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OPTIMAL MULTI-CRITERIA HUMANOID ROBOT GAIT SYNTHESIS – AN EVOLUTIONARY APPROACH

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Abstract. *Humanoid robots operating in everyday life environments must generate the gait based on the environmental conditions. Often the gait has to satisfy different objectives. In this paper, we present a new method for humanoid robot gait generation based on multiobjective evolutionary algorithms. In our method, we consider two different conflicting objectives for the humanoid robot gait generation: minimum energy and minimum torque change. In the difference from single objective genetic algorithm, the multiobjective evolutionary algorithm converges in a set of nondominated Pareto optimal gaits. Based on the environmental conditions and the user requirements, the appropriate humanoid robot gait can be selected. Simulation and experimental results using the "Bonten-Maru" humanoid robot show a good performance in the proposed method.*
Keywords: Humanoid robot, Multiobjective evolutionary algorithm, Gait synthesis

1. **Introduction.** Humanoid robots are expected to operate in every environment humans operate in. In order to achieve a humanoid robot able to operate in everyday life environments, dynamic stable motion is required. In addition, they have to change their gait based on the environmental conditions. Therefore, algorithms for generating humanoid robot gait based on the environmental conditions are central for development of humanoid robots. In the early works, the humanoid robot gait is generated based on the data taken from human motion [1]. Most of the recent work [2-4] considers minimum consumed energy as a criterion for humanoid robot gait generation. Roussel [2] considered the minimum consumed energy gait synthesis during walking. The body mass is concentrated on the hip of the biped robot. Silva and Machado [3] considered the body link restricted to the vertical position and the body forward velocity to be constant. The consumed energy, related to the walking velocity and step length, is analyzed by Channon [4]. The distribution functions of input torque are obtained by minimizing the joint torques.

In our previous works, we considered the humanoid robot gait generation during walking and going up-stairs [5] and a real time gait generation [6]. In addition to minimum consumed energy (MCE) criteria, minimum torque change (MTC) [7,8] was also considered. The results showed that MCE gait has different characteristics compared to MTC. MCE gait was similar with that of humans. Another advantage of MCE criteria is also related to the operation time when a battery actuates the motors. On the other hand, due to smooth change of torque and consequently of link accelerations, the disturbance of the robot's stability was small when humanoid robot gait was generated based on MTC criterion.

The main motivation behind this work is to generate a humanoid robot gait that satisfies a certain degree of different objectives, which belong to a multiobjective optimization problem. In a multiobjective optimization problem there may not exist one solution that is the best with respect to all objectives. Usually, the aim is to determine the tradeoff surface, which is a set of nondominated solution points, known as Pareto-optimal or noninferior solutions. Based on the environmental conditions, the humanoid robot can switch among different gaits from the Pareto optimal gaits.

In other works, the multiobjective problem was converted to a single objective problem by linear combination of different objectives as a weighted sum [9]. The important aspect of this weighted sum method is that a set of non-inferior (or Pareto-optimal) solutions can be obtained by varying the weights. Unfortunately, this requires multiple runs as many times as the number of desired Pareto-optimal solutions. Furthermore, this method cannot be used to find Pareto-optimal solutions in problems having a non-convex Pareto-optimal front. In addition, there is no rational basis for determining adequate weights and the objective function so formed may lose significance due to combining non-commensurable objectives. To avoid this difficulty, the e-constraint method for multiobjective optimization was presented. This method is based on optimization of the most preferred objective and considering the other objectives as constraints bounded by some allowable levels. These levels are then altered to generate the entire Pareto-optima set. The most obvious weaknesses of this approach are that it is time-consuming and tends to find weakly nondominated solutions.

In this paper, we present a multiobjective evolutionary algorithm (EA) [10,13] technique for humanoid robot gait synthesis. The main advantage of the proposed algorithm is that in a single run of evolutionary algorithm, humanoid robot gaits with completely different characteristics are generated. Therefore, the humanoid robot can switch between different gaits based on the environmental conditions. In our method, the basic idea is to encode the humanoid robot gait parameters in the genome and take the parameters of the nondominated optimal gaits in the next generation. The specific questions we ask in this study are: 1) whether multiobjective EA can successfully generate the humanoid robot gait that satisfies different objective functions to a certain degree, 2) whether the humanoid robot gait optimized by EA in simulation can indeed be helpful in hardware implementation.

