APPROACH TO MULTI-OBJECTIVE EVOLUTIONARY COMPITATION METHOD FOR GENERATING VARIABLE WALKING PATTERNS

[1]J.Y. Lee, M.S. Kim, J.J. Lee

[1] Department of EE and CS, KAIST, 373-1
Gusung-dong Yusung-gu Daejon, Korea
Phone: +82-42-869-5432; Fax: +82-42-869-5432
leejy79@kaist.ac.kr

Abstract: The generation of the optimal walking trajectory is an important question for a biped robot to keep walking stably. This paper is proposed for generating the walking trajectories resulted in best performance of the biped robot using multi-objective evolutionary computation. We formulate a trajectory generation problem as a multi-objective optimal problem. We obtain all Pareto-optimal solutions on the feasible solution region for various walking pattern generation of a biped robot in simulation.

Keywords: Multi objective, evolutionary computation, Pareto optimal, walking pattern, ZMP

1. INTRODUCTION

In recent years, there are many studies about the biped type robot, because the biped robot is more adaptable than the mobile robot in a varied environment. And this type can have more diverse possibilities in planning the motion. In addition, it can walk over some obstacles, so that there is no need to go a long way round. Above all it is more human-friendly than any other types. But it has also many weak points. It is easy to fall down. So, it is difficult to control the walking without falling down, we should consider the stability of biped locomotion in various terrain. Besides, the biped robot has high complexity and redundancy. So the generation of the optimal walking trajectory is an important problem for the biped robot to keep walking stably.

There are two schemes for the walking pattern generation. First, one is a scheme which a designer manually defines the parameters to generate the walking trajectory. [11] And the other is a scheme which a designer intelligently finds all parameters to satisfy the constraints required in walking. [1]- [10] While the former has to make extensive efforts of trials and errors to get the better performance, the latter does not need to repeat some efforts. So, the latter one is studied by many researchers.

In this paper, we want to have no efforts of trials and errors manually using the evolutionary Algorithm. And we want to find all possible solutions for the adaptability of this system. First we formulate the trajectory generation problem as the parameter search problem. So we confirm that our EA scheme is valid. In addition, we formulate this problem as the multi-objective optimal problem. And using multi-objective evolutionary computation, we can find all feasible trajectories, which satisfy stability condition dynamically, consume the minimum energy, and simultaneously move the robot faster. These objectives are considered simultaneously, although they are often competing. While previous evolutionary methods are applied to obtain the best solution for a specified fitness function, proposed method can find many obtained possibilities which can be applied flexibly for planning walking patterns fit for given environment. So, this paper is organized as follows. In Section 2, we describe the model of a biped robot and define the walking trajectory with the necessary parameters. Next, in Section 3, we propose the multi-objective evolutionary scheme for the walking trajectory generation. We define 4 fitness functions and apply the EA. We formulate this problem as multi-objective optimization problem. And we apply the strength Pareto-optimality improved for the walking trajectory generation. Next, we verify the proposed scheme by simulation in Section 4. Finally we conclude this paper in Section 5.

2. WALKING TRAJECTORY

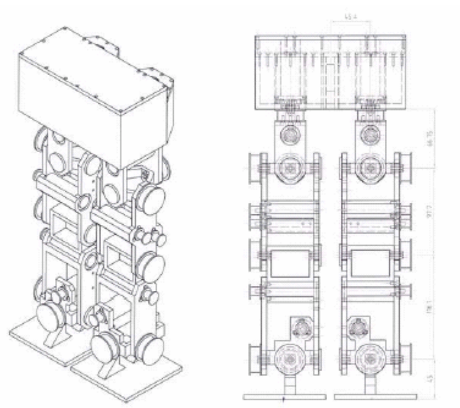

Figure 1. The biped robot

Figure 1 represents the 12DOF (degrees of freedom) biped robot. In order to easily approach the dynamics of this system, it is assumed that the robot link is a point mass. It is assumed that every parameter is known obviously. There are 3DOF in the hip joint, 1DOF in the knee joint, and 2DOF in the ankle joint. For a sagittal plane, the foot trajectory is the coordinate of the ankle position,. The hip trajectory is the coordinate of the hip position.

