

Multi-Objective Walking Trajectories Generation for a Biped Robot

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Abstract—The generation of the optimal walking pattern is an important question for a biped robot to keep walking stably. This paper is proposed for generating the walking patterns resulted in best performance of the biped robot using multi-objective evolutionary algorithm. 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 EA simulation.

I. 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. [1] 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 for given environment. So, this paper is organized as follows. In Section II, we describe the model of a biped robot and define the walking trajectory with the necessary parameters. Next, in Section III, 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 IV. Finally we conclude this paper in Section V.

II. WALKING TRAJECTORIES WITH VIA POINTS

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 1 describes the configurations of the biped robot in via point at time t . [1] 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.

III. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM(MOEA) FOR ADAPTABLE TRAJECTORIES

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.

A. 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 $x = (x_1, \dots, x_n)$ which optimizes the values of a set of objective functions $f = (f_1, \dots, f_m)$ within the feasible region of x (Figure 2). Figure 2 describes the set of Pareto optimality solutions of the minimization problem. The definition of the Pareto-optimality can be described as follows: Assume a minimization problem and consider two arbitrary vectors $a, b \in P$. It can be said that a dominate b iff

$$f_i(a) \leq f_i(b), \forall i = 1, \dots, m, \wedge \\ f_i(a) < f_i(b), \exists i = 1, \dots, m.$$

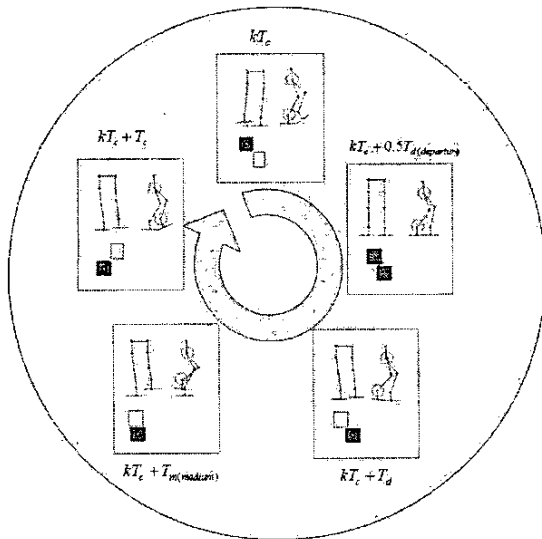


Fig. 1. The configurations of the biped robot at via points

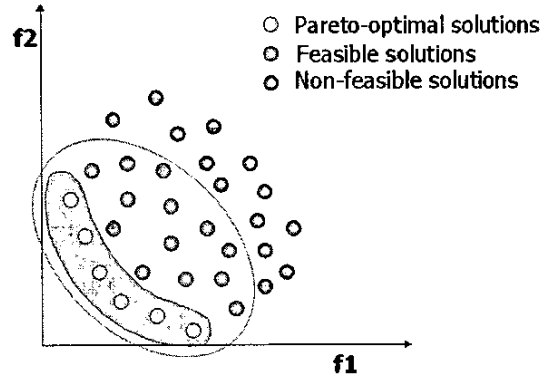


Fig. 2. The Pareto-optimal solutions

Every vector which is not dominant by any other vector are called non-dominant set or Pareto-optimal set. For the walking trajectory, we can define a set of objective functions as $f = (f_{stability}, f_{energy}, f_{mobility})$. $f_{penalty}$ should also be considered, because, if $f_{penalty}(x) \neq 0$, this vector (x) is not feasible and cease to be a solution. In multi-objective problem, there are many schemes to find the non-dominant 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. Therefore, to resolve such a difficulty, many related works have been carried out, and the methods considering such a difficult point is very appealing. The strength pareto evolutionary algorithm is one of them.

