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Modular System to Train and Test an Evolutionary Mobile Robot for Obstacle Avoidance

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نظام مضمن لتدريب واختبار روبوت متنقل تطوري لتجنب العوائق

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ABSTRACT

The field of evolutionary robotics is an interesting research area that deals with building neuro-controller systems by evolving individuals depending on the Darwinian principles of natural selection and survival of the fittest. It stems its importance from the need of building an intelligent robots that can learn to behave autonomously in unexpected situations in unknown and unpredictable environments.

Materials and Methods:

This paper produces Breeder Genetic Algorithm (BGA) as the tool in an evolutionary mobile robot system. BGAs share aspects with traditional GAs and evolution strategies. The controller is tested in the task of obstacles avoidance. Also the system is tested when two tasks are wanted to be modulated (Homing and obstacle avoidance).

Results:

It is shown that evolution enhances the performance of the system in terms of the average population fitness and the best individual fitness. It is also demonstrated that it is feasible to use several different modules that can cooperate to perform a given task.

Conclusion:

Different runs in the evolutionary systems can produce different solutions. Also, simulations can help making several important decisions concerning the initial parameters governing the evolutionary controller systems. The fitness function must properly be designed to yield the desired behavior. All the experiments exhibit an enhancement in the level of the average population fitness and best individual fitness across generations. Furthermore, the performance of evolved individuals can be evaluated subjectively by observing the trajectories and behavior made by the best controller developed by the BGA.

Key words: Modular System, Evolutionary Mobile Robotics, Breeder Genetic Algorithms and Artificial Neural Networks

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INTRODUCTION

The main objective of the field of mobile robotics is to build general purpose intelligent robot systems that can adapt to their environments and successfully perform complex tasks in unpredictable and changeable environments. Adaptation is acquired through ***learning*** to behave correctly in different situations, and to cope with changes in the environment. Learning can be made via using any known learning algorithm.

The field of mobile robotics has numerous contributions in the literature. All these contributions are try to build either a new direction in building robot control systems or trying to enhance some aspects of control systems that previously have been proposed. There are examples to approaches used explicitly written programs to control a robot (see for example [1, 2]). It will be focused on this review on the controllers that exploiting learning on "*Behavior Based Robotics*" (robots that concentrating on learning simple basic behaviors and learning to coordinate these behaviors to achieve a whole complex adaptive behavior).

The approach of ***evolutionary mobile robotics*** is mainly depends on evolving artificial neural networks (ANNs) to act as controllers in a mobile robot. Genetic Algorithms (GAs) are used to evolve appropriate internal parameters of robot neuro-controller. Each string in the population represents the parameters defining a neuro-controller for the robot. It is necessary to define a set of decoding rules for mapping the genotypic string into the neural network phenotype.

A series of experiments have been made at the endings of the 20^{th} century and the beginnings of the 21^{st} century to validate the direction ***evolutionary mobile robotics***. These experiments concentrated on different aspects of evolutionary robotic systems. For example:

1. Evolving neuro-controller systems for navigation and performing tasks[3, 4].
2. Adapting controllers to different changes in environment [5-8].
3. Studying the capability of evolutionary system to tackle complex tasks [9].
4. Presenting modular system architecture [10,11].
5. Studying perception aspect in evolutionary system [12].
6. Researching the competition in co-evolutionary robotics [13].
7. Integration of sensory-motor information over time [14].
8. Investigating the evolution of language in evolutionary robotics [15].

For more details about evolutionary robotics see [16].

A more recent studies that combine GAs and ANNs like [17] that is used as a controller aided by a low computational cost vision system. The controller uses the vision system and the ANN to detect and recognize obstacles found in the robot's path. If the object is in the controller's knowledge bank a previously registered deviation solution is applied. Otherwise, the GA must optimize a new route alternative. Also, in [18], the GA controller is fed by the obstacles' distances and the turning angle generated by the sensory network of humanoid robot to generate the next best feasible solution as the initial output. The initial output from GA and the obstacles' distances are the input to 4-layer ANN that provides the desired output. The desired output represents the turning angle for the robot. For more comprehensive review about researches in mobile robotics, see [19-24].

In the rest of the paper, the ANNs and GAs are briefly , the proposed main system is explained, the implementation and results are given, and finally discussions and conclusions are made.

MATERIALS AND METHODS

Neural networks and genetic algorithms are the main subjects that constitute the background that evolutionary mobile robot controllers stem from. ANNs are biologically motivated approaches to machine learning, inspired by ideas from neuroscience. An ANN is an *information processing system* that has certain performance characteristics in common with biological neural networks. ANNs have been developed as generalizations of mathematical models of human cognition or neural biology based on the assumptions that are[25]:

1. Information processing occurs at many simple elements called *neurons* (units, cells, or nodes).
2. Signals are passed between neurons over connection links called *synapses*.
3. Each connection link has an associated *weight*, which, in a typical neural net, multiplies the signal transmitted.
4. Each neuron applies an *activation function* (usually nonlinear) to its net input (sum of weighted input signals) to determine its output signal.

ANNs provide a method of representing relationships that are quite different from Turing machines or computers with stored programs. An ANN is characterized by [25]:

1. Its pattern of connections between the neurons (called its *architecture* which classified to: *single-layer* NN, *multi-layer* NN and *competitive-layer* NN).
2. Its method of determining the weights on the connections (called its *training* or *learning algorithm* which contain three types: *supervised*, *unsupervised* and *reinforcement* learning).
3. Its activation function (which have many types like: *binary step*, *binary sigmoid*, …,etc).

