on the use of EMOs in the ER area. Reference [11] showed the EMO used was capable to generate the controllers for abstract legged robot morphology as well as locomotion. Then, [12] showed some researchers have utilized the EMO for optimizing space robot motion trajectory and robot's body balancing. Furthermore, [13] showed the researchers have successfully generated controllers for robot's manipulator trajectories and obstacle avoidance behaviors using EMO. Reference [14] has compared again the conventional GAs and MOGA for the problem of offline point-to point autonomous mobile robot path planning for a Holonomic robot. Reference [15] showed the application of EMOs into robotic area through learning and evolution has been effectively applied to multiple task performance. In [16], the authors have investigated on a Khepera robot phototaxis behavior using EMO algorithm. Furthermore, [17] has pointed the EMOs also can be practically used in evolving a quadruped robot either in noise free or noise inclusion environment. Whilst recently, [18] showed the EMO can be practically used in generating the mobile robot controllers for RF-localization behavior and the testing results showed the robot was robust to different environment used. Nevertheless, there is still no research reported thus far for the application of EMOs into group/swarm/collective robotics area. Hence, this forms the basic motivation for this investigation.

In this study, the elitist PDE-EMO is used as the primary evolutionary optimization algorithm. There are two distinct objectives to be optimized: (1) maximizing robot's RF box-pushing behavior whilst (2) minimizing the neural network complexity in terms of number of hidden neurons used during the optimization processes. Furthermore, a fitness function used for the optimization process is also proposed. During the testing phases, the robots are expected to be capable of firstly exploring for the RF signal source. Then the robots must be able to recognize the box and push the box towards the wall.

The remainder of this paper is organized as follows. In section II, the ANN representation used is discussed. In section III, the PDE-EMO algorithm used is proposed in evolving the robot controllers. Furthermore, a clear view of the experimental setup used is proposed in section IV and it follows with the discussion of fitness function used in evolving the robot controllers. Then, the discussions are continued with the evolution and testing results obtained in the sections VI and VII. Finally, section VIII summarizes the conclusions and future work for this study.

II. The ANN Representation

Neural networks are widely used for classification, approximation, prediction, and control problems. In this paper, the experiment is conducted with five E-puck robots. Each of the E-puck robots is integrated with eight infrared obstacle distance sensors, four touch sensors, one RF signal receiver and two wheels. The infrared distance sensors, touch 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 unit on or off. Fig. 1, below depicts the morphogenesis of the chromosome into the ANN architecture.

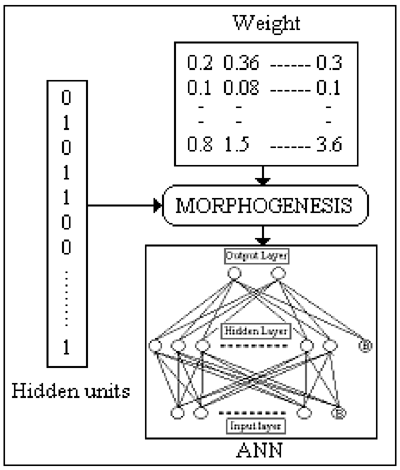


Fig. 1. The representation used for the chromosome

III. THE PDE-EMO ALGORITHM

This paper investigates a multi-objective problem which solves two objectives simultaneously: (1) maximize the collective box-pushing task based on radio frequency (RF)-localization of a group of virtual E-puck robots whilst (2) minimize the number of hidden neurons used in the neural controller. The Pareto-front thus represents a set of networks with different numbers of hidden units and different numbers of homing and box-pushing behaviors. The elements of the binary vector are assigned the value 1 with a probability of 0.5 (P(X=0.5) to give the hidden layer a 50% probability of either switching on or off a hidden unit in the vector of hidden units which is being evolved) based on a randomly generated number according to a uniform distribution between [0, 1]. The elitist PDE algorithm used in evolving the robot controller is presented next.

1.0 Begin.

2.0 Generate random initial population of potential chromosomes. The elements of the weight matrix are assigned random values according to a Gaussian distribution *N*(0, 1). The elements of the binary vector ρ are assigned the value 1 with probability 0.5 based on a random generated number according to a uniform distribution between [0, 1]; 0 value otherwise.

3.0 Loop

3.1 Evaluate the individuals or solutions in the population and label as parents those that are non-dominated according to the two objectives: maximizing RF-localization behavior and minimizing the number of hidden neurons.