B. The Proposed Algorithm Using The MOEA

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-dominant set NP (Non-dominant vectors).
- (2) Find the non-dominant members in P . However, to decide whether a vector is the member of the non-dominant set, $f = (f_{stability}, f_{energy}, f_{mobility})$ of the vector cannot be applied as it is. Because, if the position of a vector (x) at every time instance violates the penalty condition, $f_{stability}(x)$ and $f_{energy}(x)$ may equal to zero. As a result, although they cannot be the solution to satisfy feasible constraints, they can pretend to be a member of the non-dominant solutions. Therefore, each vector should be translated as much as its penalty fitness value in objective space. This way, the

feasible region is filtered by removing impurities (Figure 3). There, the non-dominant members in P are identified, and transfer them from P to NP .

(3) Leave the non-dominant members in NP , and remove the dominant members in P .

(4) If the number of the non-dominant solutions are greater than the desired number N_{nondom} , 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) Terminate the algorithm, if the number of the generation has reached the maximum number of generations, go to (2), otherwise.

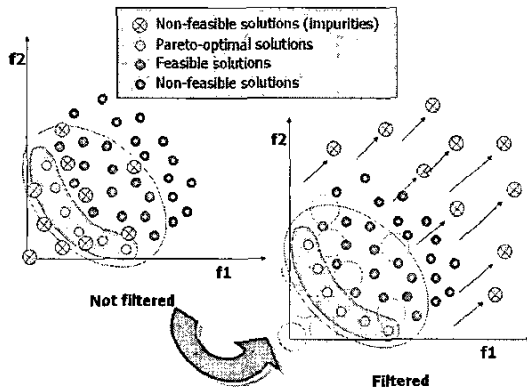


Fig. 3. The filtering of feasible space

C. Vector initialization

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

$$\left\{ \begin{array}{l} F_d : \left(\frac{F_f + F_b}{2} \right) \leq F_d \leq 2(F_f + F_b) \\ F_{mh} : F_a \leq F_{mh} \leq (F_a + L_1) \\ F_{mi} : \left(\frac{F_f + F_b}{2} \right) \leq F_{mi} \leq \left(\frac{3(F_f + F_b)}{2} \right) \\ f_b : 0 \leq f_b \leq \frac{\pi}{3} \\ f_f : 0 \leq f_f \leq \frac{\pi}{3} \\ H_{max} : (F_a + L_1) \leq H_{max} \leq (F_a + L_1 + L_2 + L_3) \\ H_{min} : (F_a + L_1) \leq H_{min} \leq H_{max} \\ d_{hf} : \left(\frac{F_f + F_b}{3} \right) \leq d_{hf} \leq (F_f + F_b) \\ d_{hb} : \left(\frac{F_f + F_b}{3} \right) \leq d_{hb} \leq (F_f + F_b) \\ \theta_{max} : 0 \leq \theta_{max} \leq \frac{\pi}{4} \\ \alpha : 0 \leq \alpha \leq 2 \\ T_c : 5 \leq T_c \leq 15.0 \end{array} \right. \quad (1)$$

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

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

$$T_m = \frac{F_{mi}}{2F_d} T_c \quad (3)$$

F_f , F_b , F_a are representing the size of the sole of a foot, and length of an ankle link. And L_1 , L_2 , L_3 are lengths of links. T_d and T_c are time values of each via point. They are considered adequately for real system consisted of actual motors with limited capacity.

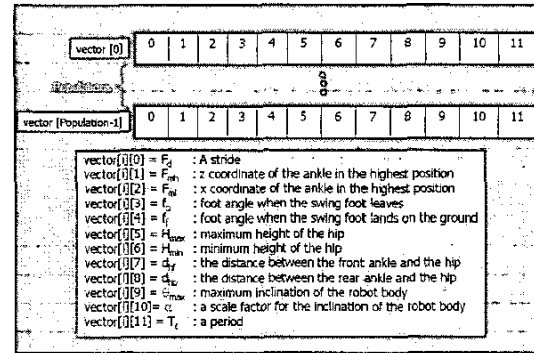


Fig. 4. The definition of the vector

D. Operation

We select the parents to produce the new offspring and population with the random tournament. There are 3 steps for this selection method. First two vectors are randomly selected in current population. And then compare the score of one vector with the other, and finally select the vector, who wins the competition, as parents

of the next generation. Prior to this procedure, the best individual is inherited to the next generation. After selection process, crossover and mutation processes get underway. To maintain the diversity of each generation, arithmetic crossover and uniform mutation is applied to this procedure.

