

EVOLUTIONARY MULTI-OBJECTIVE OPTIMIZATION FOR AUTOMATIC SYNTHESIS OF ARTIFICIAL NEURAL NETWORK ROBOT CONTROLLERS

Jason Teo

School of Engineering and Information Technology
Universiti Malaysia Sabah
Locked Bag No. 2073, 88999
Kota Kinabalu, Sabah
Malaysia.
email: jtwteo@ums.edu.my

ABSTRACT

This paper investigates the use of a multi-objective approach for evolving artificial neural networks that act as controllers for the legged locomotion of a quadrupedal robot simulated in a 3-dimensional, physics-based environment. The Pareto-frontier Differential Evolution (PDE) algorithm is used to generate a Pareto optimal set of artificial neural networks that optimize the conflicting objectives of maximizing locomotion behavior and minimizing neural network complexity. In this study, insights are provided on how the controller generates the emergent walking behavior in the creature by analyzing the evolved artificial neural networks in operation. A comparison between Pareto optimal controllers showed that ANNs with varying numbers of hidden units resulted in noticeably different locomotion behaviors. It was also found that a much higher level of sensory-motor coordination was present in the best evolved controller.

Keywords: *Evolutionary robotics, evolutionary multi-objective optimization, embodied cognition, evolutionary artificial neural networks, artificial life.*

1.0 INTRODUCTION

Research in the area of embodied cognition generally falls into two categories: (1) the evolution of controllers for creatures with fixed [4,9] or parameterized morphologies [11,15], and (2) the evolution of both the creatures' morphologies and controllers simultaneously [8,13,18]. Some work has also been carried out in evolving morphology alone [6] and evolving morphology with a fixed controller [12]. Related work using mobile robots have also shown promising results in robustness and the ability to cope with changing environments by evolving plastic individuals that are able to adapt both through evolution and lifetime learning [7].

However, considerably little has been said about the role of controllers in the artificial evolution of such creatures. It has been noted that the potential of designing more complex artificial systems through exploitation of sensory-motor coordination remains largely unexplored [14]. As such, there is currently a lack of understanding of how the evolution of controllers affects the evolution of morphologies and behaviors in physically simulated creatures. It remains unclear what properties of an artificial creature's controller allow it to exhibit the desired behavior. A better understanding of controller complexity and the dynamics of evolving controllers should pave the way towards the emergence of more complex artificial creatures with more complex morphologies and behaviors.

In this paper, the use of a multi-objective approach in evolving controllers for a fixed morphology artificial creature is investigated. By generating a Pareto-frontier consisting of multiple ANNs with differing locomotion capabilities and varying architecture complexities, a comparison of controller size against behavior fitness can be made. This study will hopefully provide some insights into the architectural complexity of controllers required for generating walking behaviors in 3D, physically simulated creatures. A further advantage of using a multi-objective approach for artificial evolution is that genetic diversity is maintained naturally during the course of the evolutionary process. It has been observed that loss of genetic diversity causes problems in the artificial evolution of virtual creatures [10]. In this paper, the Pareto-frontier is used to evolve a Pareto optimal set of artificial neural networks (ANNs) [1,2] that act as controllers for the quadruped creature.

2.0 METHODS

2.1 Evolving Artificial Neural Networks

Traditional learning algorithms for ANNs such as *backpropagation* (BP) usually suffer from the inability to escape from local minima due to their use of gradient information. Evolutionary approaches have been proposed as an alternative method for training ANNs. A thorough review of EANNs can be found in [18]. Abbas et. al. [3] first introduced the Pareto-frontier Differential Evolution (PDE) algorithm, an adaptation of the *Differential Evolution* algorithm introduced by Storn and Price [16] for continuous optimization problems, for multi-objective problems. The MPANN algorithm [1] combines PDE with local search for evolving ANNs and was found to possess better generalization whilst incurring a much lower computational cost [2]. In this paper, PDE is used to simultaneously evolve the weights and architecture of the ANN.