Breeder genetic algorithms (BGAs) share aspects with the ordinary genetic algorithms and with the evolutionary strategies, in the sense that they borrow from each of them some basic ideas. While in GAs selection is stochastic and meant to mimic -to some degree- Darwinian evolution, BGA selection is deterministic named truncation selection [26, 27]. The other strong resemblance between BGA and ESs, unlike GAs, BGAs use direct representation, that is, a gene is a decision variable (not a way of coding it) and its allele is the value of the variable. An

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immediate consequence is that the fitness function equals the function to be optimized. In addition, in a BGA chromosome there are no additional variables other than the problem variables, that is, the algorithm does not self-optimize any of its own parameters.

The strongest contact point of BGAs with ordinary GAs is the fact that both are mainly driven by recombination, with mutation are regarded as an important but background operator intending to reintroduce some of the alleles lost in the population. In the case of algorithms that make use of real-valued alleles, like BGA, mutation has to be seen as solution fine-tuner (for very small mutations) and as the main discovery force (for moderate ones) [27, 28].

BGA selection is named *truncation selection* [27, 28], a deterministic procedure driven by the so-called *breeding* mechanism which employed in livestock breeding. The breeding mechanism is an artificial selection method stating that only the best individuals - usually a fixed percentage τ of the total population size – are selected and enter the gene pool to be recombined and mutated, as the basis, to form a new generation.

Recombination is an operator combining the genetic material of $p\geq 2$ parents; the typical value is $p=2$. Let $x=(x_1, \ldots, x_n)$, $y=(y_1, \ldots, y_n)$ be two selected gene pool individuals, there are several variations have been proposed to build offspring $z=(z_1, \ldots, z_n)$ [27, 28]:

1. *Discrete Recombination (DR)*:

$$z_i \in \{x_i, y_i\} \quad \text{, chosen with equal probability.} \quad (1)$$

2. *Extended Line Recombination (ELR)*:

$$z_i = x_i + \alpha\,(x_i + y_i), \quad (2)$$

With $\alpha \in [-\delta, 1+\delta]$ chosen with uniform probability and $\delta \geq 0$ (typical $\delta=0.25$).

3. *Extended Intermediate Recombination (EIR)*:

$$z_i = x_i + \alpha_i\,(y_i + x_i), \quad (3)$$

With $\alpha \in [-\delta, 1+\delta]$ chosen with uniform probability. Same as ELR but a new α is chosen for each gene.

4. *Fuzzy Recombination (FR)*: this operator is more recent than the other three. The offspring z_i is obtained as:

$$\Pr(z_i) = \Pr(z_i)_{BT}\{e|y_i - x_i|, x_i, e|y_i - x_i|, y_i\} \quad (4)$$

Where BT is the bimodal triangular probability density function (*pdf*) with e=0.5.

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5. *Gene Pool Recombination* (*GPR*): The z_i is built out of x_i, y_i but this time the parents are selected for each i from the gene pool, DR, ELR or EIR can be used for each z_i.

Mutation is an asexual operator which applied to each gene with some probability $pr(\mu)=1/n$ so that, on average, one gene is mutated for each individual.

Two variations have been proposed [26] [27]:

1. *Discrete Mutation* (*DM*):

$$z_i = x_i + sign.\ Range_i.\ \delta \tag{5}$$

with:

$sign \in \{-1,+1\}$ chosen with equal probability,

$$range_i = p\ (r_i^{+}\ ,\ r_i^{-})\ ,\ p \in [0.1,\ 0.5] \text{ and} \tag{6}$$

$$\delta = \sum_{i=0}^{k-1} \lambda_i 2^{-i} \tag{7}$$

$\lambda_i \in \{0,1\}$ from a Bernouilli probability distribution.

2. *Continuous Mutation* (*CM*): Same as DM but with

$$\delta = 2^{-k\beta}\ ,\ \beta \in [0,1] \text{ with uniform probability.} \tag{8}$$

In this setting $(k \in N^{+})$ is a parameter originally related to the *precision*.

The basic idea behind evolutionary robotics goes as follows: An initial population of different artificial chromosomes, each encoding the control system (and sometimes the morphology) of a robot, are randomly created and put in the environment. Each robot (physical or simulated is then let free to act (move, look around, manipulate) according to genetically specified controller while its performance on various tasks was automatically evaluated. The fittest robots are allowed to reproduce (sexually or asexually) by generating copies of their genotypes with the addition of changes introduced by some genetic operators. This process is repeated for a number of generations until an individual is born which satisfies the performance criterion (fitness function) set by the experimenter [29].

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The Main System

The current work falls in the evolutionary robotics research area. This area is chosen for several reasons:

- It does not need the complete specification of the environment, robot, and behavior. Instead, it needs only general indication about the level of performance (fitness) of the current controller.
- The robot is self-adapting and self-organizing from its (proximal) point of view, rather than from the designer's (distal) point of view.
- It has experimentally proven the successfulness of this approach when it is transferred between several platforms and between simulated and real robots. All it needed when transferring is to adapt (by continuing evolution for several additional generations) to the new conditions.
- It can form a basis to study embodied and grounded agents that taking into account the physical aspects of the robot and the environment.
- It is a good tool to study, realize, and test artificial life forms and strategies to both understanding natural life phenomena and discovering new computational solutions to different problems.

In this work ***breeder genetic algorithm*** (**BGA**) is used as evolutionary tool to evolve the neuro-controllers and evaluate their performance. Figure (1) clarify the main structure of the modular control system adopted by the current study. The system contain two main modules: the control system module and the robot simulator module.

The main task that the controllers tackle is *obstacle avoidance*. This task is necessary to be learned by any autonomous robot since the robot must navigate and explore the world surroundings while performing its tasks. Also, the system is experimented when modulating two tasks: obstacles' avoidance and *homing*.

An NN is used to implement the control system. NNs are decided to be used since they resistant to noise, which is massively present in the robot/ environment interactions, and they are able to generalize their ability in new situations. Another reason is that NN can easily exploit various forms of learning during its life time, and this learning process may help speed up the evolutionary process.