E. The Proposed Fitness Functions

Here we propose the fitness functions to be appropriate for the biped robot. During a cycle, we consider stability property, energy efficient performance, mobility property, and penalty for violations of basic constraints. Each factor is used to define the fitness function. Let $f_{stability}$ be the stability function of the fitness function. The definition of this function is as follows:

$$f_{stability}(\mathbf{x}) = \frac{f_{zmp}(\mathbf{x})}{\max_{\mathbf{y} \in \Psi} f_{zmp}(\mathbf{y})} + \frac{f_{shake}(\mathbf{x})}{\max_{\mathbf{y} \in \Psi} f_{shake}(\mathbf{y})} + \frac{f_{config}(\mathbf{x})}{\max_{\mathbf{y} \in \Psi} f_{config}(\mathbf{y})} + \frac{f_{hip}(\mathbf{x})}{\max_{\mathbf{y} \in \Psi} f_{hip}(\mathbf{y})} \quad (4)$$

where Ψ represents a set of points in the current population. Each term denotes the following normalized functions:

$$f_{zmp}(\mathbf{x}) = \sum_{k=0}^N \left(\frac{\|(\mathbf{p}_{zmp} - \mathbf{p}_{dzmp})\|}{N} \right) \quad (5)$$

$$f_{shake}(\mathbf{x}) = \max y_{zmp} - \min y_{zmp} \quad (\text{if } T_d \leq t \leq T_c) \quad (6)$$

$$f_{config}(\mathbf{x}) = \frac{F_{mh}}{T_c F_d} \quad (\text{if } \frac{F_{mh}}{F_d} > C_r) \quad (7)$$

$$f_{hip}(\mathbf{x}) = \frac{H_{max} - H_{min}}{H_{max} + H_{min}} \quad (8)$$

where $N = \frac{T_c}{T_s}$, $x_{dzmp}(kT_s)$, $y_{dzmp}(kT_s)$ are the desired ZMP trajectory of a vector \mathbf{x} , $x_{zmp}(kT_s)$, $y_{zmp}(kT_s)$ are the current ZMP trajectory at sampling instants, C_r is defined as standard configuration rate, which indicates the fitness degree of its trajectory shape for a foot, and T_s is the sampling time. The first term of $f_{stability}(\mathbf{x})$ is a mean error between the desired ZMP and actual ZMP for all sampling instants. The second term represents a degree to be shaken from side to side during a single support phase. The third term is related to the configuration of foot trajectory. Thus, the larger is this value, the higher the risk is that the motor may go to the utmost limit of velocity and torque, and then the stranger is the shape of foot trajectory. The fourth term describes the motion of the hip. If this value is larger, whole configuration of walking trajectory becomes abnormal and the robot may stoop. Therefore, 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. And then let f_{energy} be the energy efficiency function. The definition of this function is as follows:

$$f_{energy}(\mathbf{x}) = \sum_{k=0}^N \left(\frac{z_a(kT_s)}{N} \right) \quad (9)$$

where z_a is the z coordinate of the ankle of the swing leg. It refers to minimizing the height of the swing leg from the ground. It can be applied for looking over the change of the joint angle slightly.

Next, let $f_{mobility}$ be the mobility performance function. The function can be derived as follows:

$$f_{mobility}(\mathbf{x}) = \frac{10}{velocity} = 10 \frac{T_c}{F_d} \quad (10)$$

It is shown that if the value of the mobility function $f_{mobility}(\mathbf{x})$ is smaller, a mobility performance is better and the motion is faster.