2.2 Representation

Similar to [1,2], the chromosome is a class that contains one matrix (denoted as Ω) of real numbers representing the weights of the artificial neural network and one vector (denoted as ρ) of binary numbers (one value for each hidden unit) to indicate if a hidden unit exists in the network or not; that is, it works as a switch to turn a hidden unit on or off. The sum of all values in this vector represents the actual number of hidden units in a network. This representation allows simultaneous training of the weights in the network and selecting a subset of hidden units. The morphogenesis of the chromosome into the ANN is depicted in Fig.1.

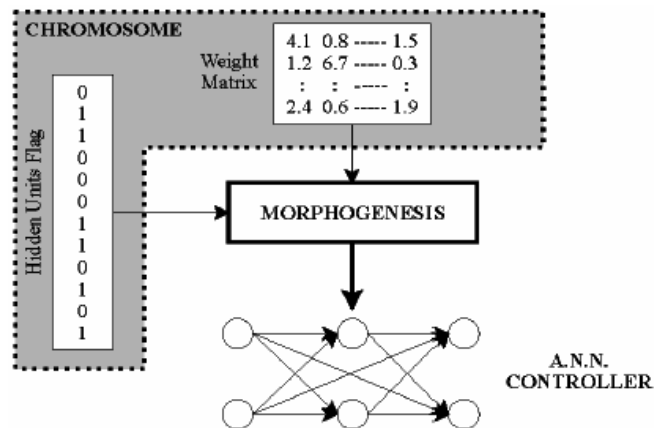


Fig. 1: The representation used for the chromosome.

2.3 The PDE algorithm

This study comprises of a multi-objective problem with two objectives, that is to: (1) maximize the horizontal distance traveled by the creature from its initial starting position, and (2) minimize the number of hidden units. The Pareto-frontier of the tradeoff between the two objectives will have a set of networks with different number of hidden units and different locomotion behaviors. An entire set of controllers is generated in each evolutionary run without requiring any further modification of parameters by the user. The PDE algorithm for evolving ANNs consists of the following steps as depicted in Table 1.

Table 1 - The PDE algorithm for evolving ANNs

1. Create a random initial population of potential chromosomes or solutions. The elements of the weight matrix Ω , 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 randomly generated number according to a uniform distribution between $[0,1]$; otherwise 0.
2. Repeat
 - a. Evaluate the individuals or solutions in the population and label those who are non-dominated according to the two objectives: (1) maximize the horizontal distance traveled by the creature from its initial starting position, and (2) minimize the number of hidden units.
 - b. If the number of non-dominated individuals (a solution is considered to be non-dominated if it is optimal in at least one objective) is less than three, repeat the following 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):
 - i. Find a non-dominated solution among those who are not labelled.
 - ii. Label the solution as non-dominated.
 - c. Delete all dominated solutions from the population.
 - d. Repeat
 - i. Select at random an individual as the main parent α_1 , and two individuals, α_2 , α_3 as supporting parents.
 - ii. **Crossover** with some uniform (0,1) probability, do

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

$$\rho_h^{child} \leftarrow 1 \quad \text{if} \quad (\rho_h^{\alpha_1} + N(0,1)(\rho_h^{\alpha_2} - \rho_h^{\alpha_3})) \geq 0.5; \quad 0 \quad \text{otherwise} \quad (2)$$

otherwise

$$\omega_{ih}^{child} \leftarrow \omega_{ih}^{\alpha_1} \quad (3)$$

$$\rho_h^{child} \leftarrow \rho_h^{\alpha_1} \quad (4)$$

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

$$\omega_{ho}^{child} \leftarrow \omega_{ho}^{\alpha_1} + N(0,1)(\omega_{ho}^{\alpha_2} - \omega_{ho}^{\alpha_3}) \quad (5)$$

otherwise

$$\omega_{ho}^{child} \leftarrow \omega_{ho}^{\alpha_1} \quad (6)$$

where each weight in the main parent, α_1 is perturbed by adding to it a ratio, $F \in N(0,1)$, of the difference between the two values of this variable in the two supporting parents, α_2 , α_3 . At least one variable must be changed. One child is created for every crossover operation. The subscripts i , h , and o refer to the input, hidden and output layers of the ANN respectively.
 - iii. **Mutate** with some uniform (0,1) probability, do

$$\omega_{ih}^{child} \leftarrow \omega_{ih}^{child} + N(0,mutation_rate) \quad (7)$$

$$\omega_{ho}^{child} \leftarrow \omega_{ho}^{child} + N(0,mutation_rate) \quad (8)$$

$$\rho_h^{child} \leftarrow 1 \quad \text{if} \quad \rho_h^{child} = 0, \quad 0 \quad \text{otherwise} \quad (9)$$
 - e. Until the population size is M .
3. Until maximum number of generations is reached.