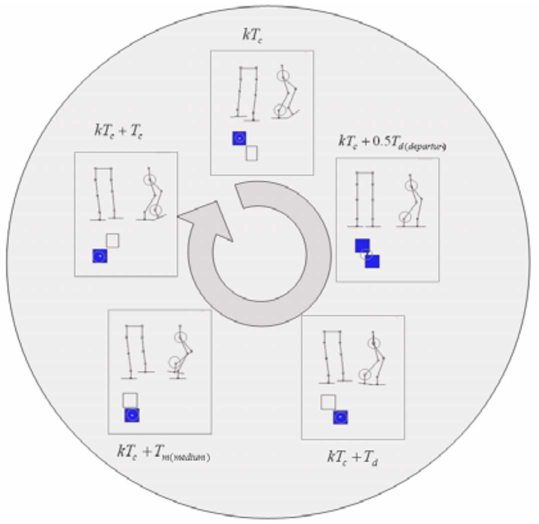

Figure 2. Walking cycle

Figure 2 describes the configurations of the biped robot in via point at time t. [11] If we select the proper parameters, which are the stride, the maximum height position of the swing foot ankle, the inclination rate of the robot side and front, and the max-min height positions of the hip, we can make a continuous trajectory for a one step of the biped robot using the interpolation technique. And we design the desired ZMP trajectory to be assured the stability of the dynamic walking. So, the total numbers of the unknown parameters are 12. In order to find the optimal trajectory, we should formulate this problem as the search problem at the variable constrained situations.

3. MULTI-OBJECTIVE EVOLUTIONARY COMPUTATION FOR TRAJECTORY PARAMETERS

In this section, we formulate the trajectory parameter problem as multi-objective optimization problem. And we propose the 4 fitness functions for three objects. First, evolutionary computation is a search algorithm known to be robust for optimization problem. This method is based on the natural selection and population genetics. So, it is based on the interaction and biological evolution between individuals and the natural environment. The survival of the fittest exists. It is very adaptable in environment. Nature produces a population with individuals that are better fit to the environment from a random population. Using this algorithm, we want to find the best parameters for all via points of walking trajectory.

3.1 PARETO-OPTIMALITY

In applications of optimization methods, the solution of such problems is usually computed by the weighted sum of the objectives. The multi-objective optimization problem finds the point $x = (x_1, \ldots, x_n)$ which optimizes the values of a set of objective functions $f = (f_1, \ldots, f_m)$ within the feasible region of x (Figure 3). Figure 3 describes the set of the Pareto optimality solutions of the minimization problem. In detail, the definition of the Pareto-optimality is as follows: Assume a minimization problem and think about two arbitrary vectors $a, b \in P$ It can be said that a dominate b.

$$f_i(a) \le f_i(b), \forall i = 1, \cdots, m, \wedge$$
$$f_i(a) < f_i(b), \exists i = 1, \cdots, m. \quad (1)$$

