Motion Generation of Multi-Legged Robot by using Knowledge Transfer in Rough Terrain

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Abstract—Walking motion generator of multi-legged robot is very complicated operation because there are many degrees of freedom required to be considered. Especially in computational intelligence approach, many iterative calculations are required for convergence the result. Furthermore, in case of the change in environment has to recalculate the walking motion again and then increase of the calculation cost is a big problem. In this study, we propose the extraction and reuse method of walking knowledge for multi-legged robot by using computer simulation. Sequences and patterns of motion are formed by using minimal generation gap model in genetic algorithm and open dynamics engine was applied to experiment. Finally, we discussed the efficiency of knowledge transfer for reducing the calculation cost.

Keywords—multi-legged robot; knowledge transfer; genetic algorithm;

I. INTRODUCTION

Effective motion generation in various problems is very important and difficult problem in a locomotion system. Especially, walking behavior of multi legged robot needs many degrees of freedom, then it is difficult to walk stably in various environments. There are many studies about the motion generation of the robot locomotion. In particular, evolutionally computation approach is the most basic technique to generate the locomotion automatically, and a number of studies had been reported. For example, there are many studies of fourlegged robot locomotion by using genetic algorithm [1][2]. Evolutionary computation and neural network methods are used to generate the multi legged robot locomotion, and which is reported in [3]. Reinforcement learning is often used for acquiring the path planning or gait motion acquisition of robot [4]. Moreover, the study which applies the combination of reinforcement learning and genetic algorithm to get walking motion, is also reported in [5]. In this way, walking motion acquisition using the technique of evolutionary calculation is studied by various approaches. However, these techniques require large computational cost because of iterative calculation for numerical search, then we must reducing the calculation cost.

In our previous work, we proposed a method by using Steady State Genetic Algorithm (SSGA) for generating the motion sequence of a six-legged robot modeled by forward kinematics [6]. We used tripod gait for reducing gene in chromosome and obtain the simple behavior because of fast walking in the flat terrain. The tripod gait about six-legged robot is to move legs in triangle position at the same time, and the pair of three legs is moved alternately in static walking motion. In this study, we use this six-legged robot and walk through in rough terrain, which is the more complex task. Tripod gait can be calculated by less computational cost because of simple symmetry walking behavior. However, the tripod gait is not appropriate in irregular rough terrain because three legs move same motion at the same time. Then, we aimed at obtain random gait which moves the six-legs independently each other. Acquisition of walking behavior is made by Genetic Algorithm (GA). Minimal Generation Gap (MGG) alternation model is used for evolution because it is difficult to get stack in local optima by maintaining genetic diversity.

The random gait of six-legged robot has high degree of freedom. Therefore, the calculation cost is to heavy. Especially, in the changing environment, we have to recalculate the gait motion and which needs the same calculation cost. Then we make a study to use the knowledge transfer for efficient behavior acquisition in case of environmental change. The transfer learning is known for the issue which preserve and translate the knowledge acquire by one or more task to new task in the aim of efficient learning. An idea of transfer learning in a workshop of Neural Information Processing Systems 1995. The research of transfer learning was made by Pan & Yang and systematical discussion was attempted [7].

In this study, we assume to obtain the walking behavior in flat terrain as the source task, and propose the reuse method of knowledge which is synthesized by characteristic motion of walking behavior. Then we verify the effect of reduction in recalculation cost by obtain walking behavior in rough terrain with obstacles as the target task.

II. SIX-LEGGED ROBOT

The six-legged robot we used in this study is shown by Fig.1. Legs are out of the body vertically and at equally spaced intervals. All legs move separately at the same time in simulation. Leg number 1 and 2 are positioned in front of the robot. The aim of the simulation is to get the forward walking behavior. The posture of the robot is calculated based on forward kinematics, then reach position $P=(p_x, p_y, p_z)$ of the leg as shown in Fig.2 is calculated by joint angle and lengths. Where θ_1 is the rotation angle around the y axis and θ_2 or θ_3 is the rotation angle around the x axis. Eq.(1) shows an arithmetic expression of three dimensional coordinate by using coordinate transformation matrix. In the equation, l_i is the length of *i*-th leg part, $\theta_{m,i}$ means the joint angle of joint *i* in *m*-th leg and *u* is a

normal vector. Symbol Tr and Rot mean translation and rotation matrix each other.

$$\boldsymbol{P} = Tr(\theta_1, l_0, 0,) \cdot Rot(\boldsymbol{y}, \theta_{m,1}) \cdot Tr(0, l_1, 0,)$$
$$\cdot Rot(\boldsymbol{x}, \theta_{m,2}) \cdot Tr(0, l_2, 0,)$$
$$\cdot Rot(\boldsymbol{x}, \theta_{m,3}) \cdot Tr(0, l_3, 0,) \cdot \boldsymbol{u}$$
(1)



Fig. 1. Six-legged robot



Fig. 2. Rotation degree of leg

III. WALKING BEHAVIOR ACQUISITION

A. Solution Search of Genetic Algorithm

Genetic Algorithm had been proposed by Holland in 1975, its algorithm is based on the evolution process of biological organism [8]. GA applies three types operation as reproduction, crossover and mutation. To apply evolutionary algorithms, first of all the encoding method must be defined. Next we have to decide about the operator of crossover and mutation, and about the generation alternation model [9]. Additionally, the evaluation method of the individuals has to be discussed.