2.4 The Simulation Model

The simulation is carried out in a physically realistic environment which allows for rich dynamical interactions to occur between the creature and its environment. This in turn enables complex walking behaviors to emerge as the creature evolves the use of its sensors to control the actuators in its limbs through dynamical interactions with the environment [17]. In a dynamic environment, physical properties such as forces, torques, inertia, friction, restitution and damping need to be incorporated into the artificial evolutionary system. The Vortex physics engine [5] was employed to generate the physically realistic artificial creature, shown in Fig. 2, and its environment. The artificial creature is a basic quadruped with 4 short legs. Each leg consists of an upper limb connected to a lower limb via a hinge (one degree-of-freedom) joint and is in turn connected to the torso via another hinge joint. It has 8 joint angle sensors (x_1 - x_8) corresponding to each of the hinge joints, 4 touch sensors (x_9 - x_{12}) corresponding to each of the 4 lower limbs of each leg, and 8 actuators (y_1 - y_8) representing the motors that control each of the 8 articulated joints of the creature. The mass of the torso is 1kg and each of the limbs is 0.5kg. The torso has dimensions of 4 x 1 x 4m and each of the limbs has dimensions of 1 x 1 x 1m. The hinge joints are allowed to rotate between -1.57 to 0 radians for limbs that move counter-clockwise and 0 to 1.57 radians for limbs that move clockwise from their original starting positions. Each of the hinge joints is actuated by a motor that generates a torque producing rotation of the connected body parts about that hinge joint. Fig. 3 illustrates the setup of the creature's central nervous system.

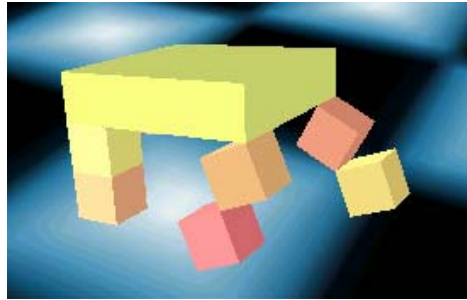


Fig. 2:- Screen capture of quadruped in the simulation environment.

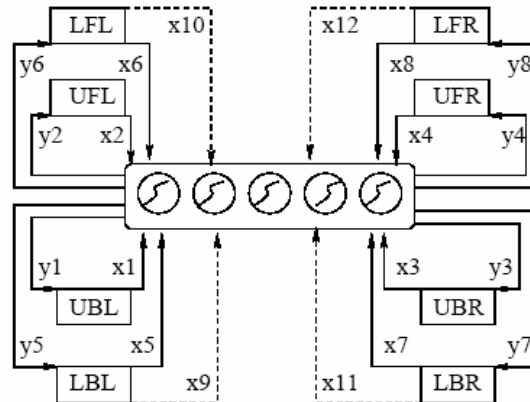


Fig. 3: The quadruped's central nervous system. The three letter abbreviations identify each of the 8 different limbs. The first letter denotes (U)pper or (L)ower, the second denotes to (F)ront or (B)ack, and the third denotes (R)ight or (L)eft.

3.0 EXPERIMENTAL SETUP

A total of 480 evolutionary runs were conducted with varying population sizes, crossover rates, and mutation rates while fixing the fitness evaluation window to 500 timesteps. The crossover rate used were 0, 0.1, 0.2, 0.5 and 1 and the mutation rates used were also 0, 0.1, 0.2, 0.5 and 1 (the evolutionary setup with a crossover rate of 0 and a mutation rate of 0 was omitted since this setup does not generate any variability at all in the population). The

maximum number of hidden units permitted in evolving the artificial neural network was fixed at 15 nodes. Each experimental setup was repeated using 10 different seeds to allow the artificial evolution to commence from different starting points in the search space. Two populations with 20 and 30 individuals were evolved for 30 and 20 generations respectively. The total number of objective evaluations was kept constant at 600 to enable a fair comparison between the effect of the two population sizes.