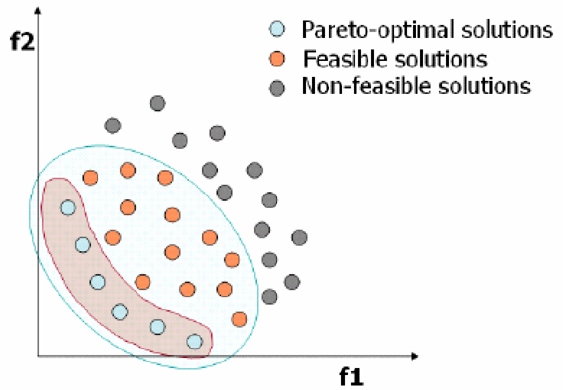

Figure 3. Pareto-optimal solutions

Every vector which is not dominated by any other vector is called non-dominated set or Pareto-optimal set. For the walking trajectory, we can define that a set of objective functions are f = (fstability, fenergy, fmobility). fpenalty should be considered, because, if fpenalty(x) $\neq$ 0, this vector x is not feasible and finally cannot be a solution. In multi-objective problem, there are many schemes to find the non-dominated set of solutions. Among the others, the strength Pareto evolutionary algorithm which is modified for the walking trajectory problem is used. In other conventional ways, there is a serious problem that the solutions to be sought out are centralized in a specified part. So to resolve such a difficulty, many related works are carried out. As a result, some methods considering such a difficult point is very useful. The strength Pareto evolutionary algorithm is one of them.

3.2 THE PROPOSED ALGORITHM USING THE MULTI OBJECITVE EVOLUTIONARY COMPUTATION

The proposed algorithm used to solve this multi-objective optimization problem is in brief as follows:

(1) Initialize the populations P (vectors) and create the empty array for non-dominated set NP (Non-dominated vectors).
(2) Find the non-dominated members in P. However, to decide whether a vector is the member of the non-dominated set, $f = (f_{stability}, f_{energy}, f_{mobility})$ of the vector cannot be applied. Because, if the position of a vector x at every time is violate the penalty condition, $f_{stability}$ and f_{energy} may be equal to zero. So although they cannot be the solution to satisfy feasible constraints, they can pretend to be a member of the non-dominant solutions. So each vector should be translated as much as its penalty fitness value in objective space. So the feasible region is filtered by removing impurities (Figure 4). And then find the non-dominated members in P. Transfer them from P to NP.
(3) Leave the non-dominated members in NP, and remove the dominated members in P.
(4) If the numbers of the non-dominated solutions are more than the desired number Nnondom, remove needless solutions in NP by clustering method.
(5) Evaluate the fitness of all vectors in P and NP.
(6) Select vectors in P and NP using genetic operations such as crossover, mutation, and tournament with replacement.
(7) If the numbers of the generation is equal to maximum generation, terminate this algorithm; else go to (2).

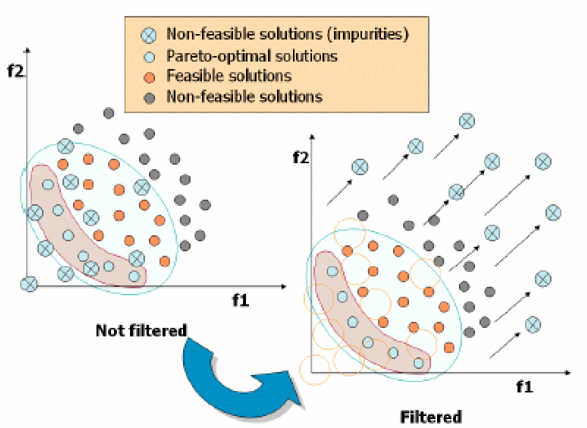

Figure 4. Filtering of the feasible solution space

3.3 DEFINITION OF GENES

Vectors consist of parameters to want to find out. As stated above, a vector means a set of the known parameters. Because the numbers of unknown values are 12, search space is so wide that it may be troublesome to converge on the global solution. To reduce such an effort, genes have some constraints. These are as follow:

$$
\begin{array}{ll}
F_d: & \left(\frac{F_f+F_b}{2}\right) \le F_d \le 2(F_f+F_b) \\
F_{mh}: & F_a \le F_{mh} \le (F_a+L_1) \\
F_{ml}: & \left(\frac{F_f+F_b}{2}\right) \le F_{ml} \le \left(\frac{3(F_f+F_b)}{2}\right) \\
f_b: & 0 \le f_b \le \frac{\pi}{3} \\
f_f: & 0 \le f_f \le \frac{\pi}{3} \\
H_{max}: & (F_a+L_1) \le H_{max} \le (F_a+L_1+L_2+L_3) \\
H_{min}: & (F_a+L_1) \le H_{min} \le H_{max} \\
d_{hf}: & \left(\frac{F_f+F_b}{3}\right) \le d_{hf} \le (F_f+F_b) \\
d_{hb}: & \left(\frac{F_f+F_b}{3}\right) \le d_{hb} \le (F_f+F_b) \\
\theta_{max}: & 0 \le \theta_{max} \le \frac{\pi}{4} \\
\alpha: & 0 \le \alpha \le 2 \\
T_c: & 5 \le T_c \le 15.0
\end{array}
$$