In order to answer these questions, we considered the MCE and MTC cost functions as criterion for "Bonten-Maru" humanoid robot gait synthesis. We employed a real number multiobjective EA. The results show that multiobjective EA generates a set of nondominated optimal humanoid robot gaits. In order to further verify how the optimized gait will perform on real hardware, we implemented the optimal gait using the "Bonten-Maru" humanoid robot. The results show that in addition to energy consumption, the optimized gait was stable and with a small impact due to the smooth change of the joint torques.

2. Multiobjective Evolutionary Algorithm.

2.1. Dominance and Pareto-optimality. In multiobjective optimization problems there are many (possibly conflicting) objectives to be optimized simultaneously. Therefore, there is no longer a single optimal solution but rather a whole set of possible solutions of equivalent quality. In contrast to fully ordered scalar search spaces, multidimensional search spaces are only partially ordered, i.e. two different solutions are related to each other in two possible ways: either one dominates the other or none of them is dominated. Consider without loss of generality the following multiobjective maximization problem with m decision variables x (parameters) and n objectives:

$$y = f(x) = (f_1(x_1, ...x_m), ..., f_n(x_1, ...x_m)) \tag{1}$$

where $x = (x_1, ...x_m) \in X$, $y = (y_1, ...y_n) \in Y$ and where x is called decision (parameter) vector, X parameter space, y objective vector and Y objective space. A decision vector $a \in X$ is said to dominate a decision vector $b \in X$ (also written as a $\succ$ b) if and only if:

$$\forall i \in \{1, ..., n\} : f_i(a) \geq f_i(b) \wedge \exists j \in \{1, ..., n\} : f_j(a) \geq f_j(b) \tag{2}$$

The decision (parameter) vector a is called Pareto-optimal if and only if a is nondominated regarding the whole parameter space X. If the set X_0 is not explicitly specified, the whole parameter space X is implied. Pareto-optimal parameter vectors cannot be improved in any objective without causing degradation in at least one of the other objectives. They represent in that sense globally optimal solutions. Note that a Pareto-optimal set does not necessarily contain all Pareto optimal solutions in X.

In extending the ideas of single objective EAs to multiobjective cases, two major problems must be addressed: 1. How to accomplish fitness assignment and selection in order to guide the search towards the Pareto-optimal set. 2. How to maintain a diverse population in order to prevent premature convergence and achieve a well distributed, wide spread trade-off front. Note that the objective function itself no longer qualifies as fitness function since it is a vector valued and fitness has to be a scalar value. Different approaches to relate the fitness function to the objective function can be classified with regard to the first issue. The second problem is usually solved by introducing elitism and intermediate recombination. Elitism is a way to ensure that good individuals do not get lost (by mutation or set reduction), simply by storing them away in a external set, which only participates in selection. Intermediate recombination, on the other hand, averages the parameter vectors of two parents in order to generate one offspring.

2.2. Strength pareto approach. In this work, the Strength Pareto Approach for multiobjective optimization has been used. Comparative studies have shown for a large number of test cases that, among all major multiobjective EAs, the Strength Pareto Evolutionary Algorithm (SPEA) is clearly superior. It is based on the above mentioned principles of Pareto-optimality and dominance. The algorithm is as follows:

Step 1: Generate random initial population P and create the empty external set of nondominated individuals P_0.

Step 2: Evaluate objective function for each individual in P in parallel.

Step 3: Copy nondominated members of P to P_0.

Step 4: Remove solutions within P_0 which are covered by any other member of P_0.

Step 5: If the number of externally stored nondominated solutions exceeds a given maximum N_0, prune P_0 by means of clustering.

Step 6: Calculate the fitness of each individual in P as well as in P_0.

Step 7: Select individuals from $P + P_0$ (multiset union), until the mating pool is filled.

Step 8: Adapt step sizes of the members of the mating pool.

Step 9: Apply recombination and mutation to members of the mating pool in order to create a new population P.

Step 10: If maximum number of generations is reached, then stop, else go to Step 2.

SPEA is unique in three respects:

- The fitness of an individual is determined from the solutions stored in the external Pareto set only; whether members of the population dominate each other is irrelevant.
- All solutions in the external Pareto set participate in the selection.
- A new niching method is provided in order to preserve diversity in the population; this method is Pareto-based and does not require any distance parameter.