4. RESULTS AND DISCUSSION

4.1 Evolutionary Parameters

Overall, there did not appear to be any obvious differences in the range and quality of the evolved controllers between population sizes of 20 and 30. Both produced a considerably similar quality of locomotion behaviors although a larger population size did seem to produce controllers that were slightly better in terms of average locomotion fitness. There were 12 different combinations of crossover and mutation rates with a population size of 30 in which the best average locomotion fitness exceeded 2.5m as compared to only 8 with a population size of 20. Both also generated a relatively similar spread of locomotion behaviors although again a larger population size did seem to produce more varied genotypes in terms of the number of hidden units that were used in the ANN. There were 12 different combinations of crossover and mutation rates with a population size of 30 that produced 11 or more different ANN architectures compared to only 10 with a population size of 20. As such, there is a very slight advantage in using a larger population size in terms of quality and spread of the locomotion behaviors.

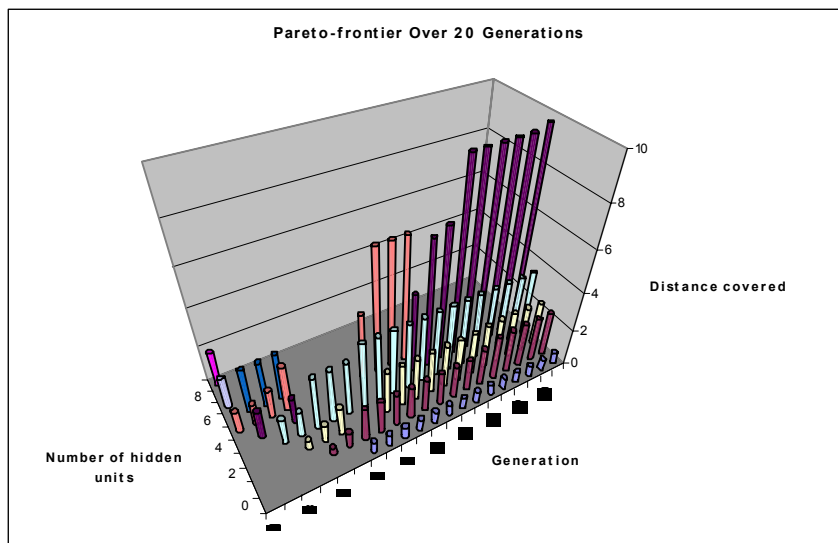


Fig. 4: Pareto-frontier over 20 generations.

The best evolved controller in terms of the maximum horizontal distance moved from its initial position had a comparatively simple architecture with only 4 hidden units. This result was achieved with an evolutionary run that had similarly low crossover and mutation rates of 0.2 with a population size of 30 over 20 generations. To enable an analysis of the evolutionary dynamics that generated the best controller, the Pareto-frontier of this particular setup is reported at each generation and is depicted graphically in Fig. 4. Overall, it is generally very hard for larger controllers with more hidden units to survive due to the strong evolutionary pressure of minimizing ANN complexity. As a result, larger controllers find it hard to compete with smaller controllers in trying to maximize the horizontal distance traveled by the quadruped.

4.2 Evolved Coordination and Synchronization Behaviors

In this next subsection, we analyze the 5 Pareto optimal controllers in operation. To conduct these analyses, the best evolved ANNs described in the previous section were used individually to control the quadruped and the simulation period was extended to 5000 timesteps. This enables analysis of not only the evolved behavior but also its behavior

beyond the fitness evaluation window. Table 2 lists the correlation coefficients between the joint angles of the respective limbs of the creature in motion over 5000 timesteps.

Table 2 - Correlation coefficients between the joint angles of the creature's 8 limbs in motion over 5000 timesteps with 4 hidden units. The three letter abbreviations are as presented and explained in Fig. 3.