With these constraints, the reminders of the trajectory parameters are as follows:

$$T_d = \frac{x_f(T_d)}{2F_d} T_c$$

$$T_m = \frac{F_{ml}}{2F_d} T_c$$

Each parameter means as follows:

F_d : A stride
F_{mh} : z coordinate of the ankle in the highest position
F_{ml} : x coordinate of the ankle in the highest position
f_b : foot angle when the swing foot leaves
f_f : foot angle when the swing foot lands on the ground
H_{max} : maximum height of the hip
H_{min} : minimum height of the hip
d_{hf} : the distance between the front ankle and the hip
d_{hb} : the distance between the rear ankle and the hip
θ_{max} : maximum inclination of the robot body
α : a scale factor for the inclination of the robot body
T_c : a period

3.4 OPERATOR

We select the parents to produce the new offspring and population with the random tournament. There are 3 steps for this selection method. First randomly select two vectors in current population. And then compare the score of one vector with the other, and finally select the vector, who wins victory in a competition, as parents of the next generation. Prior to this procedure, the best individual is inherited to the next generation. After selection process come crossover and mutation process. To maintain the diversity of each generation, arithmetic crossover and uniform mutation is applied to this procedure.

3.5 THE PROPOSED FITNESS FUNCTIONS

Here we apply the fitness function to be appropriate for the biped robot. We consider stability property, energy efficient performance, mobility property, and penalty for the basic constraints during a cycle. Each factor is used to define the fitness function. Let $f_{stability}$ be the stability function for the fitness function. The definition of this function is shown below:

$$f_{stability}(\mathbf{x}) = \frac{f_{zmp}(\mathbf{x})}{\max_{\mathbf{y}\in\Psi} f_{zmp}(\mathbf{y})} + \frac{f_{shake}(\mathbf{x})}{\max_{\mathbf{y}\in\Psi} f_{shake}(\mathbf{y})} + \frac{f_{config}(\mathbf{x})}{\max_{\mathbf{y}\in\Psi} f_{config}(\mathbf{y})} + \frac{f_{hip}(\mathbf{x})}{\max_{\mathbf{y}\in\Psi} f_{hip}(\mathbf{y})} \tag{2}$$

where ϕ means a set of points in the current population. Each term denotes the normalized functions, which is as follows:

$$f_{zmp}(x) = \sum_{k=0}^{N}\left(\frac{\sqrt{(x_{zmp} - x_{dzmp})^2 + (y_{zmp} - y_{dzmp})^2}}{N}\right) \tag{3}$$

$$f_{shake}(x) = \max(y_{zmp}) - \min(y_{zmp}) \quad (\text{if } T_d \le t \le T_c) \tag{4}$$

$$f_{config}(x) = \frac{F_{mh}}{T_c F_d} \quad (\text{if } \frac{F_{mh}}{F_d} > C_r) \tag{5}$$

$$f_{hip}(x) = \frac{H_{\max} - H_{\min}}{H_{\max} + H_{\min}} \tag{6}$$

The first term is a mean value of the error between the desired ZMP and actual ZMP for all sampling times. And the second term represents a degree to be shaken from side to side during a single support phase. And the next term is related to the configuration of foot trajectory. So the larger is this value, the higher is the risk that the motor may go to the utmost limit of velocity and torque, and then the stranger is the shape of foot trajectory. Finally, last term describes the motion of the hip. So if this value is lager, whole configuration of walking trajectory is very abnormal and the robot may stoop. So these terms should be minimized. All terms can have the relative weight rate so that the weighted ratio of each term can change results differently. We must consider these points.

