Evolutionary Multi-objective Optimization for Evolving Soft Robots in Different Environments

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Abstract. Evolutionary robotics is an approach for optimizing a robotic control system and structure based on the bio-inspired mechanism of adaptiogenesis. Conventional evolutionary robotics assigns a task and an evaluation to a virtual robot and acquires an optimal control system. In many cases, however, the robot is composed of a few rigid primitives and the morphology imitates that of real animals, insects, and artifacts. This paper proposes a novel approach to evolutionary robotics combining morphological evolution and soft robotics to optimize the control system of a soft robot. Our method calculates the relational dynamics among morphological changes and autonomous behavior for neuro-evolution (NE) with the development of a complex soft-bodied robot and the accomplishment of multiple tasks. We develop a soft-bodied robot composed of heterogeneous materials in two stages: a development stage and a locomotion stage, and we optimize these robotic structures by combining an artificial neural network (ANN) and age-fitness pareto optimization (AFP). These body structures of the robot are determined depending on three genetic rules and some voxels for evolving the ANN. In terms of our experimental results, our approach enabled us to develop some adaptive structural robots that simultaneously acquire behavior for crawling both on the ground and underwater. Subsequently, we discovered an unintentional morphology and behavior (e.g., walking, swimming, and crawling) of the soft robot through the evolutionary process. Some of the robots have high generalization ability with the ability to crawl to any target in any direction by only learning a one-directional crawling task.

Keywords: Evolutionary robotics · Soft robotics · Neural network · Pareto optimization · Artificial life

1 Introduction

For most evolutionary robots, the controller and morphology, which is inspired by real animals and insects, are given in advance [1–3]. The robot morphologies include some biases by human recognition, however, these structures of animals and insects depend on what they learn during the development, and in turn

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the structure decides how they learn. In spite of the difference between human imagination and a real evolutionary result, these biases involuntarily associate the morphologies with specific behavior based on human experiences. Obtaining a more unintentional and adaptive evolutionary robot is one of the significant challenges in the field of evolutionary robotics, and it has been studied actively in areas such as artificial life, morphological evolution and computer graphics, and animation [4–13].

Morphogenesis engineering fabricates a robot morphology based on the mechanism of self-organization in natural systems, including the development of intelligence and composition of heterogeneous components. Sims demonstrated a virtual robot that simultaneously evolves a neuro-controller and morphology, and contributed hugely to the field of robotics [14]. This robot, however, was largely problematic in that in cases in which the robot is built by simple rigid components under simple developmental rules defined in advance, the optimal robot would have almost the same form and would be unable to adapt to different environments and multiple tasks. Doursat et al. proposed a way to design virtual soft-bodied robots by growing fine-gained multicellular [15,16]. This study provides two major rules – cell adhesion and cell division – into each spherical cellular shape. A pair of two cells receives a force based on three conditions depending on the distance between them. The results of their work showed that the robot generated four limb-like parts in the body and it acquired the ability to perform two tasks: rolling a rigid sphere and walking to a place located upstairs. They provided the potential properties that each cell has a certain kind of body part such a right limb, left hand, or short length in order to grow a structure such as that of real creatures. Joachimczak et al. proposed artificial metamorphosis as a method of evolving self-reconfiguring soft-bodied robots from the viewpoint of evolution from a tadpole to a frog [17–19]. They created a robot with reduced human biases as much as possible in order to understand the evolutionary process in real creatures, and they adopted a straightforward approach by combining mere neuro-evolution method and propagation mechanism of virtual morphogens for metamorphosis. As the main result they showed that these robots evolved from fish-like creatures to bipedal creatures and ascertained that the structures of some real creatures are adaptive for moving from water to land or from land to water.

The result verified the above-mentioned wonderful findings through two-dimensional creatures; however, the research would need to focus on three-dimensional creatures such as real creatures to obtain more advanced results. In the field of computer graphics (CG) and physical animation, Geijtenbeek et al. proposed an optimization method for obtaining flexible muscle-based bipedal robots in computer simulation [20]. The approach is to optimize the place at which the virtual muscle fibers are connected to two rigid boxes and they obtained several musculo-skeletal robots that can perform more flexible and animal-like motions than robots obtained via conventional approaches. The important point in this study is that there are unexpected effective structures for improving behavioral awkwardness to obtain a desired motion. This indicates that a human-designed structure will not always be effective for an assumed task. Thus, we would need to dispose of such biases by human recognition to truly obtain a robot with an adaptive morphology to achieve a given task because there is no guarantee that every designed robot would have the ability to acquire such a skill. We believe the coupled dynamics of structure development and learning behavior of a given task would enable the construction of more complex and unintentional structures. The complicated structure obtained through their evolutionary experience of the development can be more robust and adaptive and it might be able to shed light on a different perspective of the life structure. Meanwhile, soft-bodied robots generally have higher robustness and adaptation than rigid-bodied robots because these robots can deform themselves [21,22]. In the field of evolutionary robotics, controlling the physical behavior of those soft robots is also important and challenging because the controller of a soft robot needs to control the body actuators considering their structural deformation acquired from the surrounding environmental effects.

We pursue the ultimate objective of establishing a novel way to evolve more robust and adaptive soft-bodied robots in different environments, with multiple tasks, while the robot is simultaneously evolving its morphology and intelligence. This paper discusses how to design an evolutionary strategy and simulation foundation for considering the less-biased development of soft-bodied robots in different environments. Our simulation model considers a robot structure that consists of heterogeneous materials, which enables us to suggest an embryogenesis mechanism based on physiology. We then compare the results of locomotion experiments in which soft-reconfiguration soft-bodied robots evolve on the ground and underwater to acquire the behavior to crawl around their environments, and we analyze an adaptation for these evolved robots.