3.2 If the number of non-dominated individuals (a solution is considered as non-dominated if it is optimal in at least one objective) is less than three, repeat the 3.2.1 and 3.2.2 steps until the number of non-dominated individuals is greater than or equal to three (since the Differential Evolution algorithm requires at least three parents to generate an offspring via crossover). If insufficient solutions are retained from the first layer, then 3.2.1 and 3.2.2 steps have to be repeated for the second and subsequent layers of the non-dominated solutions.

3.2.1 Find a non-dominated solution among those who are not labeled in the second layer of the non-dominated results.

3.2.2 Label the solution(s) found as the non-dominated points.

3.3 Delete only dominated solutions from the population and retain the non-dominated solutions (elitist concept).

3.4 Loop

3.4.1 Select at random an individual as the main parent α_1, and other two parents α_2, α_3 as supporting parents.

3.4.2 Crossover with some uniform (0,1) probability, do

$$\omega_{ih}^{child} \leftarrow \omega_{ih}^{\alpha_1} + N(0,1)(\omega_{ih}^{\alpha_2} - \omega_{ih}^{\alpha_3})$$

if $(\rho_h^{\alpha_1} + N(0,1)(\rho_h^{\alpha_2} - \rho_h^{\alpha_3})) \geq 0.5$;

$\rho_h^{child} \leftarrow 1$; $\rho_h^{child} \leftarrow 0$ Otherwise;

Otherwise;

$$\omega_{ih}^{child} \leftarrow \omega_{ih}^{\alpha_1}$$

$$\rho_h^{child} \leftarrow \rho_h^{\alpha_1}$$

And with some uniform (0,1) probability, do

$$\omega_{ho}^{child} \leftarrow \omega_{ho}^{\alpha_1} + N(0,1)(\omega_{ho}^{\alpha_2} - \omega_{ho}^{\alpha_3})$$

Otherwise;

$$\omega_{ho}^{child} \leftarrow \omega_{ho}^{\alpha_1}$$

3.4.3 Mutate with some uniform (0,1) probability, do

$$\omega_{ih}^{child} \leftarrow \omega_{ih}^{child} + N(0, mutation\_rate)$$

$$\omega_{ho}^{child} \leftarrow \omega_{ho}^{child} + N(0, mutation\_rate)$$

if $\rho_h^{child} = 0$

$\rho_h^{child} \leftarrow 1$; 0 otherwise

3.5 Repeat for all of the deleted solutions.

4.0 Repeat until maximum number of generations is reached.
End

IV. EXPERIMENTAL SETUP

In this study, there are five E-puck robots as well as a box used in the simulation. The box is sized with 30mm height, 275mm width, and 180mm length with 240g weight. Thus, the E-puck robots must work together in order to push the box towards the wall and within the shortest duration. However, it is impossible for less than three robots to accomplish this task. The box is purposely simulated to be three times the weight of the E-puck robot. Hence, at least three robots must work together in order to ensure they are capable to accomplish the task within the stipulated time. There are four box sensors integrated on the E-puck robot for box detection purpose. The sensors are positioned on the bottom front while the wall sensors are located on the top front of the robot. A receiver is located on the top of each of the E-puck robot in order to assist the robot to track for the signal source. It acts as a device which can receive signal from RF emitter. An RF emitter is involved and located static near to one of the corner's center and on the top of the box. The radius size used is set at 0.3m. In this sense, the receiver and emitter are utilized to assist the robot to home in towards the signal source area and the box sensors are utilized to assist the robot to recognize and push the box. The robots and box are located on the ground with four walls which forms a square, closed environment; all the walls are 30mm in height whilst the ground covers an area of $1m^2$. From preliminary tests conducted on robustness [18], it was decided to position the E-puck robot with the back of the robot facing the emitter and located far from the signal source. Fig. 2, depicts the experimental setup used in the experiment and followed by the parameter setting used as tabulated in Table I.