3. **Optimal Gait Generation.** During motion, the arms of the humanoid robot will be fixed on the chest. Therefore, it can be considered as a five-link biped robot in the saggital plane, as shown in Figure 1. The motion of the biped robot is considered to be composed from a single support phase and an instantaneous double support phase. The friction force between the robot's feet and the ground is considered to be great enough to prevent sliding. During the single support phase, the ZMP must be within the sole length, so the contact between the foot and the ground will remain. In our work, we calculate the ZMP by considering the link mass concentrated at one point. To have a stable periodic walking motion, when the swing foot touches the ground, the ZMP must jump in its sole. This is realized by accelerating the body link. To have an easier relative motion of the body, the coordinate system from the ankle joint of the supporting leg is moved transitionally to the waist of the robot ($O_1X_1Z_1$). Referring to the new coordinate system, the ZMP position is written as follows:

$$\bar{X}_{ZMP} = \frac{\sum_{i=1}^{5} m_i(\ddot{\bar{z}}_i + \ddot{z}_w + g_z)\bar{x}_i - \sum_{i=1}^{5} m_i(\ddot{\bar{x}}_i + \ddot{x}_w)(\bar{z}_i + z_w)}{\sum_{i=1}^{5} m_i(\ddot{\bar{z}}_i + \ddot{z}_w + g_z)}, \tag{3}$$

where m_i is mass of the particle "i", x_w and z_w are the coordinates of the waist with respect to the coordinate system at the ankle joint of supporting leg, $\bar{x}_i$ and $\bar{z}_i$ are the coordinates of the mass particle "i" with respect to the $O_1X_1Z_1$ coordinate system, $\ddot{\bar{x}}_i$ and $\ddot{\bar{z}}_i$ are the acceleration of the mass particle "i" with respect to the $O_1X_1Z_1$ coordinate system.

Based on the formula (3), if the position, $\bar{x}_i, \bar{z}_i$, and acceleration, $\ddot{\bar{x}}_i, \ddot{\bar{z}}_i$, of the leg part (i=1,2,4,5), the body angle, θ_3, and body angular velocity, $\dot{\theta}_3$, are known, then because $\ddot{\bar{x}}_3, \ddot{\bar{z}}_3$ are functions of l_3, θ_3, $\dot{\theta}_3$, $\ddot{\theta}_3$, it is easy to calculate the body angular acceleration based on the ZMP position. Let (0) and (f) be the indexes at the beginning and at the end of the step, respectively. At the beginning of the step, $\ddot{\theta}_{30}$ causes the ZMP to be in the position ZMP_{jump}. At the end of the step, the angular acceleration $\ddot{\theta}_{3f}$ is calculated in order to have the ZMP at the position ZMP_f, so that the difference between $\ddot{\theta}_{3f}$ and $\ddot{\theta}_{30}$ is minimal. Therefore, the torque necessary to change the acceleration of the body link will also be minimal.

4. **Objective Functions.** The gait synthesis problem, with respect to walking or going up-stairs, consists on finding the joint angle trajectories, to connect the first and last posture of the biped robot for which the consumed energy and torque change are minimal. For the MCE cost function, it can be assumed that the energy to control the position of the robot is proportional to the integration of the square of the torque with respect to time, because the joint torque is proportional with current. Therefore, minimizing the joint torque can solve the MCE problem [11].

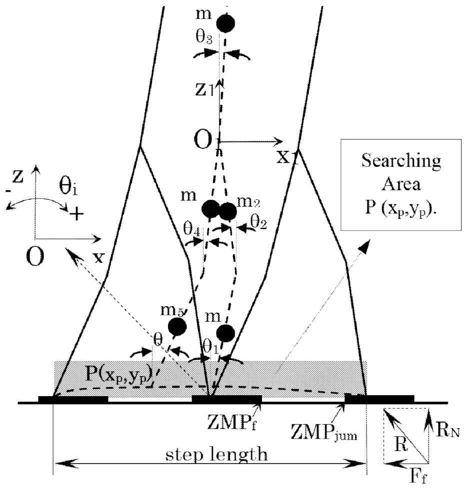


FIGURE 1. Five-link biped robot

TABLE 1. "Bonten-Maru" parameters

	Body	Lower leg	Upper leg	Lower leg + foot
Mass [kg]	12	2.93	3.89	4.09
Inertia [kg m^2]	0.19	0.014	0.002	0.017
Length [m]	0.3	0.2	0.204	0.284
CoM dist.[m]	0.3	0.09	0.1	0.136