This paper makes the following contributions: First, we establish a novel way to model a soft-bodied robot with a coupling of dynamics between morphological development and behavioral learning by using an artificial neural network. In particular, our work proposes a novel evolutionary strategy that develops the structure of the robot and simultaneously evaluates multiple types of behavior in different environments. In this way it would be able to evolve some robots considering each environmental constraint, such that they gradually adapt their behavior to these environments. Then, we discuss the way in which the morphology evolves and what the robot learns on these constraints evaluating robot morphologies and behavior to achieve multiple tasks in these environments.

2 Methods

2.1 Approach

In the following section we describe the essential concept of our development system for evolving soft-bodied robots. Here, there is a gene regulatory network (GRN) as a simple description of controlling such cellular behavior [23].

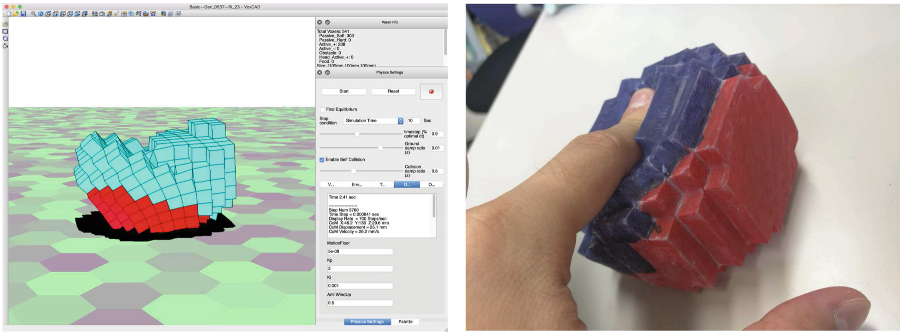

Fig. 1. (Left) A robot morphology using four material voxels developed by Voxelyze. (Right) Example of automatic design and a fabricated soft-bodied robot by Voxelyze with silicone rubber (Color figure online)

The network dominates the extent to which the fate of every biological cell is determined. We adopt an ANN to introduce the concept of GRN into our developmental system, and attempt to evolve the ANN through physical simulation that has two stages – development and locomotion – for obtaining an adaptive soft-bodied robot. We use some voxels to create robot morphology, and each voxel has the role of an actuator such as muscle or static support such as bone or fat in the general body composition of animals. One part of the simulation is the development stage in which the robot receives a signal from the network and changes its own structure with voxel material. Another part of the simulation is the locomotion stage in which the designed robot, which is obtained at the end of the development stage, moves around in a given environment in advance for a fixed period, and this stage is subsequently executed after the development stage. Our approach is not to create a central control system that manages the dynamics of all voxels in detail in order to achieve distributed control in the soft-bodied robot by using only local interaction among multiple actuators without any specifications. Besides, we never determine where every voxel is placed in advance to reduce the human bias of development as much as possible. Namely, we allow for a feed-forward ANN that develops the robot morphology and the actuator properties, and the ANN begins developing from a single voxel to design a completed robot. We believe that the straightforward approach is able to provide evolution-ranges toward more adaptive and unexpected robots. We assume that our robot is developed through sequential voxel addition and deletion. Moreover, we provide one of four material properties – hard muscle, soft muscle, bone, and fat – to all voxels based on the output of the ANN because we focus on making a model of a real-like creature as a soft-bodied robot.

2.2 Voxelyze

In 2013, Hiller et al. developed computer software named Voxelyze [24–27], for the physical simulation of a soft-bodied robot composed of material voxels. Voxelyze provides several properties – size, Young modulus, density, coefficient of

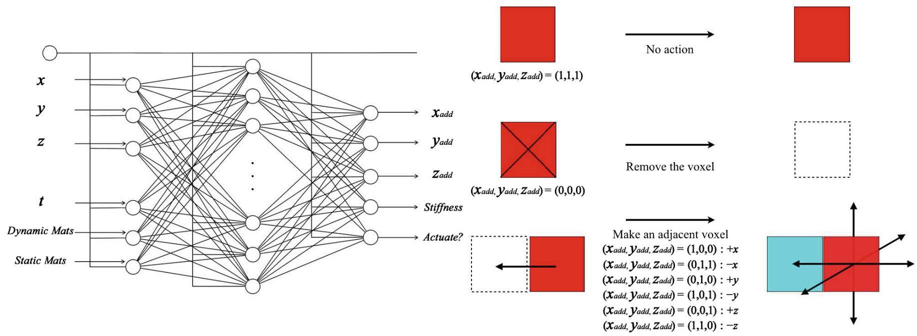

Fig. 2. (Left) The artificial neural network for making the morphology of a soft-bodied robot with homogeneous materials. (Right) The three developmental rules, which are no action, removing the voxel, and adding a new voxel.

thermal expansion, friction, and damper – for insertion into the voxel, and it can verify the control system of a more complex soft-bodied robot.

Additionally, the morphology can be constructed by using a 3D printer. Figure 1 shows a sample robot created by Voxelyze and a 3D printed robot in the real world based on Voxelyze. We define four materials for use in the voxel. The first material is a hard muscle voxel (red voxel) that has high Young modulus. The second material is a soft muscle voxel (orange voxel) that has a lower Young modulus than the hard muscle. Those voxels work as dynamic actuators in the robot body and periodically vibrate depending on a sine function. The third material is bone voxel (blue voxel) and is a static support object with the same Young modulus as the hard muscle.

The fourth material is a fat voxel (cyan voxel), and it is also a static support object with a lower Young modulus than the bone voxel. Our modeling constructs an all-connected voxel as a robot in $11 \times 11 \times 11$ design space that is able to place each voxel.