Figure (2) indicates the architecture of the proposed controller system. It consists of a neural net with eight input neurons and two output neurons and two adjustable weights biased units. Each input unit is fully connected to all output units. The eight sensors of the agent are connected to the input units of the neural net. The output units produce four possible outputs each of which represent an action the agent may take at each situation. The actions are: turn left, turn right, go forward, and go backward. Each of these actions is actually determining the speed of the two wheels of the agent depending on the configuration of the world at the current moment.

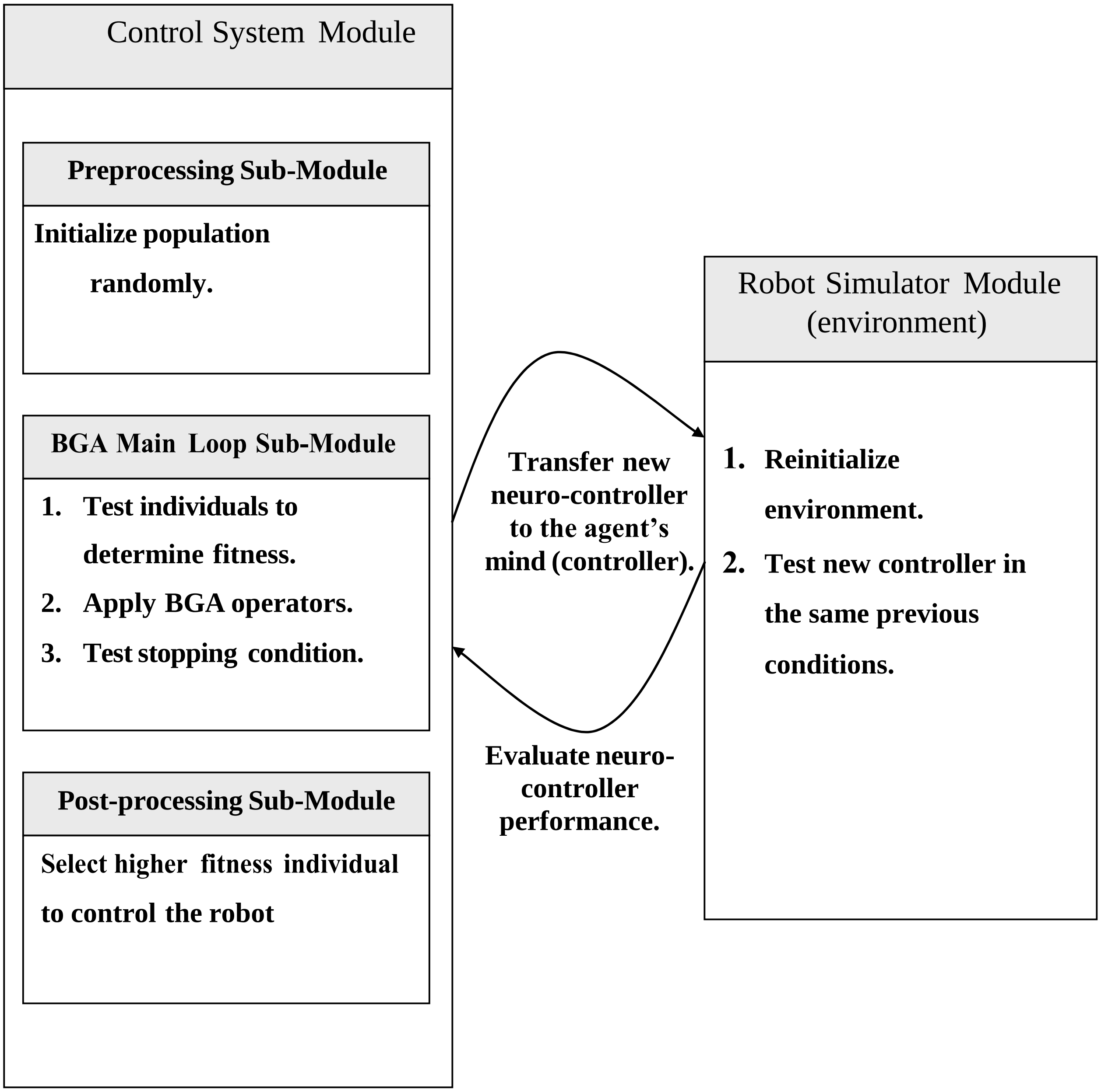

Figure 1: The general organization of the EMROV system.

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Each individual at the population is a controller which having the structure indicated in figure (2). The difference between one individual and other is in the weights that correspond to the connections between neurons. The vectors of weights that define individuals in the population are initialized randomly by assigning to each connection a small random real value. Each chromosome has a 18 gene represent a connection weight value between input neuron and output neuron. The population contains 100 individual. At the beginning of the life of each one individual, the weights defining such individual is copied into a weight matrix. Each controller is then evaluated by letting it freely to locomote in the environment and to behave according to the situations faced and collect fitness. Adjusting weights may be applied or not depending on a decision made by the experimenter. Adjusting weights means that learning is used in conjunction with evolution; otherwise the weights are only evolved.

The next stage is evaluation which is very important in the life of each individual since its life or death is decided depending on the level of performance it exhibit during its life duration. This stage actually involves several sub stages: sensing world, taking action, and evaluation. Sensing world sub stage is made as indicated in the algorithm 1 discussed above. The structure of the environment at the current moment (from the agent's point of view) leads to yielding an activation vector that will be the input vector to the neural net and this net in turn decides the action that will be taken at the current moment.

