Simultaneous Design of Morphology of Body, Neural Systems and Adaptability to Environment of Multi-Link-Type Locomotive Robots using Genetic Programming

Ken Endo and Takashi Maeno

Depertment of Mechanical Engineering
Keio University
3-14-1 Hiyoshi, Kohoku-ku, Yokohama 223-8522 JAPAN

Abstract

In this paper, morphology of body and neural systems that define the locomotion of multi-linked locomotive robots that can adapt the changes in environment are designed using the evolutionary computation. the morphology of the body and neural systems have a close relationship to each other. So the model of the robot is constructed in which the morphology of the body and neural systems emerge simultaneously. The morphology of the body and neural systems are generated using a Genetic Programming. The tasks are that the robots move on grounds including different height of hills from generation to generation in the two dimensional lateral simulated world under the effect of the gravity. The robots are evaluated based both on a moving distance and an efficiency. As a result, various combinations between the morphology of the body and neural systems of the robots were emerged. Moreover, the robot went over the hills that were not experienced.

1 Introduction

Many types of robots are suggested in recent years. Most of them mimic creatures including human. However, structures and components of the robots usually differ from those of living creatures. For example, geometry, weight and performance of electro-magnetic motors usually used as the actuators for the robots differ from those of muscles of creatures. The same discussion can be applied to body, sensors, neural systems and environment. What we should learn from the living creatures is not the structures and components themselves but how they emerged through evolution. Optimum structures of robots can be designed only when the components and morphology of the robots including artificial actuators and sensors suitable for the robots themselves are selected appropriately through evolution. Design of the robots, by the robots, for the robots, should be achieved using evolutionary method, whereas designers of the robots should only set up an environmental constraint condition for the robots.

An artificial life is one of the answers. Sims [1] generated robots which can walk, jump and swim in computer simulation. He also generated virtual creatures which compete each other to obtain one resource [2]. Ventrella [3] presented evolutionary emergence of morphology and locomotion behavior of animated characters. Kikuchi and Hara [4] studied a method of evolutionary design of robots having tree structure that change their morphology in order to adapt themselves to the environmental conditions. However, all of them do not consider how to make practical robots.

On the other hand, evolutionary method has been tried to apply to the practical robots. Kitamura [5] used Genetic Programming, GP [6], to emerge the simple linked-locomotive robot in virtual space. Lipson [7] adopted the rapid prototyping to produce the creatures that were generated in three-dimensional virtual space. However, emerged creatures can generate only simple periodical movement in assumed environment because they cannot obtain any information from the environment. So they cannot adapt the change in the environment.

In this study, a method for designing the morphology of the body and neural systems of multi-linked locomotive robots that can adapt the change in the environment is suggested. Both the morphology of the body and neural systems are represented as a simple large tree structure using GP. The robots move on the grounds including different height of hills from generation to generation in the two-dimensional lateral world under the effect of the gravity. The problem for designing such robots is treated as a multi optimization problem, MOP. It is shown as a result that the generated robots have diverse morphology of the body and neural systems and they have unique locomotive pattern and their movements are fast and efficient. The capability and adaptability of the locomotion are also shown by placing the robots on different environment.

2 Model of Robots

2.1 Body

Parts of the robots are selected so that it is easy for the robots to be produced in the future study.