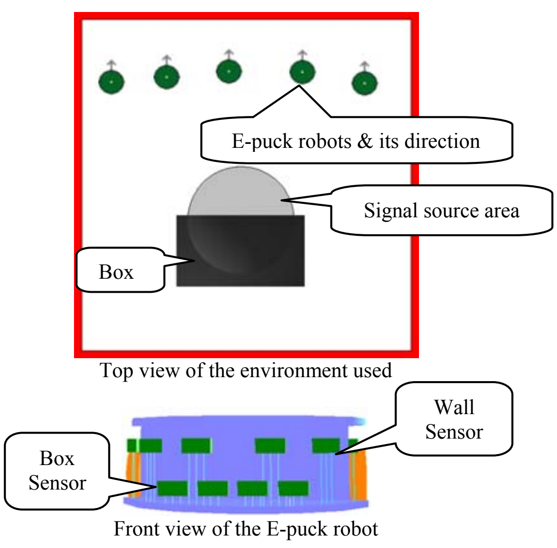


Fig. 2. Experimental setup used

TABLE 1
PARAMETER SETTINGS USED DURING EVOLUTION

Number of generation	100
Size of population	30
Simulation time steps	180 seconds
Crossover rate	70%
Mutation rate	1%
Number of hidden neurons	15 nodes
Number of repeated simulation	10
Random noise feature	Activated

Our previous study [18] has clearly showed that optimal robot controllers can be generated using the parameter settings as given above. Thus, we have decided to use the parameter setting as tabulated in Table I.

V. TEST FUNCTION USED

A number of preliminary tests had been carried out in order to obtain a suitable fitness function for the E-puck robot's collective box-pushing behavior. As a result, a combination of several criteria into one fitness function is proposed from the preliminary experimentation results. Basically, the fitness function comprises of a combination of the RF-localization behavior as well as the box-pushing behavior. Additionally, the fitness function also integrates obstacle avoidance behaviors, maximizing the average speed of the robot's wheels, maximizing the robot wheels speed, maximizing the robot RF-localization behavior and also maximizing the box pushing behavior. The formulation of the fitness function is as follows:

$$F_1 = \frac{1}{T}\sum_{t=0}^{T}(1-i)(W_L)(W_R)(V)(S)+(S)(B) \qquad (1)$$

$$0 \le (1-i),\ V,\ B,\ W_L,\ W_R \le 1$$

$$S = [1,50]$$

$$F_2 = \sum_{i=0}^{I} H_i \qquad (2)$$

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, B = highest box sensors value 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 E-puck robot is evolved with the initial orientation of facing away from the signal source. Thus, the controller always has to first evolve a behavior 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 E-puck robot must locate the source properly and attempt to stay in the source area if possible in order to track the box. Otherwise, the robot may not be able to recognize the correct orientation for pushing the box. Other components are used to avoid the robot from evolving to achieve the target through 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.

VI. Evolution Results

There were 10 trials conducted in this study and there were a total number of five robots involved in the entire conducted simulations. Each of the robots was evolved for the RF-localization behavior as well as box-pushing behavior using the elitist PDE-EMO algorithm. There was no failed evolution results obtained.

Nevertheless, most cases showed the average accumulated fitness score was very low even when 180 seconds were provided allowed for task completion during the evolutionary optimization processes. The results showed the robot always took most of the duration to explore for the box or signal source.

Some cases showed that the robot had learned to navigate successfully in avoiding from bumping into the walls. In other cases, the simulation results showed one or more robots had failed to track for the signal source with successfully during the evolution. Thus, not all of the robots were able to learn to home in towards the signal source successfully. Nevertheless, the collected results showed the optimum solutions were still able to be obtained with very few hidden neurons. Fig. 3, below depicts the evolution results collected for all of the robots involved in one of the ten trials.

Fig. 3, clearly shows the optimum solutions were able to be generated during the optimization process. The elitist PDE-EMO used was able to reduce the number of hidden neurons used by the robot controller. Some cases clearly showed the robots were capable to home in to the signal source and push the box towards the wall even with very few hidden neurons indeed, out of the permissible 15 hidden neurons. The evidence is further proven in Fig. 4, below. The graph depicts the global Pareto-frontier solutions obtained from all of the conducted simulations, respectively.

Fig. 4, clearly shows there were only two global Pareto solutions obtained in all of the conducted simulations. The graphs showed some robots were able to perform the required task successfully even using only one or two hidden neurons. Thus, we observed that the elitist PDE-EMO used was able to not only generate the required controllers for RF-localization as well as box pushing task but also using a highly minimalist controller architecture to achieve this complex robotic collective task behavior.