The neuro-controller receives the activation vector from the input neurons and at the each of the output neurons the following computation is occurred:

$$net_j = \sum_{i=1}^{n} (w_{ij} \times x_i) \qquad (9)$$

where w_{ij} is the weight of the synapse connecting *ith* input neuron and *jth* output neuron; n is the number of input neurons, and x_i is the *ith* input value. The net_j is then used to determine the activation of the *jth* output neuron using the binary step activation function:

$$f(x) = \begin{cases} 1 & if\ x \geq \theta \\ 0 & if\ x < \theta \end{cases} \qquad (10)$$

The output of the two output neurons constitute a two valued binary vector which represent four possible actions the agent may take at each situation. These actions are:

1. ***Go Forward***: This action is taken when $y_1=0$ *and* $y_2=0$.
2. ***Go Backward***: This action is taken when $y_1=1$ *and* $y_2=0$.
3. ***Turn Left***: This action is taken when $y_1=0$ *and* $y_2=1$.
4. ***Turn Right***: This action is taken when $y_1=1$ *and* $y_2=1$.

At the end of each action, the evaluation sub-stage begins where the fitness of each individual is updated according to the following formula:

$$fitness = fitness + v \times (\sqrt{1-\Delta v}) \times (1-xj) \qquad (11)$$

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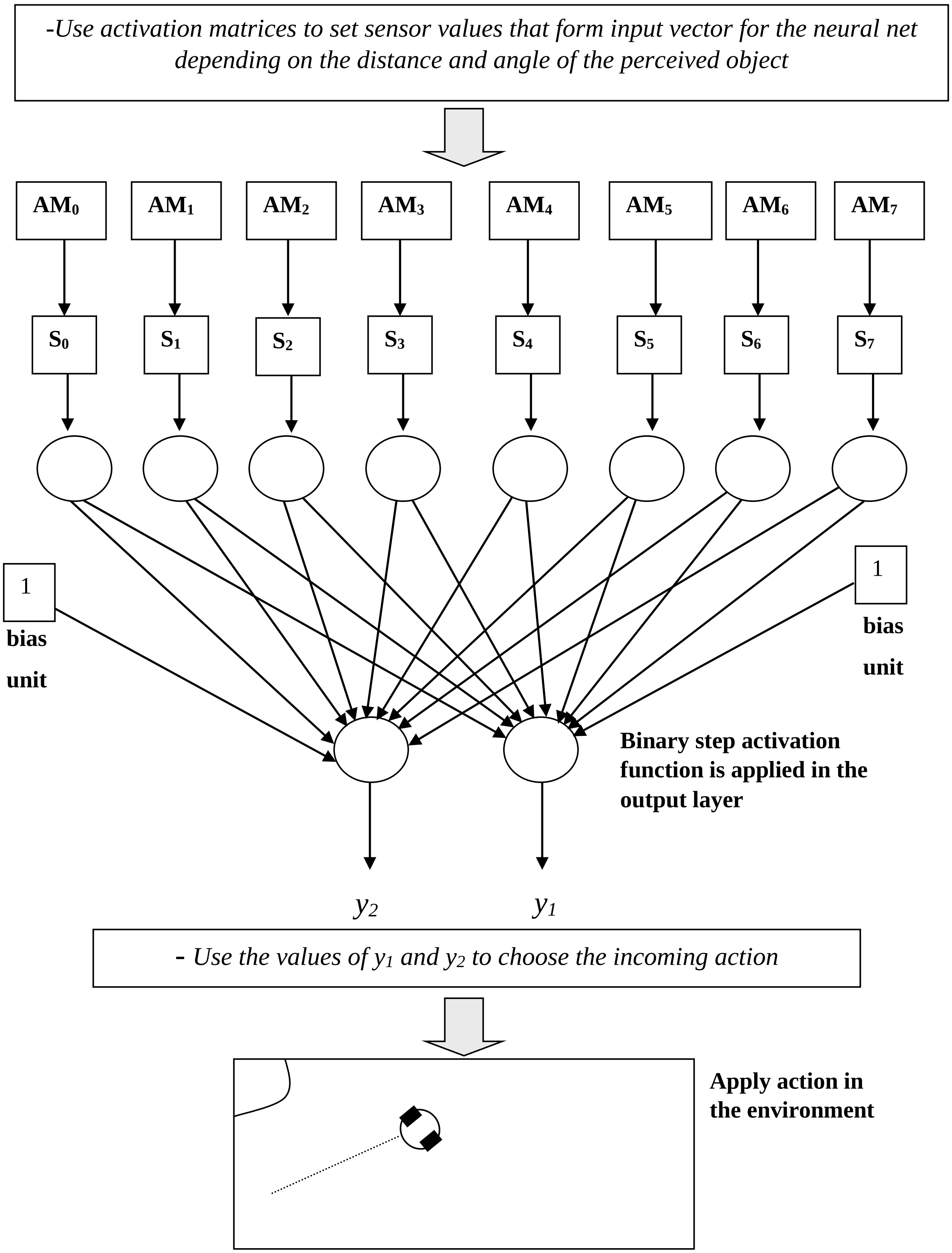

Figure 2: The structure of the controller system. Each of the sensors is connected to one of the input neurons and each output neuron is defining one possible action. AM_i is the ith activation matrix and S_i is the *ith* sensor activation.

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where :

$$\Delta v = \frac{|vLeft + vRight|}{(2 \times vMax)} \qquad (0 \le \Delta v \le 1) \qquad (12)$$

$$v = \frac{|vleft| + |vright|}{(2 \times vMax)} \qquad (0 \le v \le 1) \qquad (13)$$

vLeft: is the velocity of left motor.
vRight: is the velocity of the right motor.
vMax: is the highest velocity that the motors can move according to.
x_j: is the highest activation value in the current vector of activation sensors. Usually the values of the activation sensors are ranged between 0 and 1023, but in our case they are normalized to be in the [0, 1] interval.

v is a measure of the average rotation speed of the two wheels, Δv is the algebraic difference between the signed speed values of the two wheels (positive one direction and negative the other) transformed into positive values.