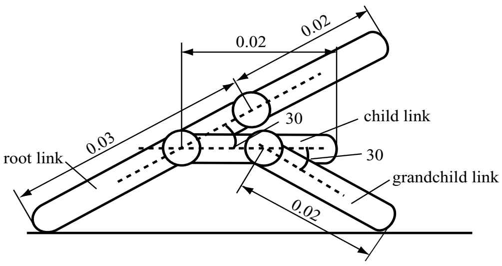


Fig. 1: Morphology of the body of robot

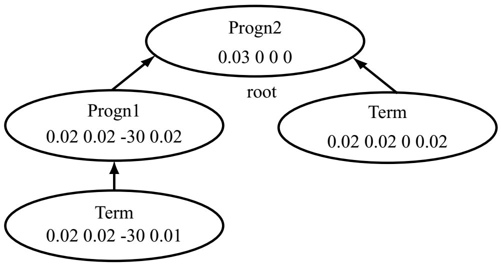


Fig. 2: Tree structure of the morphology of body

Robots are composed of simple two-dimensional links as shown in Fig. 1 as an example. Each link has the parameters such as length of link, L, spring constant of joint, k, the first angle of joint, θ, and the location of connecting point from the edge of the link, J. Values of these parameters are obtained in the evolutionary computation. When the values of these parameters are defined, the structure of the robot is also defined. Morphology of the robot is expressed as a tree structure including these parameters. First, a root link is defined. Then, several child links are connected to the root link at J. Other links can also be connected to the child links. Now, the robots that have bodies composed of links are simply expressed by tree structure including parameters, L, k, θ and J. If zero, one and two links are connected to one link, structure of the links is expressed in the program as Progn1, Progn2 and Term, respectively. For example, if one robot has morphology as shown in Fig. 1, it can be expressed as S expression of LISP language.

```
(Progn2 [0.03 0 0 0]
          Progn1 [0.02 0.02 -30 0.02]
                  Term [0.02 0.02 -30 0.01]
         Term [0.02 0.02 0 0.02]
)
```

This robot can be expressed as a tree structure as shown in Fig. 2. One link can at most be connected to two links. The maximum depth of the tree is two. So the robots have at least two links and at most seven links.

2.2 Neural systems

The driving torque of the each joint of the links which decides the locomotion pattern is decided by the neural system that exists in each joint. Input to the neural system includes contact condition of some links and angle condition of some joints. Output from the neural system is the driving torque of each joint at the next step in simulation. Because of this, the emerged motion patterns are closely related to the contact conditions with ground and angle of joints. The neural system is composed of program language whose functions are defined in advance. The grammar of this program causes the neural system to construct a tree structure. The maximum depth of this tree is five. Six neural systems, DD, AA, ND, NA, DA and AD are developed for comparing the capability of the robots caused by the difference in the quantity of information from/to the environment. DD and AA mean a digital and an analog neural models in which inputs/outputs are digital and analog values, respectively. ND and NA are models to output digital and analog torque without obtaining information from environment as an input. DA is a model which obtains the information from the environment as a digital value and generate the driving torque as a analog value. AD is opposite to DA model.

Table 1: Nodes used in a digital neural model

Function nodes	Number of argument
AND	2
NOT	1
IF	3
OR	2
$=$	2
Variable nodes	Explanation
C_i	Contact information of link i
A_i^k	Angle information of joint i
1	Constant
0	Constant
E_i	Output before one time step

(a) Digital neural model

The digital neural model, DD, is the neural system in which the information of contact with ground and angle are Boolean values. Table 1 shows the function and variable nodes used in the digital neural model. It is necessary for all information from environment to be expressed as Boolean value. For example, if the link i is in contact and not in contact with the ground, C_i is 1 and 0, respectively. The range of angle that link can rotate is separated into four parts and this information is decoded to two bits that are contributed to A_i^1 and A_i^2.

The function "-" is used as the root of the tree of digital neural model. This enables the digital neural model to provide three values, 0, 1, and -1 as outputs. The function "-" takes two arguments. First and second values are E_1 and E_2 at the next time step, respectively. Finally, when the output value is -1, 0, and 1, driving torque of the joint where the neural system is located is -0.2, 0, and 0.2 Nm respectively.

(b) Analog neural model

Table 2 shows the function and variable nodes used in the analog neural model, AA. The outputs of all nodes vary from $-\pi/2$ to $\pi/2$. The function sig is a

Table 2: Nodes used in an analog neural model

Function nodes	Number of argument
sig	4
sin	2
tan	2
not	1
if	3
Variable nodes	Explanation
C_i	Contact information of link i
A_i	Angle information of joint i
N	Constant
E	Output before one time step

sigmoid function represented by,

$$sig(r) = \frac{1}{e^{-r} + 1} \tag{1}$$

where, r is the sum of four arguments. Second argument of sin is the phase. if is the function that provides the second argument and third argument as an output if the first argument is positive and negative, respectively. not multiplys the argument by -1.

If the total mass of the robot is M and the external force to the link i is F, contact information C_i is given by

$$C_i = \frac{F\pi}{Mg} - \frac{\pi}{2} \tag{2}$$

A_i means the information of the angle of joint i. So, if the angle of joint i can rotate from $-\pi/3$ to $\pi/3$, A_i is defined by

$$A_i = \frac{3}{2}\theta \tag{3}$$

Thus the output P of the analog neural model also varies from $-\pi/2$ to $\pi/2$. Driving torque is defined by

$$\tau = 0.2P \cdot \frac{2}{\pi} \tag{4}$$

With this, the driving torque varies from -0.2 Nm to 0.2 Nm.