2.3 Evolving Artificial Neural Network

The ANN is a well-known brain model and consists of a set of neurons and synapses. Our network is composed of six input neurons and five output neurons (see Fig. 2). We provide a time signal that merely increases in [0:1] and the three-dimensional position – in x-, y-, and z-coordinates – as inputs to the ANN. Additionally, we introduce two morphogen neurons into the ANN, and the ANN can consider interaction among adjacent voxels by corresponding to two virtual morphogens, namely the rate of dynamic voxels (hard and soft muscle) and the rate of static voxels (bone and fat) in the surrounding voxels. Figure 2 shows the structure of the ANN and the construction rule of voxels by the ANN. There are two types of output neuron to determine which direction creates the new voxel and which material defines the voxel. For one type of three output neurons (xadd, yadd and zadd) shown in Fig. 2, the ANN chooses one of three developmental actions – no action, adding a new voxel, and removing the voxel – by three neurons. The second of the two output neurons shown in Fig. 2 enables the ANN to determine one of four materials to add to the voxel. The value of input and output neurons is defined by Eqs. (1) and (2). We use the ReLU as an activation function for each neuron. All outputs are converted into zero or one depending on the output neuron of the ANN.

$$u_i = \sum_j \omega_{ji} v_i \tag{1}$$

$$v_i = \max(0, u_i) \tag{2}$$

If the addition rule is selected, the new voxel is created toward the direction determined by the ANN unless no empty space is retained, If not, the operation is aborted. All voxels are able to create a new voxel toward six kinds of direction from adjacent space every 100 steps of the development stage. Meanwhile, all voxels deal with the deletion rule as a priority even before the addition is activated, in which case the addition is not executed; however, no deletion happens when the total number of voxels equal to one or robot is separated into two or more parts. The total number of voxels is as many as 1331 to prevent a declining calculation speed if the number of created voxels exceeds each limitation. Figure 2 shows an overview of the addition and deletion processes (see right figure).

2.4 Age-Fitness Pareto Optimization

Age-fitness pareto optimization (AFP) is an evolutionary algorithm for multiple objective optimization proposed by Schmidt [28]. Adjusting weights in the ANN is required to obtain the desired dynamics because the initial statement of the network randomly outputs a value and, in many cases, these values are meaningless for achieving a task. It is difficult, however, to explicitly optimize a set of weights in the ANN when the virtual robot has a more complicated morphology, many actuators, and has been given a complex task or situation. We adopt AFP to improve the connection weights of our ANN because AFP showed high performance for many optimization benchmark problems and it is also applied to optimize multiple finesses. The AFP can treat a set of weights of the ANN as a real-valued vector and approximately improve these weights while maintaining the diversity of the vectors. These vectors are known as individuals in evolutionary algorithms. Basically, the AFP has concepts of a population, i.e., a set of individuals and a generation, i.e., the number of times of improvement. The classic evolutionary algorithm repeatedly conducts three evolutionary operations – crossover, mutation, and selection – to multiple individuals to retain the good features of the previous population in the next population. The crossover operation creates a new individual by exchanging a part of two parent individuals. The mutation operation creates a new individual by changing some elements of the parent individual. The selection operation chooses more appropriate individuals based on any evaluation criterion. Here, as the important factor of the

AFP, there is the concept of aging [29,30]. All individuals have age and the age merely increases while the generation increases. The AFP optimizes the fitness function with the age and the solution is considered more optimal if the age is below that of other individuals. Optimizing the fitness function by minimizing the age prevents the early convergence of solution search. Thus, the AFP adds a rule of adding a zero-age individual into the current population in three evolutionary operations of the classic evolutionary algorithm.

Our crossover operation chooses a couple of individuals with the crossover probability Pc and selects one of the output units and by adopting BLX-α as the crossover. BLX-α determines new individual y_i from two parent individuals $x_1 = (x_{11}, x_{12}, \ldots)$ and $x_2 = (x_{21}, x_{22}, \ldots)$ based on Eqs. (3) and (4).

$$y_i = \alpha d_i r + x_{1i} \tag{3}$$

$$d_i = x_{2i} + x_{1i} \tag{4}$$

The basic concept of BLX-α is that a more optimal individual exists in the solution space between two parent individuals. Our simulation does not include the mutation operation because BLX-α includes the meaning of the mutation operation. Our selection operation also randomly chooses a couple of individuals with the more optimal individual overwriting another individual, and it is conducted by comparing the fitness function and age between two individuals. If the fitness value of one individual is larger than that of another individual and the age is below that of another individual, the inferior individual is removed from the current population. The selection is named tournament selection and all individuals are retained unless they are removed from the population.

2.5 Dynamics Computation

As mentioned above, our simulation uses Voxelyze to simulate a soft-bodied robot and fluid motions. Our simulation model calculates buoyancy F_b and drag F_d to represent resistance in fluid. Basic translational and rotational motion at the center of the mass are used to describe the motion of one voxel. Eqs. (5) and (6) show the equation of motion,

$$F = m\frac{dv(t)}{dt} \tag{5}$$

$$T = \frac{dL(t)}{dt} \tag{6}$$

where F is the force vector, m the mass of the voxel, v the linear velocity of the voxel, t the time, T the torque, and L the angular velocity of the voxel. The conceptual design in Fig. 3 is intended to clarify our approach. We employ thermal expansion for the muscle voxels. At the end of the development stage, the muscle voxels vibrate depending on the frequency ω, the amplitude A, and phase shift ϕ, and those two values are used in Eq. (7).