At last, let $f_{penalty}(\mathbf{x})$ be the penalty function for the constraints. Above all, penalty function has the highest priority. Because, if a certain vector violates the penalty condition, other functions cannot be evaluated. If vector $f_{penalty}(\mathbf{x})$ has singularity positions, there can be no solution of the inverse kinematics so that the other functions cannot be defined around those positions. If the position at every time instant is violated the penalty condition, $f_{stability}(\mathbf{x})$ and $f_{energy}(\mathbf{x})$ may equal to zero.

$$f_{penalty}(\mathbf{x}) = \min \left(\sum_{k=0}^N P(kT_s), P_{MAX} \right) \quad (11)$$

where

$$P(kT_s) = \begin{cases} 1, & \text{if ZMP isn't kept in stable region.} \\ 1, & \text{if the vel. of the swing leg is negative.} \\ P_{max}, & \text{if there is no solution of the inverse kinematics.} \end{cases} \quad (12)$$

where $P(kT_s)$ is a function to obtain a penalty value at time kT_s , P_{MAX} and P_{max} are the maximum values in relation to the total value $f_{penalty}$ and $P(kT_s)$.

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.

F. The 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.

IV. SIMULATION

In this section, we will verify the proposed scheme for the walking trajectory generation of a biped robot by some simulation results with this robot. 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 planning problem can be solved.

The parameters used in the simulation are listed in Table I.

TABLE I
PARAMETERS OF EA

Parameters	value
Parent size	150
Offspring size	300
No. of generation	300
Crossover ratio	0.3
mutation ratio	0.05
system parameter(δ)	2

As can be seen in 5, this method is capable of obtaining various feasible solutions. 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 MOEA process. Because they satisfy the Pareto-optimal condition each other, every solution has an advantage that the fitness property is better than any other solutions on at least one objective space. In EA, we need to iterate the procedure many times to achieve similar results with MOEA. 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 Table II.

Finally, we can generate various walking patterns by properly selecting the solutions mentioned above (such as Figure 7). 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.

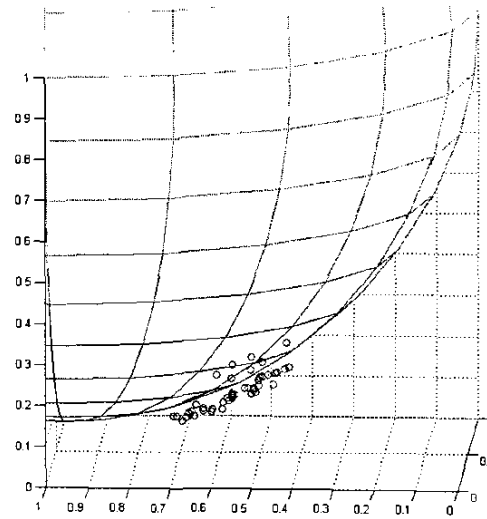


Fig. 5. The Pareto-optimal solutions for this problems: No. of NP=45

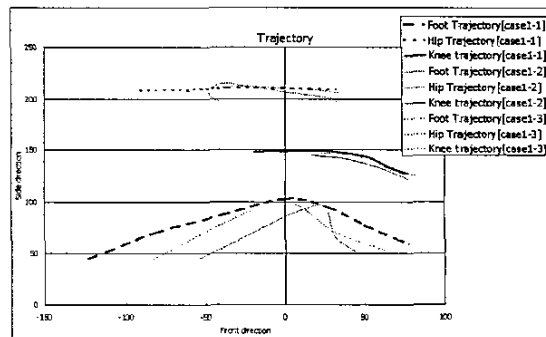


Fig. 6. Examples of the walking patterns using the Pareto-optimal solutions

V. 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

TABLE II
SOLUTIONS USED FOR CASE 1

	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

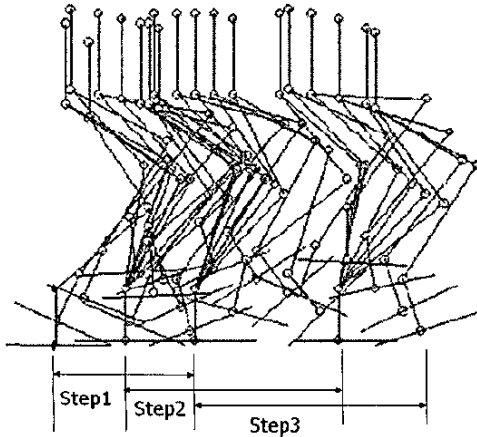


Fig. 7. Simulation example of the walking patterns

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.