(c) Other models

For other models, ND, NA, DA and AD, descriptions of the input or output are the same as DD and AA models when the first or second character is the same.

3 Method

3.1 Genetic Programming

Both the morphology of the body and neural systems are represented by one large tree structure as shown in Fig. 3. The tree structures of the neural systems are placed in each joint. One of the evolutionary computations, GP is used to deal with this tree structures including the information of both the morphology of the body and neural systems, because GP can handle the tree structures directly. Robots with low-fitness are eliminated by selection. New robots are produced using crossover and mutation in this method. Then their morphology of the body and neural systems are generated from generation to generation and finally converge to a reasonably optimal solution.

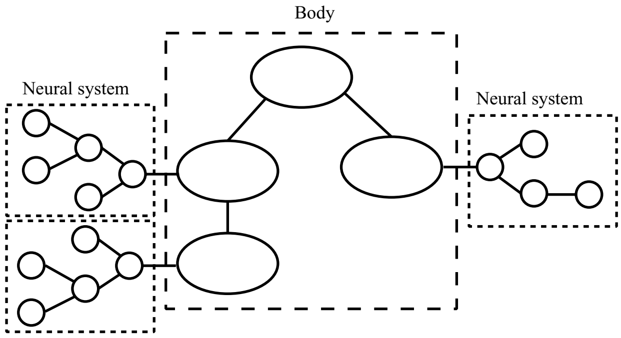


Fig. 3: Tree structure of the robot

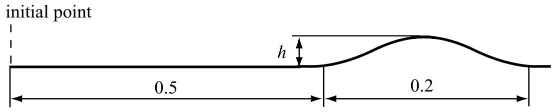


Fig. 4: Environment for movement

3.2 Multi Optimal Problem

The design of the robot is taken as the multi optimal problem, MOP, in which two evaluate functions are considered. A distance of movement is often used for emergence of the ability of moving robot. However this evaluation function largely depends on the size of the robot. So we define one of the fitness as,

$$f_{movability} = \frac{d}{M} \tag{5}$$

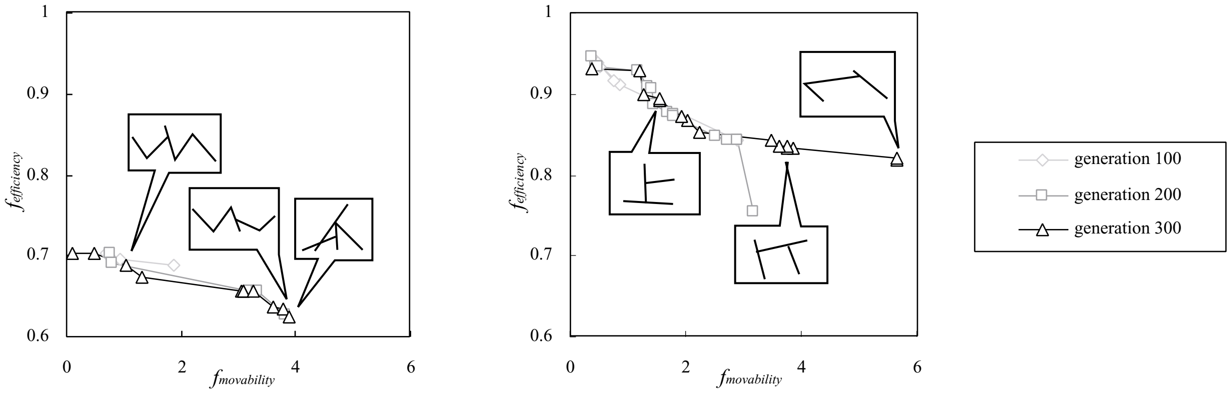
where, M is a mass of the robot and d is a moving distance of the robot during eight-second simulation. The efficiency of movement is taken as a second evaluate function. The larger the sum of driving torque of all joints of the robot is, the smaller the efficiency is. So as the second fitness,

$$f_{efficiency} = \frac{1}{1 + \tau_{all}} \tag{6}$$

is defined, where, τ_{all} is the sum of driving torque of all joints per a unit time step. Moreover, we use the method that is combined with pareto preserving strategy, vector evaluated GA and sharing as well.