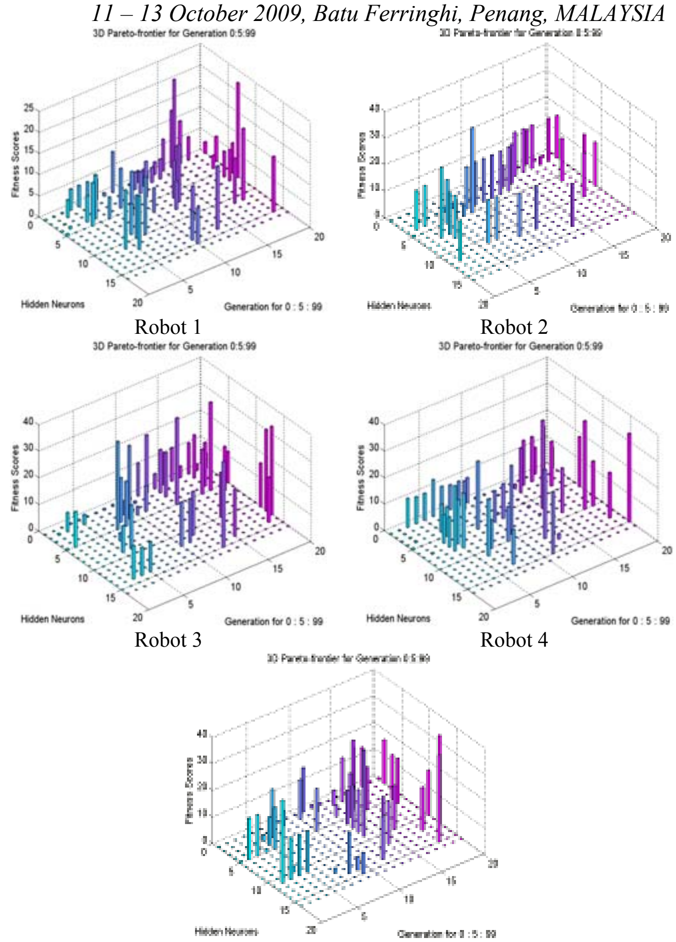


Fig. 3. A 3D Pareto for one of the generated trial results

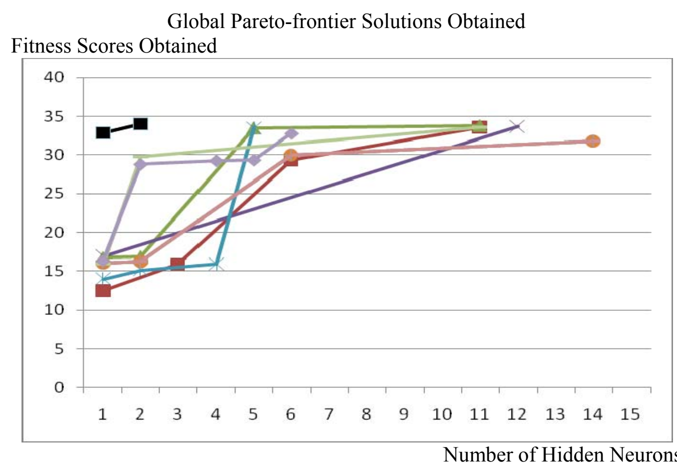


Fig. 4. Overall Pareto solutions obtained from all of the evolutionary runs. The solid black line depicts the global Pareto front obtained for this particular experiment.