	UBL	UFL	UBR	UFR	LBL	LFL	LBR	LFR
UBL	1	-0.29	0.95	-0.11	-0.55	-0.29	0.09	-0.28
UFL		1	-0.24	0.73	-0.07	0.89	0.02	0.98
UBR			1	-0.07	-0.45	-0.24	0.09	-0.23
UFR				1	-0.13	0.88	0.02	0.71
LBL					1	-0.09	-0.04	-0.06
LFL						1	0.02	0.88
LBR							1	0.03
LFR								1

The correlation analysis of the best evolved controller with 4 hidden units has 7 strongly positive correlation coefficients (>0.7). This indicates that the creature has evolved an ANN that has learned how to coordinate the movement of 7 sets of its limbs in order to achieve the most successful locomotion behavior among the Pareto optimal controllers. In summary, the creature achieves locomotion by coordinating the movements between: -

1. upper limbs of its back legs (0.95)
2. upper and lower limbs of its front left leg (0.89)
3. upper and lower limbs of its front right leg (0.71)
4. upper limbs of its front legs (0.73)
5. lower limbs of its front legs (0.88)
6. opposing limbs of its front legs (0.98, 0.88)

Some of these coordinated movements are quite obvious when inspecting the movement of the quadruped visually during simulation, for example the coordination present between the front legs and between the back legs. However, some coordinated movements are less obvious visually, for example the movements of opposing limbs in the front legs. Such complex coordinations are expected in locomotion of legged creatures, which largely explains why hand-designing controllers for such creatures tends to be extremely difficult and normally results in less than desirable behaviors. The illustrations that follow in Fig. 5 graphically illustrate the correlation between the 8 limbs during motion over 5000 timesteps along with the number of times each leg makes contact with the ground.

Analysis of the less successful Pareto optimal networks reveals that there is far less coordination achieved by these controllers. At most 3 strongly correlated sets of limb movements were obtained using these controllers compared to 7 strongly correlated sets of limb movements using the best evolved controller. It can be seen from the graphical illustration that the best evolved controller with 4 hidden units achieved high coordination between all of the creature's front limbs as well as in one set of its back limbs. However, with all of the other less successful controllers, coordination was only achieved in some of its front limbs and no coordination was present at all in the back limbs. In these latter cases, the creature is only able to generate useful movements from its front legs with no contribution at all from its back legs which resulted in poor locomotion behavior. Furthermore, 5 strongly negative correlations (<-0.8) were detected in the controller with 1 hidden unit. These limbs are not only uncoordinated but are generating forces that act in direct opposition to each other, thereby further hindering the creature's ability to move.

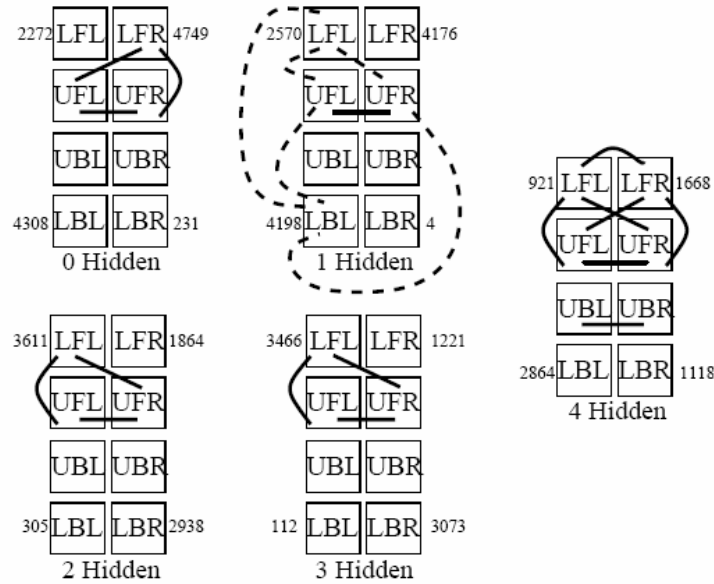


Fig. 5: Illustration of correlation between limbs for Pareto optimal controllers. The three letter abbreviations are presented and explained in Fig. 3.