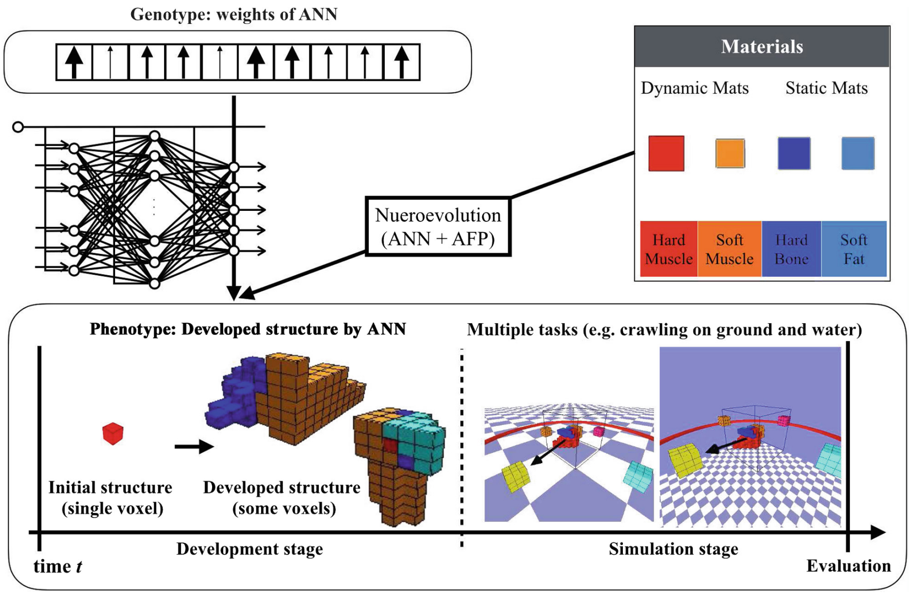

Fig. 3. Concept of our evolutionary strategy for robot development. Our simulation has two simulation stages: development and locomotion. The genotype of our simulation means a set of weights in the ANN and the phenotype is a morphology developed by the ANN from a single voxel during the development stage. The robot is evolved to accomplish a crawling task on the ground and underwater.

$$K_t = A \sin(2\pi\omega t + \phi) \tag{7}$$

where K is the temperature in the voxel, t the current simulation time, ϕ is the minimum angle between a normal vector of six surfaces of the voxel and the normalized vector from the voxel centroid to the target source. If all the surfaces of voxels have contact with other voxels or if the inner product of those vectors is smaller than zero or there is no target source, the angle ϕ equals zero. Voxelyze cannot calculate fluid forces in the default situation. Implementing calculation expressions supports buoyancy Fb and drag Fd in fluid [31], defined in Eqs. (8) and (9),

$$F_b = \rho V g \tag{8}$$

$$F_d = \frac{1}{2}\rho S C_d u_f^2 \tag{9}$$

where ρ is the fluid density, V the volume of the voxel, and g is the gravitational acceleration. Further, S is the voxel surface area of each direction, C_D is the coefficient of drag force, and u_f the relational velocity between the voxel and the fluid.

Table 1. Set of parameters for our evolutionary experiment with physical simulation by Voxelyze

Parameter	All	Hard muscle	Soft muscle	Bone	Fat
Size [cm^3]	$1.0 \times 1.0 \times 1.0$	-	-	-	-
Ambient temperature [C]	30.0	-	-	-	-
CTE	2.0×10^{-2}	-	-	-	-
Collision damper	5.0×10^{-1}	-	-	-	-
Global damper (ground)	1.8×10^{-5}	-	-	-	-
Global damper (water)	8.9×10^{-4}	-	-	-	-
Young's modulus [Pa]	-	1.0×10^{7}	1.0×10^{6}	1.0×10^{7}	1.0×10^{6}
Density (voxel)	-	1.1×10^{3}	1.1×10^{3}	2.0×10^{3}	9.0×10^{2}
Density (air)	1.2	-	-	-	-
Density (water)	9.95×10^{3}	-	-	-	-
Kinetic friction	5.0×10^{-1}	-	-	-	-
Static friction	6.0×10^{-1}	-	-	-	-
Amplitude (expansion)	-	7.0	7.0	0.0	0.0
Period [s] (expansion)	-	2.0×10^{-2}	2.0×10^{-2}	0.0	0.0

3 Experiments

3.1 Experimental Details

The evolved robots were analyzed in different environments from the viewpoint of morphological evolution and behavioral control. Our experiment prepared ground and underwater environments in virtual space and provided a pushing task involving a box object for the robots developed by the ANN. The evolution of the robot is compared in the different environments by dividing the experiment into three parts, which are (1) evolution on the ground, (2) evolution underwater and (3) multiple objective evolutions in both environments. Figure 3 shows the evolutionary concept of the NE and the physical simulation by dynamics computation. The development stage of the simulation is for 100 time steps and the morphology of the robot is updated every 1 step (=0.01 [s]) by the calculation of the ANN. After the end of the development stage, the simulation transits the locomotion stage. For the locomotion stage, the developed robot is simulated for 10.0 [s] in each environment and the behavior is evaluated at the end of the locomotion stage. In the case of multiple objective evolutions in both environments, the locomotion stage sequentially executes two simulations in both environments, after which we evaluate each behavior. The side length of single voxel is 1.0 cm. The box object is built by using $3 \times 3 \times 3$ voxels, and it is placed along the x-axis 15 voxels away from the center of the design space, which is $11 \times 11 \times 11$ voxels. The experiment consists of 30 runs, each with a population size of 30, evolved for 200 generations. Tables 1 and 2 present a set of parameters that were used in the evolutionary experiments.