The cost function J, which is a quantity proportional to the energy required for the motion, is defined as follows:

$$J = \frac{1}{2}\left(\int_0^{t_f} \tau^T dt + \Delta\tau_{jump}^2 \Delta t + \int_0^{t_f} C dt\right), \tag{4}$$

where t_f is the step time, τ is the torque vector, $\Delta\tau_{jump}$ and Δt are the addition torque applied to the body link to cause the ZMP to jump and its duration time, and C is the

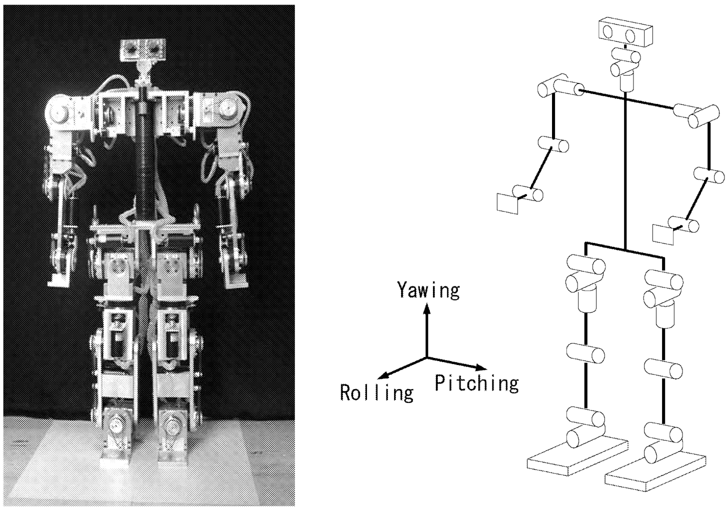


FIGURE 2. "Bonten-Maru" humanoid robot

constraint function, given as follows:

$$C = \begin{cases} 0-if\ the\ constraints\ are\ satisfied, \\ c_i-if\ the\ constraints\ are\ not\ satisfied, \end{cases}$$

c denotes the penalty function vector. We consider the following constraints for our system.

1) The walking to be stable or the ZMP to be within the sole length.
2) The distance between the hip and ankle joint of the swing leg must not be longer then the length of the extended leg.
3) The swing foot must not touch the ground prematurely.

The torque vector is calculated from the inverse dynamics of the five-link biped robot as follows:

$$J(\theta)\ddot{\theta} + X(\theta)\dot{\theta}^2 + Y\dot{\theta} + Z(\theta) = \tau, \tag{5}$$

where $J(\theta)$ is the mass matrix (5x5), $X(\theta)$ is the matrix of centrifugal coefficients (5x5), Y is the matrix of Coriolis coefficients (5x5), $Z(\theta)$ is the vector of gravity terms (5x1), τ is the generalized torque vector (5x1), and $\theta, \dot{\theta}, \ddot{\theta}$ are 5x1 vectors of joint variables, joint angular velocities and joint angular accelerations, respectively.

The MTC model [7,8] is based on smoothness at the torque level. The cost is the integrated squared torque change summed over the joints and the movement. In the MTC, the objective function to be minimized is expressed by:

$$J_{torquechange} = \frac{1}{2}\left(\int_0^{t_f} \left(\frac{d\tau}{dt}\right)^T \left(\frac{d\tau}{dt}\right) dt + \left(\frac{\Delta\tau}{\Delta t}\right)^2 + \int_0^{t_f} C dt\right). \tag{6}$$

5. **Simulation and Experimental Results.** In the simulations, we use the parameters of the "Bonten-Maru" humanoid robot. The parameter values are presented in Table 1 and the robot is shown in Figure 2. The "Bonten-Maru" is 1.2m high, each leg has 6 degrees of freedom and is composed by three segments: upper leg, lower leg and the foot.

The foot length is 0.18m. A DC servomotor actuates each joint. The control platform is based on Common Object Request Broker Architecture (CORBA), which allows an easy updating and addition of new modules [12].

Due to difficulties of binary representation when dealing with continuous search space with large dimension, real coded EA [13] is used in this study. The decision variables are represented by real numbers within their lower and upper limits. We employed a standard crossover operator and the non-uniform mutation. In all optimization runs, crossover and mutation probabilities were chosen as 0.9 and 0.3, respectively. The population size was selected as 50 individuals and the optimization terminated after 100 generations. The maximum size of the Pareto-optimal set was chosen as 50 solutions.