3.3 Method in detail

The environment on which the robots move includes the simple hill as shown in Fig. 4. Height of the hill, h, changes randomly from generation to generation. The range of h is from zero to 0.02 m. At first, the center of mass of the root link is on the initial point. Environment is just flat from the initial point to the point apart for 0.5 m from the initial point. Then, a simple hill appears. Flat ground continues after the hill. So the robots that can go through the flat-hill-flat environment faster and more efficiently can survive. Dynamic simulation is conducted to calculate



(a) Digital neural model (b) Analog neural model

Fig. 5: Pareto optimal solutions

the movement of the robots resulting from their interaction with the environment. Equations of motion of the robot are constructed using a Newton-Eular method. One time step is 5 ms. Contact response with ground of links is accomplished by a hybrid model using both spring and damper under the influence of friction and gravity. GP parameters used for the calculation is as follows:

Population Size	200
Generation	300
Mutation Ratio	0.02

Note that the crossover ratio changes when the number of pareto optimal solutions changes from generation to generation.

4 Results

4.1 Digital neural model

Calculation using GP is conducted for the digital neural model, DD. At first, all robots can move only a little bit and the value of $f_{movability}$ is low. Gradually, the robots that can move efficiently are emerged and their moving distance increase. Finally, some robots reach and overcome the hill. As shown in Fig. 5(a), eleven pareto optimal solutions are emerged at generation 300. Six of them can overcome the hill of 0.02 m height. As a preferred solution, the robot whose value of $f_{movability}$ is the largest among the six solutions is selected.

The morphology of the body of the preferred solution of the digital neural model is shown in Fig. 6. Joints are numbered as joint 1, 2, and 3 as shown in Fig. 6. This robot mainly moves using joint 1 and joint 3. The distance between the link 1 and ground, and the driving torque of joint 1 are shown in Fig. 7. The negative and positive driving torque of joint 1 is generated when the root link is in contact and not in contact with the ground, respectively. Similar phenomena can be seen for the joint 3 and link 2. Note that the locomotion pattern is generated not because each neural systems can generate the rhythm but because the relationship between the neural systems and environment works cooperatively. Figure 8 shows the locomotion pattern of the robot and the angle of joints.

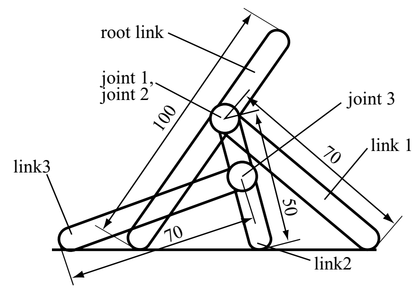


Fig. 6: Morphology of preferred solution of digital neural model

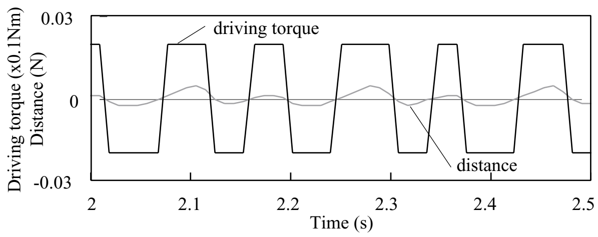


Fig. 7: Driving torque of the joint 1 and distance between the ground and link 1

The angle of each joint moves periodically when the robot move on the flat ground. The periodical locomotion pattern changes when the robot moves on the hill. When the environment returns to the flat ground, the locomotion pattern also returns to the periodical one. The robot changes its length of step shorter to adapt the change in the environment. Calculation is also conducted when the environment is changed. Then the robot can also move on the environment including several hills whose width is inexperienced. This means that both the morphology of body and neural systems of the robot enable the robot to adapt the change in environment.

4.2 Analog neural model

As shown in Fig. 5(b), fifteen pareto optimal solutions are emerged for the analog neural model, AA, at generation 300. The robots with the analog neu-

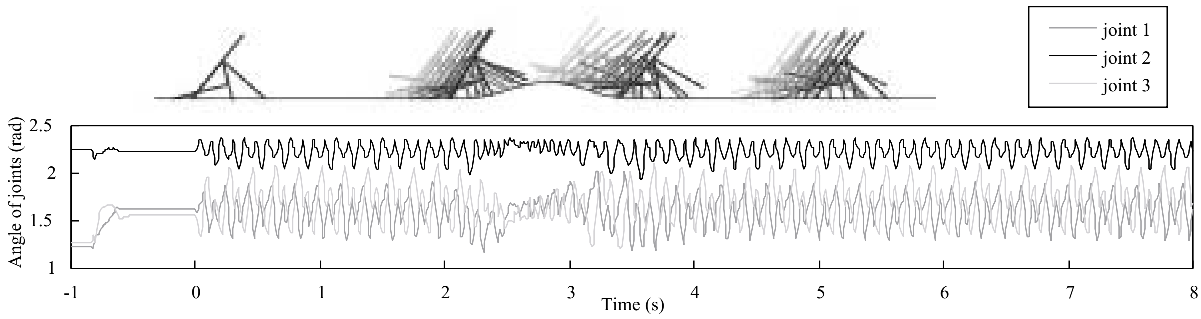


Fig. 8: Stick figure and angle of joints of preferred solution of digital neural model