This fitness function is chosen because it encourages motion, straight direction and low sensor activation. Without the first component, a robot standing far from a wall would achieve maximum fitness. Without the second component in the fitness function, the maximum fitness could be easily achieved by fast spinning in the same place (wheels turning at maximum speed in opposite directions) far from walls. Without the third component, evolution would develop robots moving straight (frontally or backward) at maximum speed until they crashed against a wall.

At the end of individual's life, the fitness is averaged over all life steps to get the final evaluation of the individual such that $0 \le \text{fitness} \le 1$, as indicated in the algorithm.

The fitness function is considered as an automatic way of evaluating individuals. This implies that the fitness function should compute only information that is available to the robot through its internal or external sensors. The fitness function indicated in equation 4.3 is an example of that, where it uses information that is available to the robot through its infra-red sensors and its internal sensors of the state of the motors.

THE MODULAR MODE

To test the performance of the system when an additional task is performed in addition to obstacle avoidance, the task of *homing* is considered. To simulate this task the robot is equipped with a simulated battery that lasted after a pre-specified action steps (150 step). A simulated battery charger, having a different color, is put in the left upper corner under a light source. To charge the battery, the robot must pass through the recharging area. Additional sensor is put underneath the robot to measure the floor brightness. When the robot is happened to pass through

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the recharging area the battery is immediately filled and the age of the robot increased 150 actions.

A module is added whose task is to lead the robot to the recharging area when its energy minimized. A simple switching procedure is also added to switch between the *obstacles' avoidance mode* to the *modular mode*. In the obstacle avoidance mode, the robot is navigate and avoid obstacles, while in the modular mode, which is selected when the energy in the simulated battery reached low levels, the robot directs its movement to the recharging area and at each step it decides to select either obstacle avoidance behavior or goal directed movement, depending on the sensation of the robot at that moment. The light source helps the robot to know the location of the recharging area, where a light following procedure is implemented to reach recharging area that sensed by the underneath sensor. When the underneath sensor receive a different value the battery is recharged. The algorithm listed in figure (3) gives the outline of the modular mode behaviour.

Algorithm 1*: Modular mode;*
Input*: level of battery energy;*
Output*: switching behavior;*
Begin*:*
    While *life* ***do***
        Check battery level;
        If *energy minimized*
        1. *Switch to the modular mode;*
        2. ***While*** *the battery not filled* ***do***
            a. *Sense surroundings;*
            b. ***If*** *obstacle faced, avoid it;*
            c. ***Else*** *direct the robot movement to the area having greater light intensity measure;*
            d. *Check the value of the underneath sensor;*
            e. ***If*** *changed then fill the battery immediately;*
        3. ***End (do)***
        Else
        Switch to the obstacle avoidance mode;
    End*(do)*
End*.*

Figure 3: Modular mode algorithm.

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RESULTS AND DISCUSSION

Table 1 indicates the parameters and settings that is used in the experiments at the implementation phase.

When the system is traced during implementation, several types of individuals are noticed that exhibit the following undesired behaviors:

1. Spinning at the same location.
2. Oscillation between two adjacent cells.
3. Individuals that still constant in the same cell without changing direction or position.

These types of individuals are "killed" after a pre-specified number of life-steps (10 life-steps are specified) if they do not improve their behavior. According to the fitness function used, individuals of type 1 and two are tend collect a good credits if they take the chance to "live" to the maximum number of life-steps. The "age" of individual is taken into account when evaluating its performance by multiplying its fitness by the following term:

$$\text{Fitness} = \text{fitness} \times (\text{age} / \text{maximum life-steps}) \qquad (14).$$

This decreases the fitness of short age individuals and increases the fitness of long age individuals.

Three environments were used to test the system performance:

1. *env1*: A simple environment with only borders as obstacles and a lamp on the upper left corner(see figure 4).
2. *env2*: An environment having seven circular obstacles that made a line in the middle of the environment (see figure 5).
3. *env3*: An environment having six circular obstacles that made two lines in the environment (see figure 6).

Table 2 gives the layout of all experiments and there parameters and the corresponding figures and graphs.

Several sets of experiments were performed, these are:

Set1*:* Investigating the feasibility and the degree of successfulness of the system in several different environments.

Set2*:* Investigating the effect of combining the obstacle avoidance task with another task (homing) on the behavior of the evolved individuals.

Four run replications are used for each experiment and the best individual from the four runs is tested in the environment. 500 life steps for each individual are performed during evaluation stage.

The discussions concerning each of the sets of experiments is given below:

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1. **Set 1 experiments:**
    a. The experiments indicate the successfulness of the controller system to evolve individuals exhibit the desired behavior. The evolved individuals can avoid obstacles while navigating.
    b. The 8 infra-red sensors give a good and sufficient specification of the surrounding environment that enable the robot to behave properly after evolution.
    c. From comparing the behavior of the robot before and after evolution, we can conclude that the fitness function used (equation 11) is a good tool to automatically evaluate population individuals.
    d. The evolutionary process succeeded to evolve good individuals to all environments; especially notice env3 where the robot can even find a trajectory between the two sets of obstacles.
    e. The evolutionary process can evolve the population to a better levels of fitness performances and can discover a better individuals as evolution progresses.
2. **Set 2 experiments:**
    a. This set contains only one experiment that shows the successfulness of modulating two behaviors.
    b. The evolutionary system discovers individual that can navigate and periodically directs its movement to the recharging area to recharge its battery.

Table 1: Parameters and settings used in the experiments.