Furthermore, we explain about the encoding method of walking behavior into the gene of a chromosome for the robot which introduced at chapter II. The walking behavior is expressed by a series of posture of the robot, it has been translated from each joint angle of the leg to the single gene. The structure of the chromosome is indicated on Fig. 3. We compose 1 chromosome by 1 cycle movement of walking. In order to assume the number of the postures included in 1 cycle movement to be a variable, the posture number n has been added as the additional gene and the postures P_n are increased or decreased according to the number of n. Each posture is made up by six-legs L and each leg contain three joint angle θ . Then the chromosome of this model contains n postures and each posture is containing 6 times 3 numbers of genes, then the total number of genes are n times 18.

To use this chromosome, the genetic operation is made by following manner. The individual of next generation is created by one pair of parents. The new individual's genes are placed by the cross genes of both parent by means of one-point crossover as shown in Fig.4. Crossing point is selected from shorter length of postures at random place. In a similar way, two types of mutation named insertion and deletion are performed by chromosome order. These situations are illustrated in Fig.5. Insertion and deletion point of chromosome is also selected randomly. In the case of insertion mutation, inserted posture is generated by overlapping of both side posture as the weight with Gaussian distribution. Insertion and deletion are limited by the maximum or minimum length of chromosome. If it will be over or less the limitation length, mutation is not performed.



Fig. 3. Gene structure of chromosome



Fig. 4. Crossover of chromosome (single point crossover)



Fig. 5. Mutation of chromosome (Insertion, Deletion, Exchange)

In this study, we apply the minimal generation gap (MGG) as the generation alternation model. MGG have been proposed by Sato et al. in 1996, which to improve early convergence by lowered the selection pressure in the first stage of search, and suppress evolutionary stagnation in the last stage of search by maintain the diversity of individual in population. It is based on

the idea of the difference in individual distribution between generations to minimize [10].

The MGG generation alternation is performed by the following steps. At the first, two individuals are selecting without replacement from parent population in random manner. A sub-group of offspring is generated from this pair of parent using cross-breed, and they are adapted by crossover and mutation in same time. And then, the system adds two parents into sub-group to make a survival select population. From this population, we select an individual of the maximum fitness and an individual of roulette selection with the weight of fitness. Then, we add the selected two individuals into parent population and construct the parent population of next generation. The conceptual scheme of MGG is shown in Fig.6 and procedure sequence is shown in Algorithm 1.



Fig. 6. MGG generation alternation model

Algorithm1: Minimal Generation Gap
begin;
t=0;
From the population P(t), and evaluate fitness of individuals
while termination condition is false, do;
$t \leftarrow t + 1;$
select 2 parents C(t) randomly from P(t);
$P(t) \leftarrow P(t) - C(t);$
generate offspring C'(t) and evaluate individuals;
chose the best B and roulette-wheel selection R from C'(t)
and include its in the population P(t);
$P(t) \leftarrow P(t) + B + R;$
enddo;
end;

The fitness of each individual illustrated in Fig. 7 is calculated from the moving distance and the posture angle of the robot in one trial by the following equation;

$$f = \eta^a \cdot f_a + \eta^q \cdot f_q + \eta^d \cdot f_d \tag{2}$$

where f is the fitness value of the each individual. η^a , η^q and η^d are weights. f_a is related to the direction of movement of the robot, f_q is the inner product of the robot's posture and the moving direction vector. f_d is the moving distance d(t) in Fig. 7. We deal only with straight movement then f_a is calculated based on the φ_r in Fig. 7 as follows;

$$f_a = exp(-\varphi_r^2) \tag{3}$$

Since the increasing in moving distance also increases the degree of adaptation, our problem is a maximization problem searching for the maximum value of f in Eq. (2).



Fig. 7. Direction of movement and movement distance of the robot

B. Transfer the Walking Behavior

Transfer learning is the problem of retaining and applying the knowledge learning in one or more tasks to efficiently develop an effective hypothesis for a new task. There are three common measures by which transfer might improve learning. First is the jumpstart, where it is the initial performance achievable in the target task using only the transferred knowledge, before any further learning is done, compared to the initial performance of an ignorant agent. The second is time to threshold, which is the amount of time it takes to fully learn the target task given the transferred knowledge compared to the amount of time to learn it from scratch. Third is asymptotic performance, which is the final performance level achievable in the target task compared to the final level without transfer. Fig.8 illustrates these three benefits of transfer learning.



Fig. 8. Three ways in which transfer might improve learning

To increase the generalizing capability of knowledge transfer, we estimate the feature of walking behavior from the generated movement. In this study, we think that the trajectory pattern of each legs and the phase between legs are as the common knowledge. So we get the walking behavior on flat train as source task, and estimate the characteristic motion value of 1 cyclic gait. Then we translate the estimated feature quantity to the target task as a generalized knowledge.