Table 2. Set of parameters for the evolving artificial neural network and the age-fitness pareto optimization

Evolving artificial neural network		Age-fitness Pareto optimization	
Parameter	Value	Parameter	Value
Layer	3	Runs	30
Input	6	Population size	30
Hidden	20	Generations	200
Output	5	Tournament size	2
Bias	1	Crossover rate	0.9
Weight range	[−1.0:1.0]	Crossover α	0.5

3.2 Tasks and Penalties

The aim of the task is to determine how the robot pushes the box a long distance, and the robot needs a way to be able to crawl to the box and the body structure that moves while the robot is pushing the box. Thus, the task achievement detects whether to shift the box from the initial position or not. The behavior of the robot when carrying out the task evaluates the fitness function f (Eq. (10)).

$$f = \frac{1.0 + D_{box}}{1.0 + D_{robot}} \tag{10}$$

where D_{box} is the distance between the initial position of the box and the final position of the box, and D_{robot} is the distance between the final position of the robot and that of the box. The fitness function means maximizing the distance the box moves and minimizing the distance between the box and the robot. If the robot cannot achieve moving the box, the value of the distance the box moves equals zero and the situation inhibits the evolution of the robot. In order to prevent the situation, the minimum value of the evaluation for the movement of the box is defined as 1.0. Besides, the minimum value of the evaluation for the distance between the box and the robot equals 1.0 to prevent the distance from becoming zero by using the equation. Therefore, the minimum value of the fitness function becomes a positive value.

As the result of the calculation of the ANN, if the body of the robot separates into two parts or more, the individual AFP is replaced by a new individual with random values and repeatedly processes the development stage until the robot develops a single body. In case all voxels of the robot are static material voxels, the individual is also replaced by a new random individual. This is the reason why the evolution of the AFP is not able to gradually create the actuated robot when there are many static robots in the population.

4 Results

Videos of our soft-bodied robots locomotion are available at http://www.junogawa.com/evolutionary-soft-robotics/.

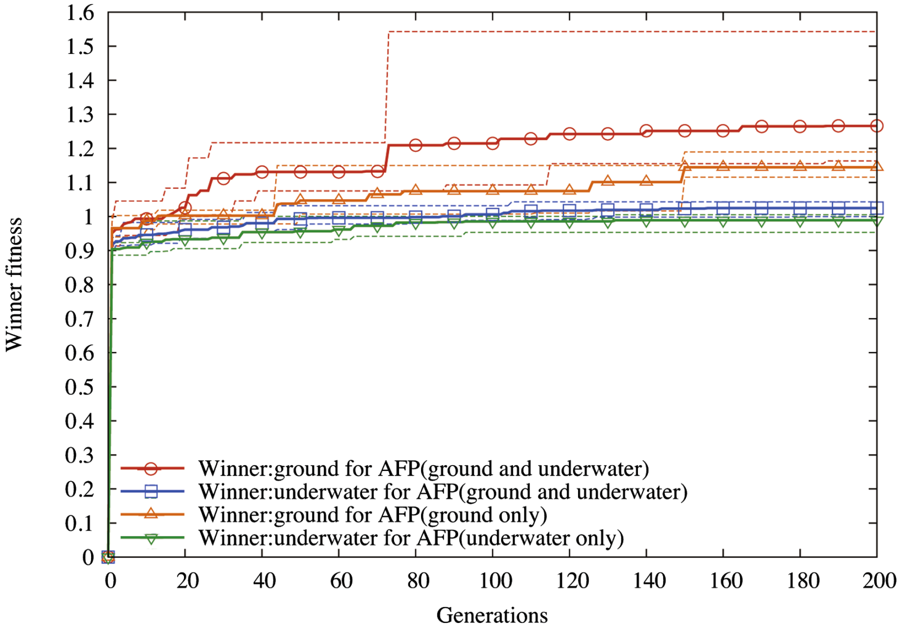

Fig. 4. Time series changes in the fitness value of the best robot, which means the winner in the current population, in each experimental environment. These results are the average values of 30 runs by the single and multiple objectives AFP. If the fitness value exceeds 1.0, the robot surely has contact with the target box object.

4.1 Single vs. Multiple Objectives Optimization

In order to quantitatively evaluate the performance for single and multiple objective optimization, Fig. 4 shows the time series changes of the best robot in each experimental environment, which are on the ground only, underwater only, and both of these environments. In Fig. 4, the best robot by the multiple objectives AFP is higher than the single objective AFP in both environments. It is clarified that the existence of the ground surface and the difference between both environments contributed some specific effects to the behavior of the robot because there is a difference between the time series changes of the evaluations on the ground and underwater. The multiple AFP always retains the best robots in both environments in the current population, and it mechanically composes the structure of the best robots in both environments in the process of evolution.

The result shows that the multiple objectives AFP discovers the robot morphology with better control systems earlier than the evolved robot in a single environment.

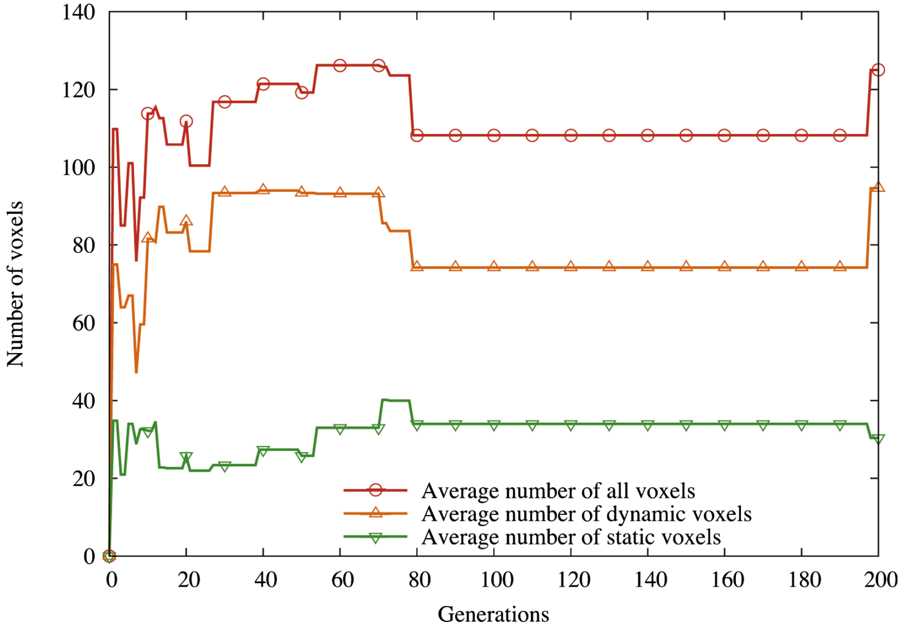

Fig. 5. Time series changes in the average number of voxels used for evolving the robot on the ground.