BGA Parameters	
size of population	100
length of chromosome	18
number of generations	100
maximum age of each individual	500
initial population gene initialization formula	(random(100)/10000)
number of elitist individuals (q)	1
percentage of the population best individuals that would contribute in the next generation (τ)	25%
selection type	truncation selection
recombination type	EIR
mutation type	CM
NN Parameters	
network type	single - layer feed- forward network
activation function type	binary step function
threshold (θ)	0

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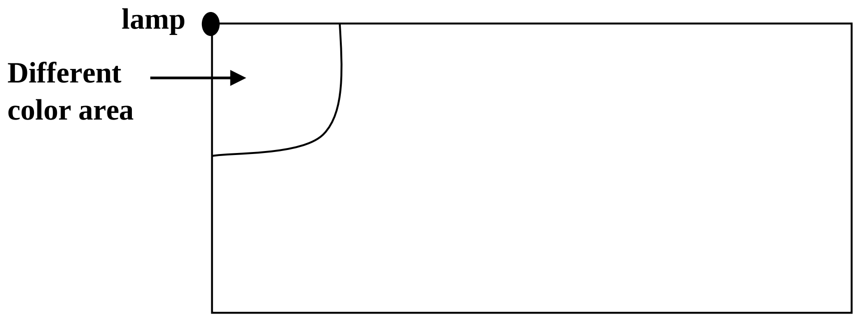

Figure 4: *env1*, a simple environment with borders only obstacles.

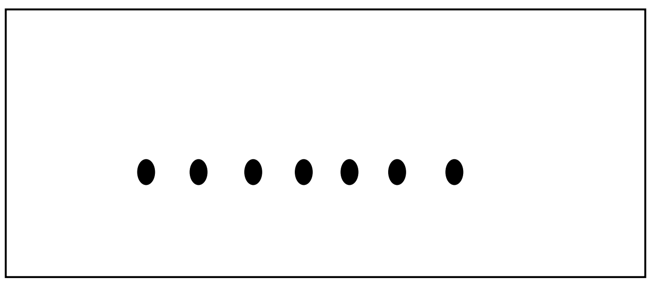

Figure 5: *env2*, an environment with 7 circular obstacles in addition to borders.

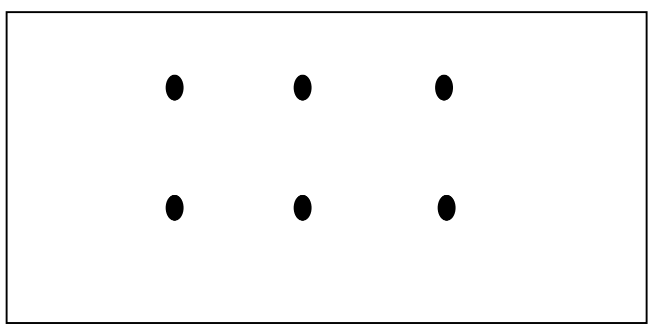

Figure 6: *env3*, an environment with 6 circular obstacles in addition to borders.

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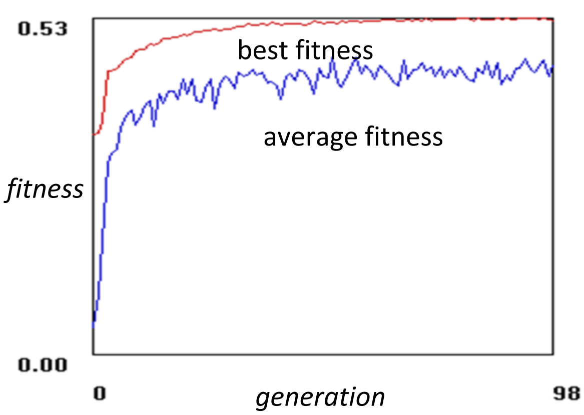
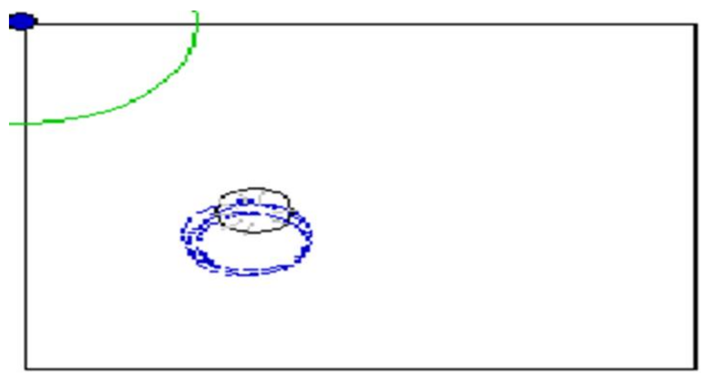
Table 2: Experimental layout.

Obstacle Avoidance Mode (one task)					
Set1 experiments					
Experiment no.	Environment	Run replications	Life steps	No. of sensors	Corresponding figures
1	*env1*	4	500	8	7, a, b, c
2	*env2*	4	500	8	8, a, b, c
3	*env3*	4	500	8	9, a, b, c
Modular Mode (two tasks)					
Set2 experiments					
Experiment no.	Environment	Run replications	Life steps	No. of sensors	Corresponding figures
1	*env1*	4	500	8	10, a, b, c

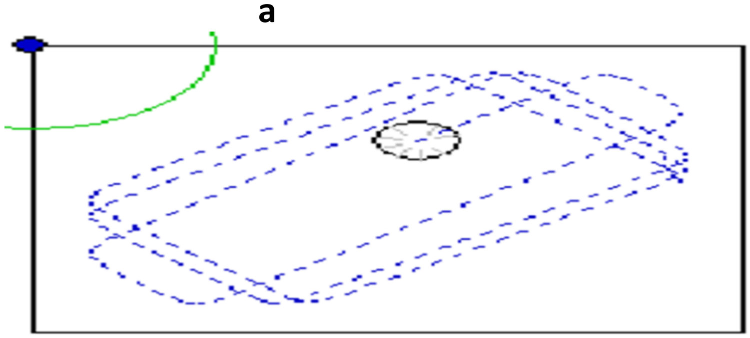
Set1 Experiments (testing the performance of the system- 8 sensor robot