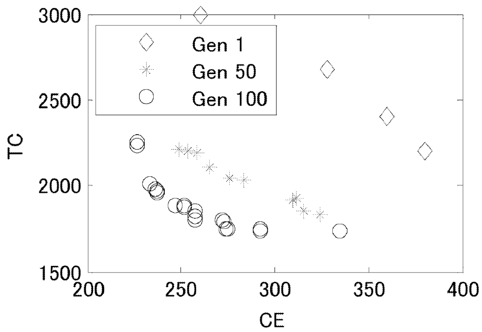


Figure 3. Pareto optimal solution for different generations

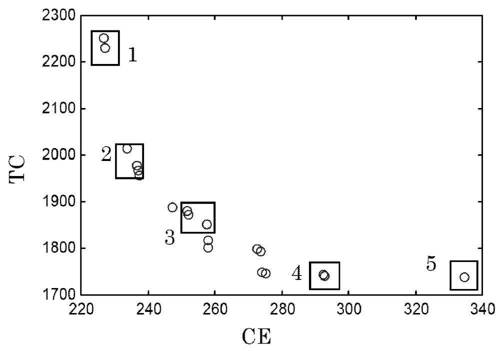
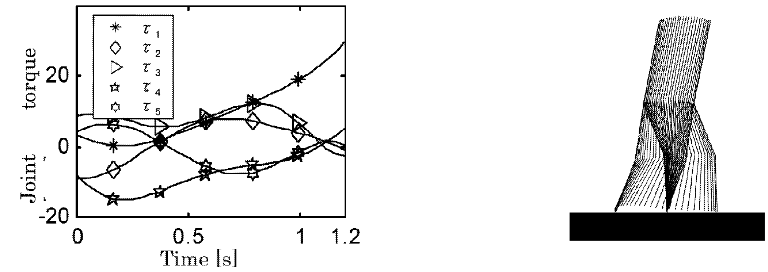


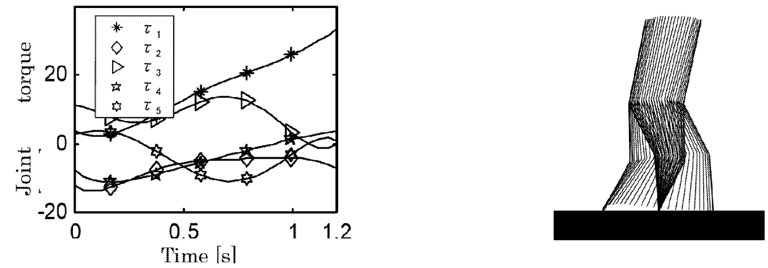
Figure 4. Pareto front of nondominated solutions after 100 generations

Based on the parameters of the “Bonten-Maru” humanoid robot the step length used in the simulations varies from 0.2m to 0.55m. The bounds, within which the solution is sought, change according to the step length and step time. In the following, we present the results for the step length 0.42m and step time 1.2s.

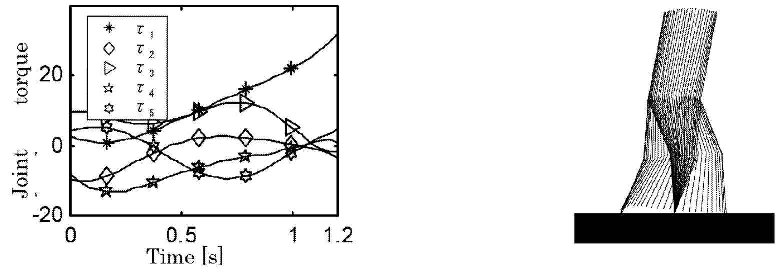
Figure 3 shows the Pareto optimal front for generations 1, 50 and 100. During the first 50 generations there is a great improvement on the quality and distribution of Pareto optimal solutions. From this figure, it can be deduced that the multiobjective EA is equally capable of finding the best solution for each objective when two conflicting objectives are considered simultaneously.