IV. COMPUTER SIMULATION

A. Simulation Environment

We use the Open Dynamics Engine (ODE) in the computer simulation. ODE is an open source physics engine [11]. The robot model in ODE is displayed in Fig. 9. Table I shows the operation range and initial values of the angles for robot leg. The parameter settings including the probability of insertion or deletion mutation of Genetic Algorithm is presented in Table II. The detail of rough terrain is as follow. The size of obstacles is 10-20% length rectangular block compared with the robot. We allocate these blocks in the flat terrain totally 400 pieces. Obstacles are set in a reticular pattern with random direction. The figure on the right side of Fig.9 shows the rough terrain, which created by the ODE simulator. If robot reaches the boundary of the area, it forced back to the center of coordinate and calculation will be kept on continuously. At Fig.9, the figure on the left side is the source task environment, and on the right side is the target task environment.



Fig. 9. Simulation environment(Flat terrain and Rough terrain)

TABLE I. PARAMETERS OF THE JOINT ANGLES

	1st joint	2nd joint	3rd joint	
range	$-45^{\circ} \leq \theta_1 \leq 45^{\circ}$	$0^{\circ} \leq \theta 2 \leq 60^{\circ}$	$0^{\circ} \leq \theta_3 \leq 60^{\circ}$	
initial	0°	45°	45°	

TABLE II. PARAMETERS OF GENETIC ALGORITHM	
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Parameter	Value	
Number of individuals	20	
Number of sub offsprings	10	
Min. number of posture	3	
Max. number of posture	6	
crossover	single point	
inseart mutation rate	0.15	
delete mutation rate	0.15	
replace mutation rate	0.1	
weight η a	1.0	
weight ηq	1.0	
weight η d	2.0	

TABLE III.

Leg1	Leg2	Leg3	Leg4	Leg5	Leg6
hase1	phase2	phase2	phase1	phase3	phase3

B. Result

Each simulation of the evolutionary process is repeated 5 times and the average is calculated. Fig.10 shows the transition of fitness in strait walking on flat terrain. Horizontal axis describes the generation of GA and Vertical axis describes the fitness value calculated by Eq. (2). Solid line shows fitness of the best individual and doted line shows the average fitness of parent population. Near the 1000 generation, the trend of asymptotic to maximum fitness is seemed. Fig.11 observed the percentage change of the individuals, which include the number of postures in the chromosome. The percentage of

individuals which have three postures is reach to 80% about 200 generations, and the percentages are maintained. Of course the best individual is comprised in the three postures group. The reason of this phenomenon is thought to be the difficulty of acquire the efficient behavior in forward walking for many number of postures stochastically. Fig.12 shows each foot path in one cycle of gait motion of the best individual after 1000 generations of evolution. The combined motion vector this foot movement locus is shown in Fig.13. Table III shows the phase classification of each leg. By using these values, an individual which has the chromosome with the knowledge for transfer is made by inverse kinematics to reflect the motion vectors and phases. In the same manner, it created 10 chromosome samples from each of the best individual of 10 times trial in the source task. The result of the evolutional calculation applying the knowledge transfer in the target task in rough terrain is shown in Fig.14. In order to verify the effects of knowledge transfer, evolutionary result of calculations are overlapping when the locomotion system is without using knowledge transfer. The best and the average fitness is appeared in the figure by a solid line and a dotted line against the knowledge transferred population. Likewise, the best and the average fitness applied by a dashed line and the two-dot chain line against no knowledge transfer. The jumpstart of the calculation of early stage and the advantage of the degree of fitness following that were confirmed. The advantage of asymptotic to the maximum fitness near the final generation is also observed. From this result, by using the transfer of knowledge, it is possible to produce a high fitness individual with less generation and confirmed that calculation cost can be reduced.

Effect is greatly affected by the correlation of the source task and the target task by the re-use of knowledge. Transfer learning is sometime falling into a local pole due to the effect of the translated knowledge, and it has also been reported in the previous study [12]. We used Genetic Algorithm to search the solution, and we make consideration about diversity of individuals for difficult to fall into a local pole.



Fig. 10. Fitness courve on flat terrain



Fig. 11. Percentage of the umber of postures in population



Fig. 12. The each foot path in one cycle of gait motion



Fig. 13. Composition of foot path



Fig. 14. Percentage of the umber of postures in population

V. CONCLUSION

In this study we simulated the knowledge transfer according to the walking behavior of six-legged robot in flat terrain as source task and rough terrain as target task. We generated the walking behavior of the robot by using MGG alternation model in Genetic Algorithm. We try to estimate the knowledge of walking behavior from the trajectory and the phase relation of each legs acquired in the flat terrain. Then we transfer the knowledge to initial population of target task, we confirmed the effect to reduce the calculation cost.

As future work, we intend to study the extraction of generalized walking knowledge and the effectiveness of knowledge transfer in various dynamic environment.

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