ACKNOWLEDGMENT

This research was supported by University IT Research Center Project in the Republic of Korea.

REFERENCES

- [1] G. Capi, S. Kaneko, K. Mitobe, L. Barolli, Y. Nasu, "Optimal trajectory generation for a prismatic joint biped robot using genetic algorithms", *Robotics and autonomous systems*, v.38, no.2, pp.119-128, 2002.
- [2] C. Zhou, Q. Meng, "Dynamic balance of a biped robot using fuzzy reinforcement learning agents", *Fuzzy sets and systems*, v.134 no.1, pp.169-187, 2003.

- [3] J.H. Park, "Fuzzy-logic zero-moment-point trajectory generation for reduced trunk motions of biped robots", *Fuzzy sets and systems*, v.134, no.1, pp. 189-203, 2003.
- [4] J.G. Kim, K.G. Noh, K. Park, "Human-Like Dynamic Walking for a Biped Robot Using Genetic Algorithm", *Lecture notes in computer science*, no.2210, pp.159-170, 2001.
- [5] Y.F. Zheng, J. Shen, Jr. F.R. Sias, "A motion control scheme for a biped robot to climb sloping surfaces", *Robotics and Automation, Proceedings., IEEE International Conference on*, pp.814-816, 1988.
- [6] M.Y. Cheng, C.S. Lin, "Genetic algorithm for control design of biped locomotion", *Systems, Man and Cybernetics, Intelligent Systems for the 21st Century., IEEE International Conference on*, v.2, pp.1315-1320, 1995.
- [7] L. Rodrigues, M. Prado, P. Tavares, K. Da Silva, A. Rosa, "Simulation and control of biped locomotion-GA optimization", *Evolutionary Computation, Proceedings of IEEE International Conference on*, pp.390-395, 1996.
- [8] A.L. Kun, W.T. Miller, "Adaptive Static Balance of A Biped Robot using Neural Networks", *Robotics and manufacturing*, pp.245-248, 1997.
- [9] T. Arakawa, T. Fukuda, "Natural Motion Generation of Biped Locomotion Robot Using Hierarchical Trajectory Generation Method Consisting of GA, EP Layers", *Proceedings - IEEE International Conference on Robotics and Automation*, v.1, pp.211-216, 1997.
- [10] G. Capi, Y. Nasu, L. Barolli, K. Mitobe, K. Takeda, "Application of Genetic Algorithms for biped robot gait synthesis optimization during walking and going up-stairs", *Advanced robotics : the international journal of the Robotics Society of Japan*, v.15 no.6, pp.675-694, 2001.
- [11] Q. Huang, K. Yokoi, S. Kajita, K. Kaneko, H. Arai, N. Koyachi, K. Tani, "Planning walking patterns for a biped robot", *IEEE Transactions on Robotics and Automation*, v.17, no.3, pp. 280-289, June 2001.
- [12] R.P. Paul, B. Shimano, and G.E. Mayer, "Kinematic Control Equations for Simple Manipulators", *IEEE Transactions on Systems, Man and Cybernetics*, SMC-11, 6, PP.449-455, 1981.
- [13] H. Tamaki, H. Kita, S. Kobayashi, "Multi-objective optimization by genetic algorithms: a review", *Evolutionary Computation, Proceedings of IEEE International Conference on*, pp.517-522, 1996.
- [14] E. Zitzler, L. Thiele, "Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach", *IEEE transactions on evolutionary computation : a publication of the IEEE Neural Networks Council*, v.3 no.4, pp.257-271, 1999.