Next, the synchronization between the touch sensors is analyzed. The value used in this analysis represents the total number of times each pair of legs either contact the ground or is in the air, as explained in the equation below:

$$\bullet \text{ Touch} = \frac{\text{count}(x_i=x_j)}{\text{Total number of timesteps}} \quad (10)$$

Table 3 - Touch synchronization between the creature's legs in motion over 5000 timesteps with 4 hidden units. The three letter abbreviations are as presented and explained in Figure 3.

	LBL	LFL	LBR	LFR
LBL	1	0.35	0.53	0.34
LFL		1	0.63	0.65
LBR			1	0.50
LFR				1

The previous equation was used for all networks on the Pareto frontier. The best spread of synchronization between pairs of legs is achieved in the controller with 4 hidden units, which demonstrated the best locomotion behavior, as shown in Table 3. This can be attributed to the fact that a balance between the number of times each leg synchronizes with a particular leg, for example to balance the body, as well as with other legs, for example to push the creature forwards, needs to be achieved in order to generate useful locomotion. Looking at the controllers with less numbers of hidden units, a larger spread of synchronization can be noticed, which means that the creature has pairs of limbs that spend the majority of the time either balancing the body or attempting to push the creature forwards without striking a balance between these two critical aspects of successful locomotion. A plot depicting the path taken by the overall best controller is shown in Fig. 6.

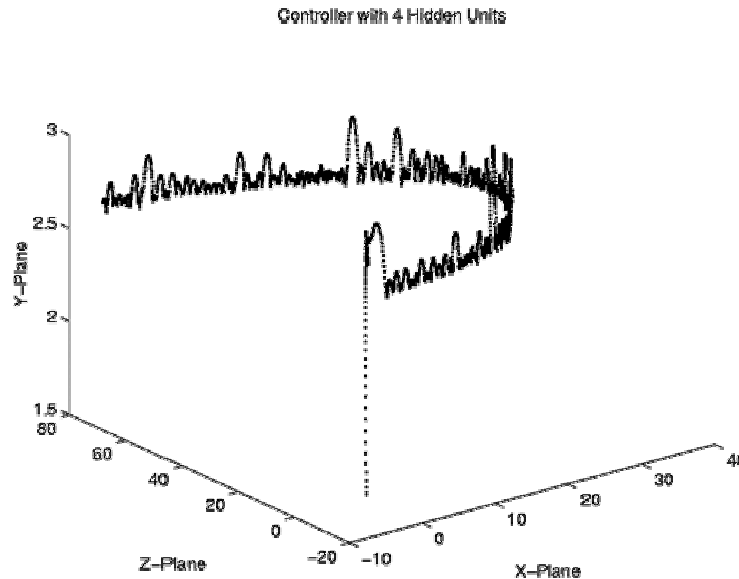


Fig. 6: Path of movement using controller with 4 hidden units.

5.0 CONCLUSION

We have demonstrated a multi-objective approach to evolving artificial neural networks for controlling the locomotion of a 3D, physically simulated artificial creature. The evolutionary dynamics for controller synthesis were analyzed to provide a high-level view of the progression of the artificial evolution. The Pareto-frontier that resulted from each single evolutionary run provided a set of ANNs which maximized the locomotion capabilities of the creature and at the same time minimized the size of the controller. Correlation and path analyses of the Pareto optimal controllers in operation provided an insight into how the complex coordination and synchronization between the quadruped's different limbs generated the emergent locomotion behavior. For future work, we intend to investigate the effects of controller complexity when both the morphology and controller are co-evolved simultaneously.