And then let fenergy be the energy efficiency function. The definition of this function is shown as follow:

$$f_{energy}(x) = \sum_{k=0}^{N}\left(\frac{z_z(kT_s)}{N}\right) \tag{7}$$

, where the za is the z coordinate of the ankle of the swing leg. It means that the height of the swing leg from the ground is minimized. It can be applied for looking over the change of the joint angle slightly.

Next, let fmobility be the mobility performance function. The function can be derived as follow:

$$f_{mobility}(x) = \frac{10}{velocity} = 10\frac{T_c}{F_d} \tag{8}$$

It is shown that if the value of the mobility function is less, a mobility performance is better and the motion is faster. So, these three fitness functions which are mentioned above are objects for the multi-objective optimization.

At last, here, let penalty function for the constraints. Above all, penalty function has the highest priority, because, if a certain vector violates the penalty condition, we cannot evaluate the other functions. If vector x has singularity positions, there can be no solution of the inverse kinematics so that the other functions cannot be defined about such positions. If the position at every time is violating the penalty condition, fstability and fenergy may be equal to zero. So, it is as follows:

$$f_{penalty}(x) = \min\left(\sum_{k=0}^{N}\left(P(KT_s), P_{MAX}\right)\right) \tag{9}$$

, where $(P(KT_s)$ is a function to obtain a penalty value at each sampling time, P_{MAX} is the maximum values in relation to the total value fpenalty.

After all, we may be able to make the single object optimization problem by weighted summation of all fitness function. But we should tune weighted ratios so that we can obtain the best trajectory which has the desired performances. Because there is no chance that we cannot choose another solution, this work is very delicate. So, as previously stated, the walking trajectory problem should be regarded as multi-objective optimization problem. Because this problem is to simultaneously optimize several incommensurable and often competing objectives. We can have more chances that we may choose.

3.6 APPLIED PARETO-OPTIMALITY

To solve this multi objective optimization problem, we applied Strength Pareto algorithm [14] in the fitness assignment and clustering of non-dominant vector set. We add the penalty term to the fitness assignment terms in order to find the penalty-zero solutions.

4. SIMULATION

In this section, we will verify the proposed scheme for the walking trajectory generation of a biped robot by some simulation results. The proposed evolutionary scheme improved for the biped robot shows that several trajectories optimized for robot walking can be obtained by this method. And

importing multi-objective concept, we show that possible solutions of trajectory problem can be solved at a time.
The parameters used in the multi-objective optimization evolutionary computation simulation are listed in Table 1.

Table 1. Parameters of multi-objective evolutionary computation process

Parameters	*value*
Population size	200
Non-dominant vector size	50
No. of generation	200
Crossover ratio	0.3
mutation ratio	0.1
system parameter(b)	2