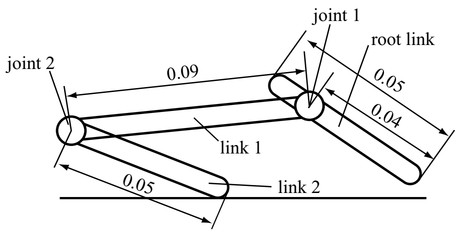


Fig. 9: Morphology of preferred solution of analog neural model

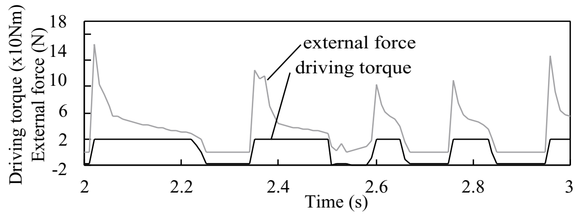


Fig. 10: Driving torque of joint 2 and external force of the link 2

ral model have much better fitness both on $f_{movability}$ and $f_{efficiency}$ than those of the digital neural one. It means that the analog neural model can be more adaptive toward the change in environment than the digital neural model. It is because the analog neural model can exchange much information with the environment than the digital one. Note that the obtained morphology of the body having large fitness lift their certain link by other links as mammals lift their bodies by their limbs, whereas most results for the digital neural model were creeping motion without lifting their links as worms do. The result of this study correspond to the fact that higher animals have more complex neural systems.

Eight of the pareto optimal solutions can overcome the hill of 0.02 m height. The robot whose value of $f_{movability}$ is the largest in the eight solutions is selected as a preferred solution.

The morphology of the preferred solution of the analog neural model is shown in Fig. 9. Joints are numbered as shown in Fig. 9. This robot mainly moves using joint 2. The relationship between the driving torque of the joint 2 and the external force of the link 2 from the ground is shown in Fig. 10. The driving torque is decided according to the strength of external force of link 2. Not only the information of contact or no contact with the ground, but the strength of the force from the ground which works at the contact point of the link is obtained as an input in the analog neural model. Similar to the digital neural model, this robot can move using information from the environment in the neural systems. Fig. 11 shows the locomotion pattern of this robot and the angle of joints. Even through this robot has the simple morphology, it can overcome the hill of 0.02 m heights. When the robot reaches the hill, larger external force works from the ground to the link 2 than that on the flat ground because the root link is lifted by the hill. Then larger driving torque is generated to the joint 2 to overcome the hill. However the robot does not change its periodical locomotion pattern so much as that of the digital neural model when it moves on the hill. Only the amplitude and period of the joint angle are changed. This locomotion pattern of the robot is similar to a walking motion of the higher animals. The robot can adapt the change in the environment by changing the strength of the driving torque of joint 2. This robot also can move on the environment including several hills whose width is inexperienced as the same as the robot with the digital neural model can. The obtained simple three link morphology of the body of the robot is similar to the robots by Doya [8] and Kawachino [9] by chance. Emerged locomotion pattern of these three studies are also similar. It means that the morphology of the robots by Doya and Kawachino are optimum. It also means that the validity of our method is confirmed because the generated morphology of the body and neural system and the locomotion pattern is adequate even if the way of expression of the robot is different.

4.3 Other models

The pareto optimal solutions of other four models at generation 300 are shown in Fig. 12. The robots with NA and ND neural models cannot generate pattern to move to a long distance. We can conclude that information from the environment is important to move. Movability of DA model is better than DD model. However, they couldn't overcome the hill. We can say that harmony of input/output is important. Only the AD neural model can move and overcome