The search for the best robot underwater converges earlier than the search on the ground. The task difficulty and the replacement between the separated robot and a new robot would cause the convergence. The problem of early convergence is resolved by adjusting the task difficulty; for example, changing the simulation time in each environment or the initial position of the box. The destruction of the separation robot and the creation of a new robot are introduced into the AFP optimization to avoid the separation of the body of the robot. As a result of using the replacement operation, the evolutionary search increasing the elements of the random search; however, it is easy to discover better robots than with a normal AFP in each generation.

4.2 Robot Size and Material Types

Our experiments calculate the number of voxels in the robot to analyze the relationship between the size of the robot and the task accomplishment. Figure 5 shows the average number of voxels in the best robot on the ground, and Fig. 6 represents the time series changes in the average number of voxels in the

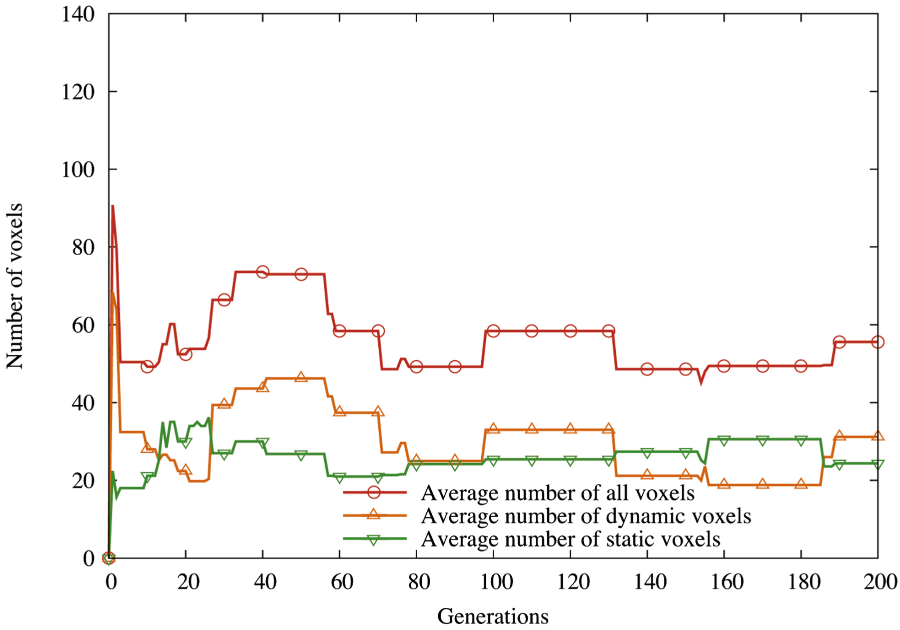

Fig. 6. Time series changes in the average number of voxels used for evolving the robot underwater.

best robot underwater. Besides, these figures also show the average number of dynamic voxels (hard muscle and soft muscle) and the average number of static voxels (bone and fat) in the robot. In the case of our evolutionary experiment on the ground, the total number of voxels in the best robot is approximately 110, and the number of dynamic and static voxels is approximately 75 and 35, respectively. The best robot on the ground accounts for 8% of the design space. In the evolution underwater, the number of used voxels in the best robot is about 60, and this value is similar to half of the number of voxels in the robot on the ground. Figure 7 shows the rate of dynamic and static voxels in the best robot in each environment. There is no large difference between the number of static voxels in both environments from Fig. 7. Therefore, our evolutionary approach acquired a robot structure that includes many muscle voxels, which directly produce power from the friction on the ground surface, in the evolution on the ground. As a result of the evolution underwater, the size of the robot is smaller than that of the robot that evolved on the ground. This robot is able to produce the power for accomplishing the same task underwater. Thus, it was clarified that the importance of muscle voxels is less important than the behavior on the ground when the structure of the robot is developed to optimize the dynamics among the vibration power by muscle voxels and the drag forces of all voxels from the water for the task.

4.3 Morphologies

In order to understand the morphological change in the best robot for each task we visualize the time series of the evolved structure of the best robot in Figs. 8 and 9. The morphology of the evolved structures is actually quite indescribable looking during early generation in both environments. During the end of evolution on the ground, these structures gradually transit to morphologies such as a wing (see first line in Fig. 8), a slug (see second line in Fig. 8), a dome (see fourth line in Fig. 8), and some limb-like parts. Partly, the appearance of the robot with four limb-like parts (see fifth line in Fig. 8) resembles that of a real robot or real four-legged insects. Basically, the evolved robots have parts to catch or push the box and the robots use those parts to retain the box near those parts until the simulation finishes accomplishing the task. Most of the robots underwater gradually become very simple structures such as fish or a propeller for the evolution. For the left robot of the third line and the middle robot of the fifth line In Fig. 8 the robot left of the third line and the robot in the middle of the fifth line are those that are the best in both environments at generation. Our evolutionary approach was able to discover that the common structures have a morphological adaptation to crawl in both environments in the evolution process.