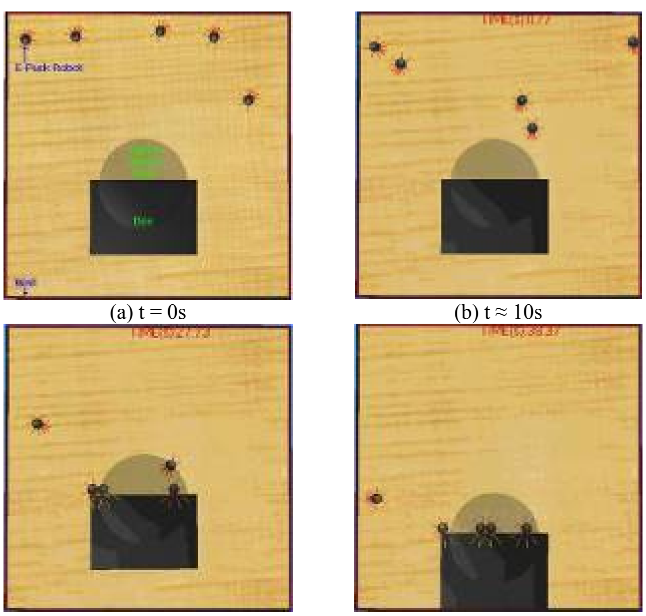
VII. Testing Results

Tests had been performed for all of the generated controllers. Each of the generated controllers had been tested five times in a similar environment as that used during evolution. The average time taken for the robots to home in towards the signal source and for the robots to push the box towards the wall has been tabulated. Furthermore, the average success rate obtained has also been recorded. The robots are expected to be capable of firstly exploring and homing in towards the RF signal source. Then, the robots are expected to be able to recognize the box and push the box towards the wall. Nevertheless, some testing results showed the robots learned some different, unpredicted behaviors. The average time taken and average success rate for all of the testing results are tabulated in Table II.

TABLE II
AVERAGE TESTING RESULTS OBTAINED

No. of Robots\Average	**Success Rate (%) in homing towards signal source**	**Time Taken (s)**	**Success rate (%) to push the box towards the wall**	**Time Taken (s)**
Only One Robot	13.33	10.36	0	Max
Two Robots	26.67	12.37	0	Max
Three Robots	97.67	13.54	96	43.44
Four Robots	93.33	13.78	56	37.42
Five Robots	88.67	11.68	30	30.67

Table II clearly shows, most of the robots were able to explore and home in towards the signal source successfully during testing phase with an average of less than 50 seconds. Furthermore, the robots were able to recognize the box and push the box towards the wall within the permissible period. However, the objective may not be achieved if only one or two robots were used during the testing phases, which clearly shows that a cooperative behavior between at three robots are required to complete the task successfully. Fig. 5, below depicts one of the successful runs obtained during testing phases.



(a) t = 0s (b) t ≈ 10s (c) t ≈ 30s (d) t ≈ 40s

Fig. 5. Testing results obtained

The robots achieved the objectives with different paths, different time steps, and different movements even with the same number of hidden neurons used. Some cases showed that there were a number of unpredicted behaviors learned by the robots even though the robots had never been explicitly evolved for such behaviors. The unpredicted behaviors are summarized and presented below.

The robot may remain static on the ground without performing any movement, particularly when the robot moves too near to the wall. This is probably due to the fact that the robot had learned to stop when it moves too close to the wall.

The robot may learn a robot-following behavior. Some of the robots moved together as a coordinated group but without performing the box pushing task. The robot may perform the robot-following behavior when other robots move near to that particular robot. Subsequently, both robots moved in circular, looping movements to follow and track each other.

The robot also learned a rather complex obstacle avoidance behavior. It is not surprising if a robot is capable to avoid from bumping to the sensed obstacle. However, it was noticed that in some cases, the robot chose to stop and not restart its movement when other robots moved too close to it. Hence, the robot had also learned to avoid from bumping to a sensed robot which is too close to it. Consequently, the robot would thus have failed to work together in pushing the box towards the wall since one of the robots had stopped and not restarted its movement.

The robot learned the RF-localization behavior but failed to learn the box pushing behavior. Some cases showed the robot was able to explore and track for the signal source successfully and stay in the signal source area as long as possible. However, some of the robots then chose to stop and do nothing in front of the sensed box. Subsequently, the robot may sense and follow the movement of the box, if other robots pushed the box toward the wall but do not actually contribute towards pushing the box itself.

Some robots learned to track for the box without RF signal source assistance. The robots may push the box once the box had been sensed. However, the robot was unable to push the box in the correct direction. Thus, the robot may push the box towards another undesired direction.

VIII. CONCLUSIONS

This investigation has showed that using the PDE-EMO algorithm, it was possible to obtain an optimum solution of a collective swarming behavior in a group of simulated robots for a box-pushing task with extremely few hidden neurons used in the controller. Furthermore, the testing results also showed that some of the evolved robots were robust to the environment and were able to successfully explore and home in towards to the signal source during early stages of the task duration. Nevertheless, not all of the evolved robots were able to push the detected box towards wall. Importantly though, the elitist PDE-EMO used was able to generate the required controllers for the collective swarming behavior of box-pushing as a group of multiple, cooperative robots that required only a minimalist controller architecture that had been successfully minimized.

ACKNOWLEDGMENT

This research work is funded under the ScienceFund project SCF0002-ICT-2006 granted by the Ministry of Science, Technology and Innovation, Malaysia.

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