REFERENCES

- [1] H.A. Abbass. "A memetic Pareto evolutionary approach to artificial neural networks" in *14th International Joint Conference on Artificial Intelligence (IJCAI-2001)*, 2001, 1–12, Berlin, Springer-Verlag.
- [2] H.A. Abbass. "An evolutionary artificial neural network approach for breast cancer diagnosis". *Artificial Intelligence in Medicine*, Vol. 25, No. 3, 2002, 265–281.
- [3] H.A. Abbass, R. Sarker & C. Newton. "PDE: A Pareto-frontier differential evolution approach for multi-objective optimization problems" in *Congress on Evolutionary Computation*, 2001, 971–978, Piscataway, IEEE Press.
- [4] J.C. Bongard & R. Pfeifer. "A method for isolating morphological effects on evolved behavior" in *7th International Conference on the Simulation of Adaptive Behavior*, 305–311, 2002, Cambridge, MIT Press.
- [5] CM Labs. "Vortex" [online]. <http://www.cm-labs.com> [cited - 5 September 2004].
- [6] P. Eggenberger. "Evolving morphologies of simulated 3D organisms based on differential gene expression" in *4th European Conference on Artificial Life*, 205–213, 1997, Cambridge, MIT Press.
- [7] D. Floreano & J. Urzelai, J. "Evolutionary robotics: The next generation" in *Proceedings of Evolutionary Robotics III*, 231–266, 2000, Ontario, AAI Books.

- [8] G.S. Hornby & J.B. Pollack. “Body-brain coevolution using L-systems as a generative encoding” in *Genetic and Evolutionary Computation Conference*, 868–875, 2001, San Francisco, Morgan Kauffman.
- [9] A.J. Ijspeert. “A 3-D biomechanical model of the salamander” in *2nd International Conference on Virtual Worlds*, 225–234, 2000, Berlin, Springer.
- [10] M. Komosinski & A. Rotaru-Varga. “Comparison of different genotype encodings for simulated three-dimensional agents”. *Artificial Life*, Vol. 7, No. 4, 2001, 395–418.
- [11] W.P. Lee, J. Hallam & H.H. Lund. “A hybrid GP/GA approach for co-evolving controllers and robot bodies to achieve fitness-specific tasks” in *3rd IEEE International Conference on Evolutionary Computation*, 384–389, 1997, Piscataway, IEEE Press.
- [12] L. Lichtensteiger & P. Eggenberger. “Evolving the morphology of a compound eye on a robot” in *3rd European Workshop on Advanced Mobile Robots*, 127–134, 1999, Piscataway, IEEE Press.
- [13] H. Lipson & J.B. Pollack. “Automatic design and manufacture of robotic lifeforms”. *Nature*, Vol. 406, 2000, 974–978.
- [14] S. Nolfi & D. Floreano. “Synthesis of autonomous robots through evolution”. *Trends in Cognitive Science*, Vol. 6, No. 1, 2002, 31–36.
- [15] C. Paul & J.C. Bongard. “The road less travelled: Morphology in the optimization of biped robot locomotion” in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 226–232, 2001, Piscataway, IEEE Press.
- [16] R. Storn & K. Price. “Differential evolution: A simple and efficient adaptive scheme for global optimization over continuous spaces”. *Technical Report TR-95-012*, 1995, International Computer Science Institute, Berkeley.
- [17] T. Taylor & C. Massey. “Recent developments in the evolution of morphologies and controllers for physically simulated creatures”. *Artificial Life*, Vol. 7, No. 1, 2001, 77–87.
- [18] X. Yao. “Evolving artificial neural networks”. *Proceedings of the IEEE*, Vol. 87, No. 9, 1999, 1426–1447.

BIOGRAPHY

Jason Teo received the B.Comp.Math. degree from University of Western Australia in 1993 majoring in IT and biochemistry, the M.IT degree with distinction from Charles Sturt University, Australia in 2000, and the Dr.IT degree from University of New South Wales in 2003. He is a lecturer in computer science at the School of Engineering and Information Technology, Universiti Malaysia Sabah. He has authored over 30 papers in peer-reviewed international journals and conferences in the areas of evolutionary computation, artificial life, evolutionary robotics and swarm intelligence. His current research interests include artificial flying creatures, evolution of bipedal locomotion, automated drug discovery and evolutionary data mining. Dr. Teo is a reviewer for the IEEE Transactions on Evolutionary Computation, Adaptive Behavior and Soft Computing journals. He is also a member of program committees for several conferences including IEEE Conference on Cybernetics and Intelligent Systems (IEEE-CIS'04) and the 2nd Australian Conference on Artificial Life (ACAL'05).