a

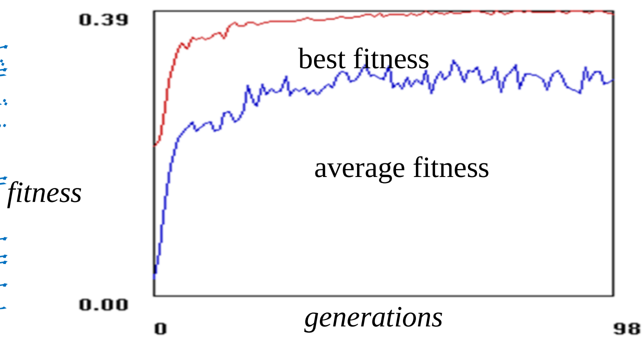


b

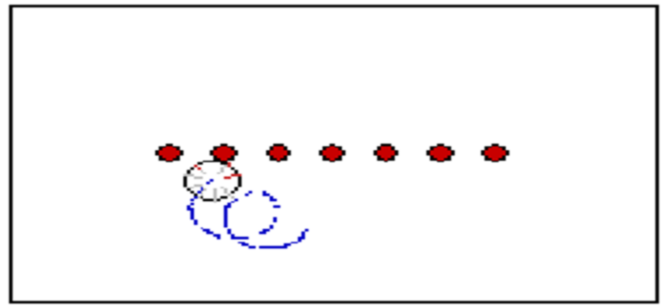


c

Figure 7: 8-sensor robot is trained to explore *env1*. **a.** the fitness of the best individual and the average population fitness across generations, **b.** the behavior of the best individual before evolution, and **c.** the behavior of the best individual after evolution.



a



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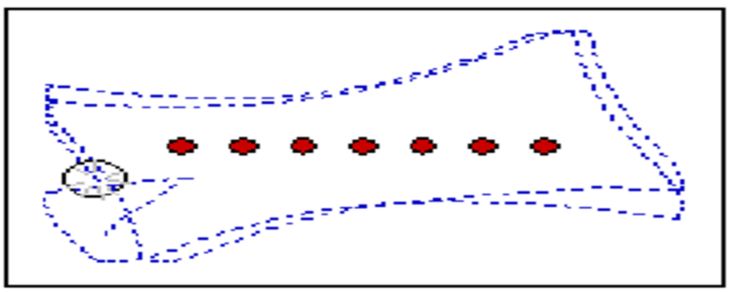
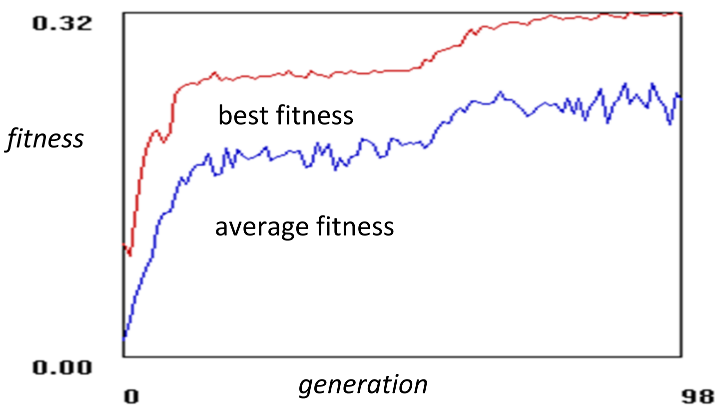
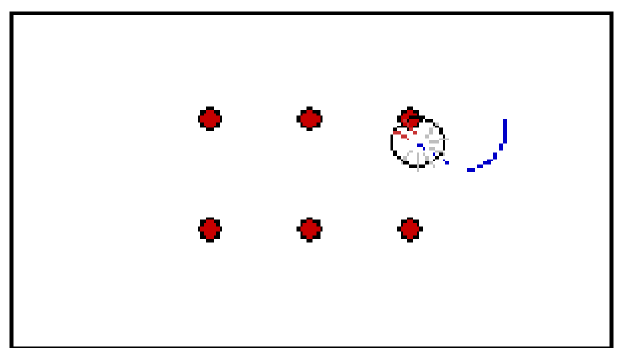


c

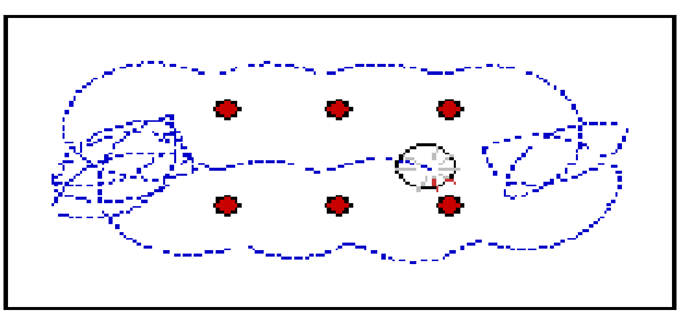
Figure 8: 8-sensor robot is trained to explore *env2*. **a.** the fitness of the best individual and the average population fitness across generations, **b.** the behavior of the best individual before evolution, and **c.** the behavior of the best individual after evolution.



a



b



c

Figure 9: 8-sensor robot is trained to explore *env3*. **a.** the fitness of the best individual and the average population fitness across generations, **b.** the behavior of the best individual before evolution, and **c.** the behavior of the best individual after evolution.