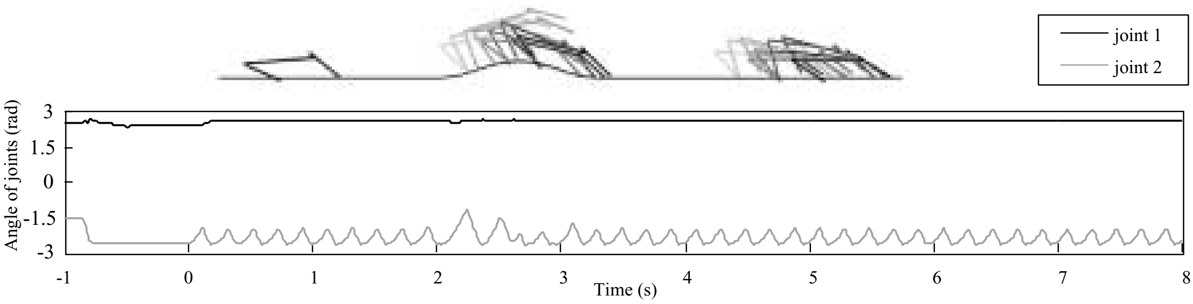


Fig. 11: Stick figure and angle of joints of preferred solution of analog neural model

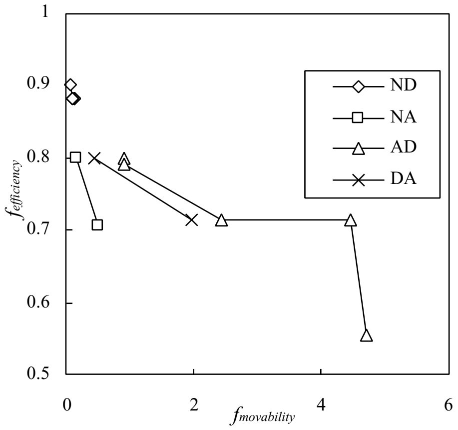


Fig. 12: Pareto optimal solutions

the hill. We can say that the quantity of information from the environment is more important than that of output in order to adapt the change in the environment.

5 Discussions

The purpose of this study is to suggest a method to design the morphology of the body and neural systems of the robots that can adapt the unknown environment. Various combination of the morphology of the body and neural systems of the robots are emerged and they can move because the relationship between the morphology and locomotion work cooperatively. This means that it is effective for the robots to generate the morphology of the body and neural systems simultaneously. Especially, it is confirmed that the analog neural model is the most adaptive to the change in the environment compared with other models. It is because the analog neural model can exchange much information from the environment than the other models. Simple link-type structure is only constructed and the characteristic of the real motors is ignored in this study to simplify the argument. If this study is expanded to three dimensional robots considering characteristics of motors and sensors, results will be more practical. The three dimensional robots emerged using this method will be actually produced to confirm the effectiveness of this method in the future study. The robots will be easily made and controlled because they are composed of the parts that are easy to be produced, controlled and adapted to environment.

6 Conclusions

A method for designing the morphology of the body and neural systems of the link-type robots which generate the unique morphology and locomotion is suggested. Various combinations of the morphology of the body and neural systems that can move fast and efficiently are emerged. It is confirmed that the robots emerged in this method, especially the analog ones, have adaptability to the inexperienced environment.

References

[1] Karl Sims, "Evolving Virtual Creatures", Computer Graphics Proceedings, pp. 12-22, 1994.

[2] Karl Sims, "Evolving 3D Morphology and Behavior by Competition", Artificial Life IV, pp. 28-39, 1994.

[3] J. Ventrella, "Exploration in the Emergence of Morphology and Locomotion Behavior in Animated Characters", Artificial Life IV, pp. 436-441, 1994.

[4] Kohki Kikuchi and Fumio Hara, "Evolutionary Design of Morphology and Intelligence in Robotic System", Proceedings of the fifth international conference on SAB, pp. 540-545, 1998.

[5] Shinzo Kitamura, Yuzuru Kakuda, Hajime Murao, Jun Gotoh and Masaya Koyabu, "A Design Method as Inverse Problems and Application of Emergent Computations", SICE, Vol. 36, No. 1, pp. 90-97, 2000. [in japanese]

[6] J. Koza, "Genetic Programming II", ISBN, MIT Press, Cambridge, Massachusetts, 1994.

[7] H. Lipson and J. B. Plollack, "Automatic design and manufacture of robotic lifeformsm, Nature, Vol. 406, No. 6799, pp. 974-978, 2000.

[8] Kenji Doya, "Selforganization of Motional Patternm, SICE, JSS6-6, 1987. [in japanese]

[9] Akihiro Kawachino and Takashi Maeno, "Generation of Motion Pattern of a Serial Link-Type Locomotive Robot using evolutionary Computation", JSME Conference on Robotics and Mechatronics, 2P2-31-035, 2000. [in japanese]