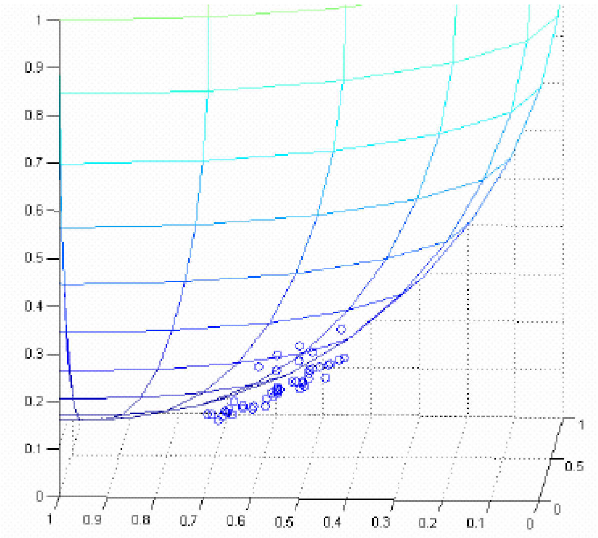

Figure 5. The Pareto-optimal solutions for this problem: Numbers of NP = 45

As you can see, Figure 5 shows that this method can enable to obtain various feasible solutions in at all. Every solution is different from each other. They are non-dominant vectors. Actually, we can search so many other feasible sets of trajectory parameters, as continuously repeating this multi-objective evolutionary computation process. Because they satisfy the Pareto-optimal condition each other, every solution has advantage that the fitness property is better than any other solutions in one objective at least. In EA, we need to iterate so many times this procedure for getting similar results with multi-objective evolutionary computation. As previously stated, we already obtain many solutions which have different features of walking trajectory. Now we investigate several cases for the walking patterns as follows (Table 2).

Table 2. Solutions of multi-objective evolutionary computation process

	Solutions		
	Case 1-1	Case 1-2	Case 1-3
vector[0]	123.011755	53.811797	82.587302
vector[1]	62.21682	56.034036	60.770987
vector[2]	134.275185	77.461114	82.866849
vector[3]	0.426906	0.487901	0.346573
vector[4]	0.911742	0.391433	0.771708
vector[5]	211.714223	214.965783	212.968968
vector[6]	208.69717	197.12557	206.377906
vector[7]	32.441752	32.951596	33.82173
vector[8]	60.752912	55.13491	66.071869
vector[9]	0.449804	0.51535	0.46066
vector[10]	0.747206	0.987681	0.840519
vector[11]	5.935924	5.264871	6.552376
stability	0.051932	0.228587	0.05523
mobility	0.414531	0.702854	0.549971
energy	0.348089	0.135315	0.258184

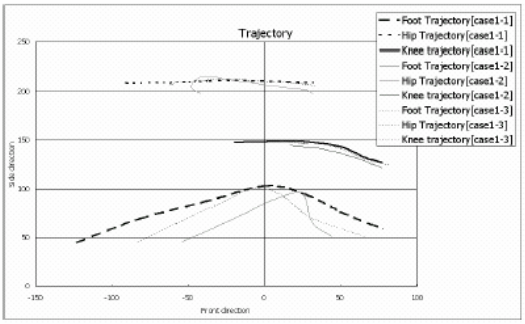

Figure 6. Examples of the walking patterns using the Pareto-optimal solutions

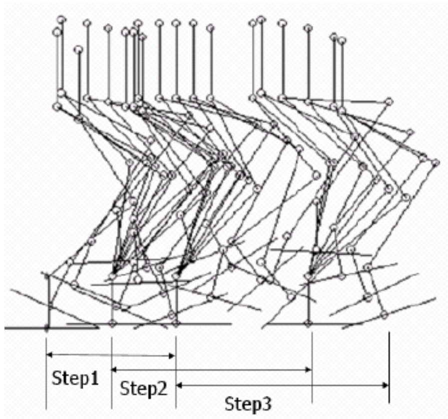

Figure 7. Simulator result of the walking patterns

Finally, we can generate some kind of walking patterns properly selecting the solutions mentioned above. Among them, Figure 7 describes three steps. Second step is different from the other steps in step length property. In this way, it is confirmed that there are many possibilities that we can obtain diverse walking patterns.

6. CONCLUSION

In this paper, EA is proposed to find the solution without the manual efforts mentioned above. We propose three objects. First, the one is about stability of walking trajectory. And next is about efficiency of energy. Finally, the other is about the mobility of robot. EA, for a single objective optimal problem of walking trajectory generation, is applied to optimize the weighted sum of three normalized object values and one penalty function. So, by this processes, we can obtain a optimal solution for walking trajectory of biped robot. But this is not so good. Because these objects have a conflict each other, we cannot optimize at the same time. So we propose the multi-objective evolutionary computation algorithm to find many useful solutions all at once. And we can obtain the multiform patterns using these solutions for walking like human. To apply the multi-objective problem, we use the modified the strength Pareto-optimality algorithm for this situation. At last, in simulations, proposed algorithm to generate the walking trajectory is verified.

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