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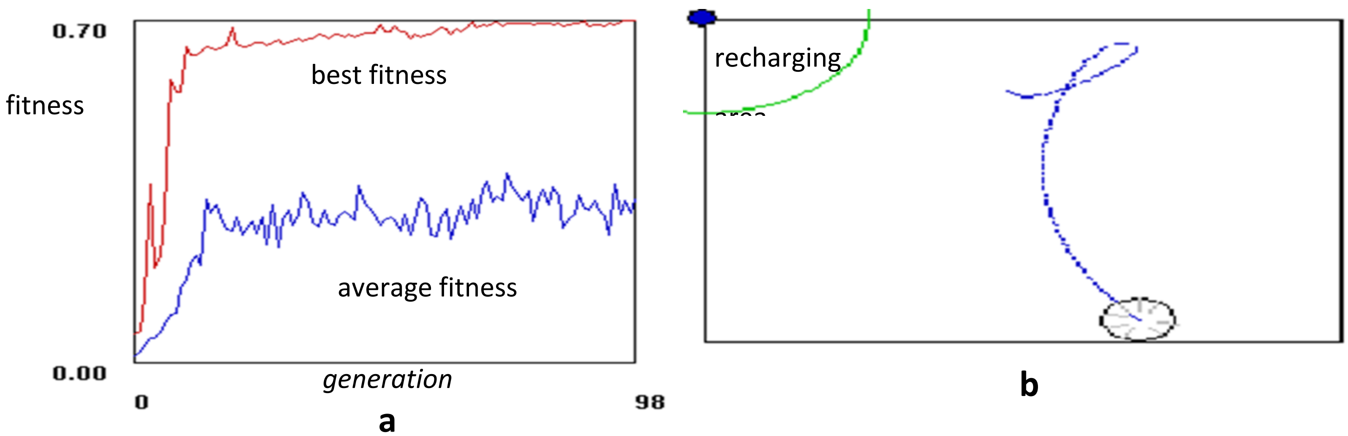
Set2 Experiments (testing the performance of the system- two tasks modulated)



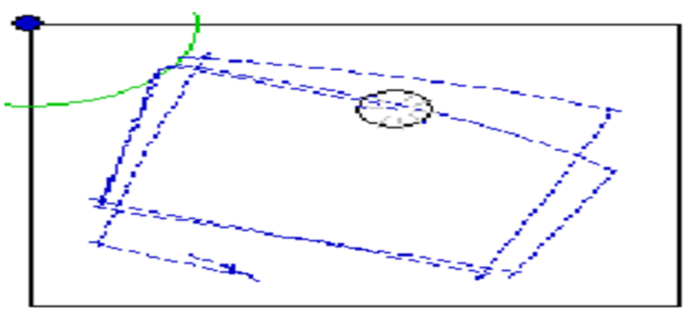


Figure 10: 8-sensor robot is trained to explore *env1* and to recharge the simulated battery. **a.** the fitness of the best individual and the average population fitness across generations, **b.** the behavior of the best individual before evolution. **c.** the behavior of the best individual after evolution.

CONCLUSIONS

1. Different runs in the evolutionary systems can produce different solutions, for the same problem, with different performances, as it is noticed in the experiments done. It is more suitable to develop the evolutionary process in simulation to replicate several runs for the same experiment.
2. Simulations can also help making several important decisions concerning the initial parameters governing the evolutionary controller systems like the structure of the NN, the initial weights matrix, the structure of the environment, the type and number of sensors, etc.
3. The fitness function must properly be designed. The function used in eq. 11 encourages motion, straight direction, and obstacle avoidance. The first component, V, is maximized by wheel speed. The second component, $(\sqrt{1-\Delta v})$, is maximized by straight motion. The third component, $(1-x_i)$, is maximized by obstacle avoidance. All the three components are necessary to yield the desired behavior.
4. The fitness function can be considered as objective metric to measure the performance of the system. All the experiments exhibit an enhancement in the level of the average population fitness and best individual fitness across generations. Furthermore, the performance of evolved individuals can be evaluated subjectively by observing the trajectories and behavior made by the best controller developed by the BGA.

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Conflict of interests.

There are non-conflicts of interest.

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الخلاصة

يعد مجال الروبوتات التطورية مجالًا بحثيًا مثيرًا للاهتمام يتعامل مع بناء أنظمة التحكم العصبي من خلال تطوير الأفراد اعتمادًا على المبادئ الداروينية للانتقاء الطبيعي والبقاء للأصلح. وتنبع أهميتها من الحاجة إلى بناء روبوتات ذكية يمكنها تعلم التصرف بشكل مستقل في المواقف غير المتوقعة في بيئات غير معروفة ولا يمكن التنبؤ بها.

طرق العمل:

في هذا البحث تم تجربة الخوارزمية الجينية الموجهة (BGA) لتكون الأداة التطورية في نظام الروبوت المتحرك التطوري. تشترك BGAs في الجوانب مع GAs التقليدية واستراتيجيات التطور. يتم اختبار وحدة التحكم في أداء مهمة تجنب العوائق. كما يتم اختبار النظام عند الحاجة إلى تضمين مهمتين. تم اختيار مهمة العودة لإعادة الشحن ليتم تضمينها مع مهمة تجنب العوائق.

الاستنتاجات:

عند تنفيذ البرنامج في الأنظمة التطورية عدة مرات فإن ذلك يؤدي الى انتاج حلول مختلفة. كما يمكن أن تساعد عمليات المحاكاة في اتخاذ العديد من القرارات المهمة المتعلقة بالمعلمات الأولية التي تحكم أنظمة التحكم التطورية. يجب أن تكون دالة الصلاحية مصممة بشكل صحيح لتحقيق السلوك المطلوب. تظهر جميع التجارب تحسنا في مستوى متوسط صلاحية المجتمع وكذلك صلاحية الفرد الافضل عبر الأجيال. أيضًا، يمكن تقييم أداء الأفراد المتطورين بشكل شخصي من خلال مراقبة مسارات وسلوك اللذين اظهرتهما أفضل وحدة تحكم طورتها BGA.

الكلمات المفتاحية:

النظام المضمن، الروبوتات المتنقلة التطورية، الخوارزميات الجينية الموجهة، الشبكات العصبية الاصطناعية

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