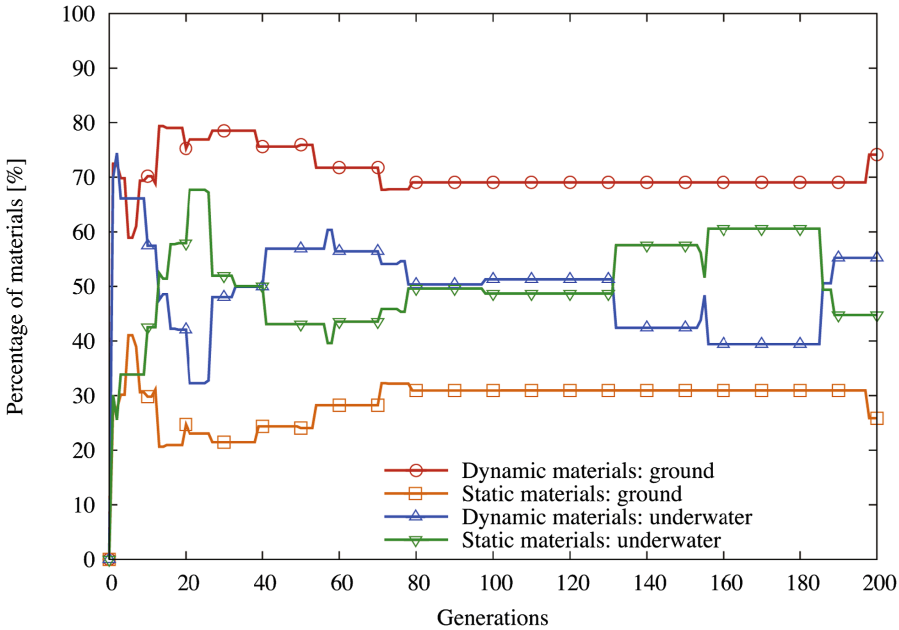

Fig. 7. Rate of used dynamic voxels in the best robot in each evolutionary experiment. The percentage of dynamics voxels in the robot on the ground is about 70%. This result means that the robot crawling on the ground needs many actuators in the body. Underwater, the difference between these rates is insignificant, and it shows that both material voxels have the role of obtaining power at the same level.

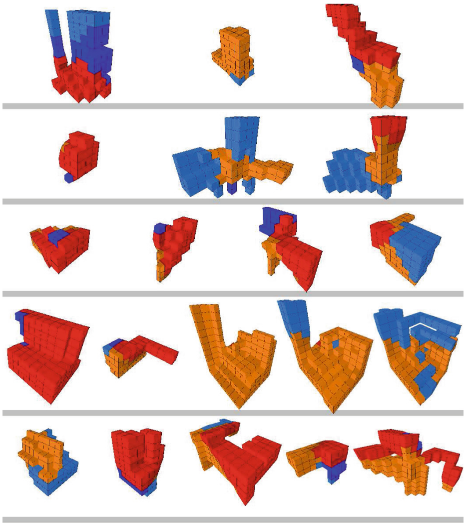

Fig. 8. Time series changes in the morphologies of soft-bodied robot to crawl on the ground environment. From left to right, the morphology of the best robot is transited. From top to bottom, we show the evolved morphology for five examples for the result of runs of the AFP.

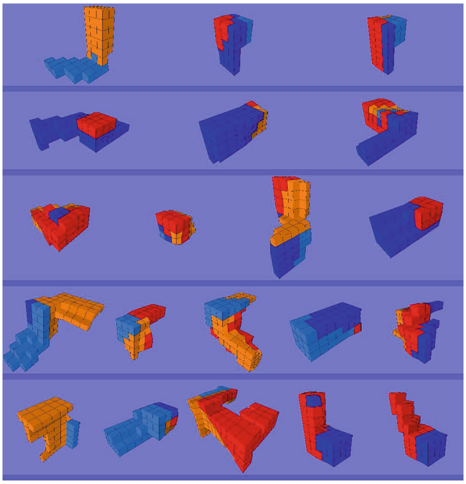

Fig. 9. Time series changes in the morphologies of soft-bodied robot to swim underwater. From left to right, the morphology of the best robot is transited. From top to bottom, we show the evolved morphology for five examples for the result of runs of AFP.

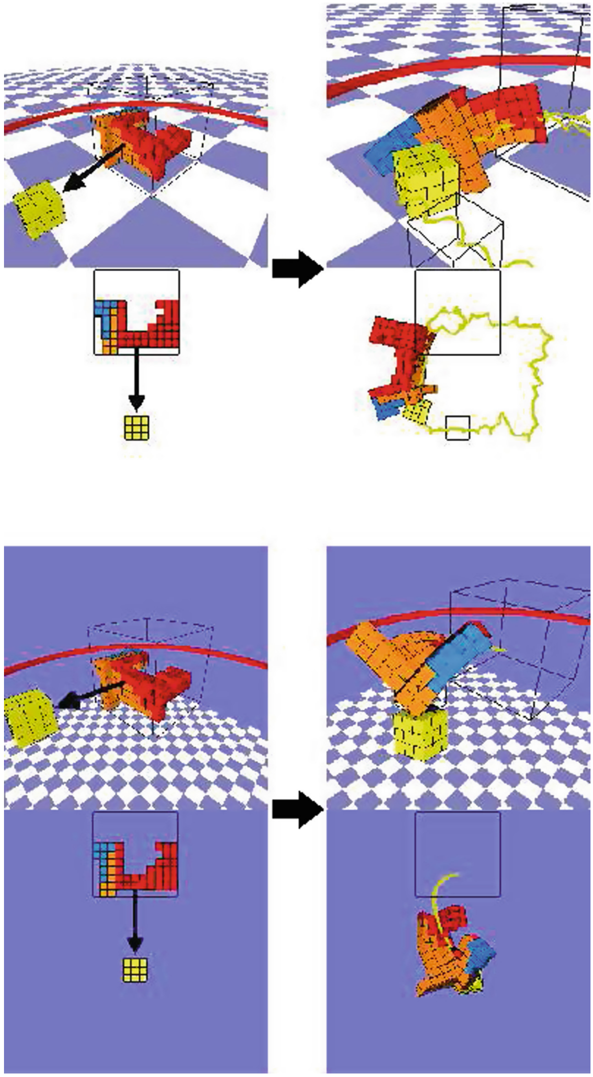

Fig. 10. Trajectory of behavior of the robot in the middle of the fifth line in Fig. 9. This robot is able to reach the box object in both environments.

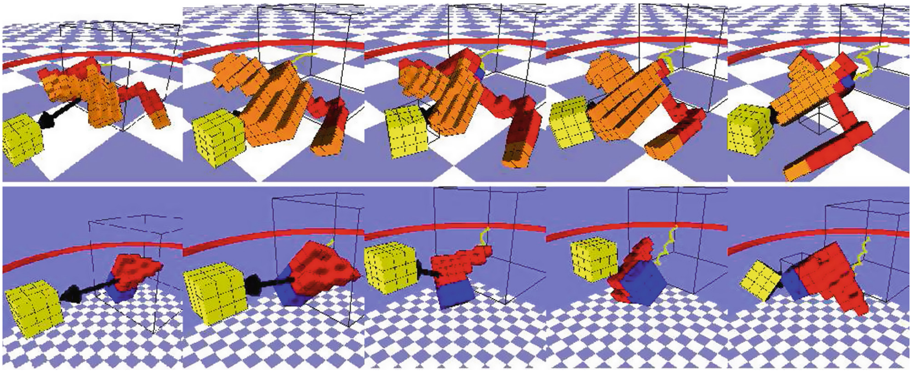

Fig. 11. Time series changes in the behavior of two final robots to the right of the fifth line in Figs. 8 and 9. Those robots have the evolutionary experience of being the same structure before generation.

4.4 Behavior

According to the evolutionary transition of the fifth line in Fig. 9, the same robot is chosen as the winner for both environments. The behavior of this robot is shown in Fig. 10. This robot was able to reach to the position of the box in both environments. As a result, in Fig. 10, the ground robot is pushing the box while walking around by using four limb-like parts; however, the underwater robot was reached by twisting its body and swimming as though it is drawing an arch trajectory. This result showed that the same soft-bodied robot changes its adaptive behavior depending on the surrounding environment.

After that, the robot finally evolved into different morphologies in each environment. The behavior of those robots is shown in Fig. 11. The final morphology of the ground robot repeatedly expands and contracts by two legs on a diagonal, and the robot was able to effectively push the box by moving these legs. Then the final underwater robot was gradually rotating by using the muscle voxels like the tail of a fish to advance in the direction of the box. The robot also acquired pushing behavior. Moreover, both robots retained their pushing behavior when the position of box was changed by their behavior (Fig. 12). From the viewpoint of morphology, the ground robot evolved like a terrestrial creature and the underwater robot evolved like a fish.

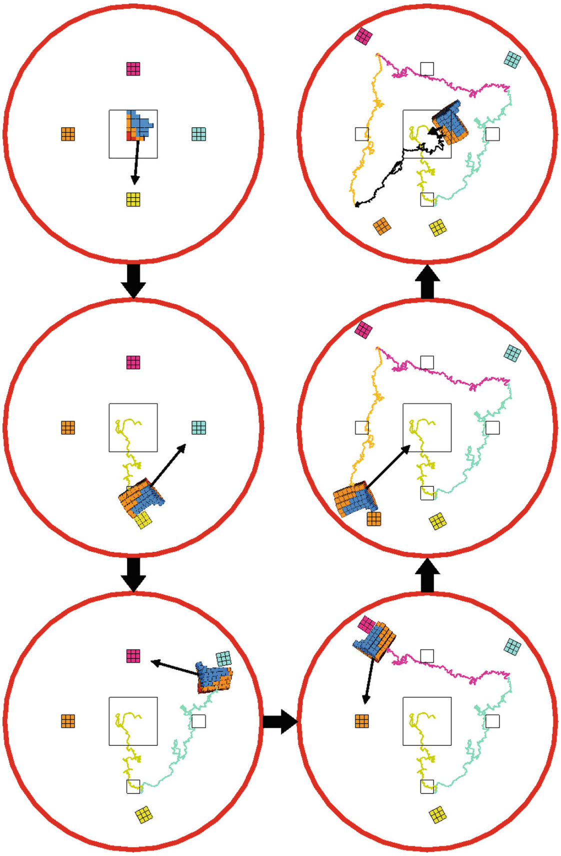

Fig. 12. Simulation prepares the evolved robot for pushing the yellow box and four boxes. We positioned them on the ground. The robot changes the target box depending on the current elapsed time. First is the yellow box and the simulation time is for 10.0 s, after which the robot changes the target box counterclockwise every 20.0 s. The simulation result confirmed that the robot was able to crawl in any direction. (Color figure online)

5 Conclusion

In this work we proposed a novel way of developing evolutionary soft robotics from the viewpoint of morphological evolution with adaptation in different environments. Our method was able to acquire more interesting morphologies of a soft-bodied robot by reducing the human bias in the morphological evolution. By introducing the role of sensing function into a voxel, our evolved robot was able to conduct more controllable and adaptive behavior than the evolved rigid-bodied robots in most conventional evolutionary robotics approaches. We ascertain that there exist many unintentional and complex robots depending on the different experimental situation. Besides, our simulation would be available for creating more robust soft-bodied robots. This work led to the finding of the possibility of evolutionary robotics in the future development of soft robots toward environmental adaptation and multi-objective learning. The result of optimization continues to remain incomplete for maintaining the diversity of robot morphology because the morphology obtained from AFP converges at an early stage. In future, we would need to focus on improving the acceleration of the simulation speed with the NE. We suggest solving the problem by applying a GPU acceleration mechanism to Voxelyze.

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