(a) Box 1 result (MCE)



(b) Box 5 result (MTC)



(c) Box 3 results

FIGURE 5. Different results from Pareto-front solutions

Figure 4 shows the Pareto-optimal trade-off front after 100 generations. We can observe the existence of a clear tradeoff between the two objectives. In addition, the obtained reference solution set has a good distribution (similar to uniform distribution). One of the interesting features of the resulting Pareto front is the almost exponential relation between the MCE and MTC cost functions. Results in Box 1 and Box 5 are at the extreme ends of the Pareto front. Box1 represents Pareto solutions with high value of MTC function, but low energy consumption. Based on the Pareto-optimal solutions, we can choose whether to go for minimal CE (Box 1 in Figure 4) at the expense of less smooth in the torque or choose some intermediate result. If we are interested in a low consumed energy humanoid robot gait, without neglecting the smoothness in the torque change, the results shown in Boxes 2, 3 are the most important. The results in Box 2, show that by a small increase in the energy consumption (2.2%), we can decrease the MTC fitness function by around 12.1%. Also, the energy can be reduced by 14.5% for a small increase in the MTC cost function (Box 4).

The torque vector (τ_i) and the optimal gaits for different results of pareto front solutions are shown in Figure 5. The humanoid robot gait generated based on the results of Box 1 and Box 5 are very similar with the results presented in [5] for MCE and MTC, respectively. As shown in Figure 5(a), the robot posture is straighter, similar to humans, for MCE cost function. Torque value is low for MCE gait (Figure 5(a)) and the torques change smoothly for MTC gait (Figure 5(b)). The optimal gait generated by Box 3 solutions satisfies both objective functions. The energy consumption is increased by 9% but on the other hand the value of MTC cost function is decreased by 19.2%.

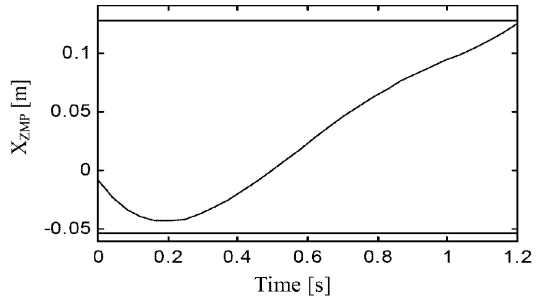


FIGURE 6. ZMP position

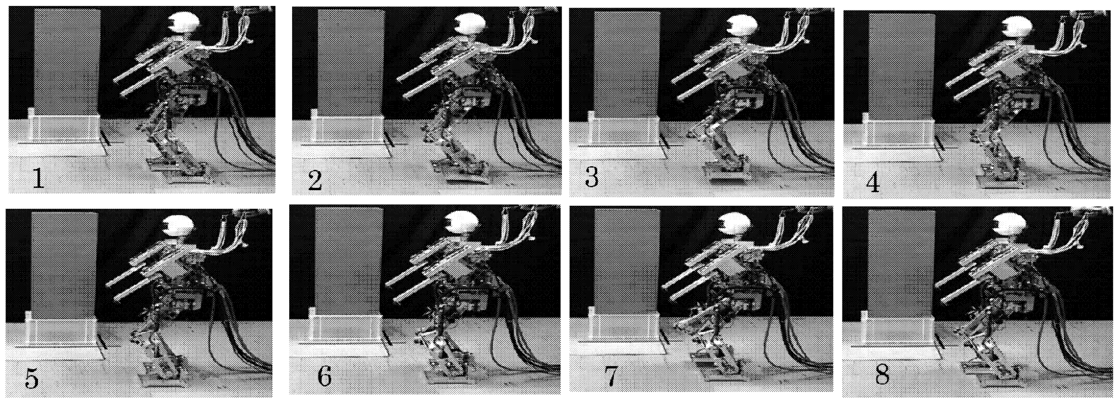


FIGURE 7. Video capture during robot motion

The ZMP position is presented in Figure 6 for humanoid robot gait generated by Box 3 result. The ZMP is always between the dotted lines, which present the length of the foot. At the end of the step, the ZMP is at the position ZMP_f, as shown in Figure 1. At the beginning of the step, the ZMP is not exactly at the position ZMP_{jump} because of the foot's mass. It should be noted that the mass of the lower leg is different when it is in supporting leg or swing leg.

In order to investigate how the optimized gaits in simulation will perform in real hardware, we use the optimal gaits that satisfy both objective functions on the "Bonten-Maru" humanoid robot (Figure 7). The experimental results show that in addition to a reduction in energy consumption, the humanoid robot gait generated by Box 3 solutions was stable. The impact of the foot with the ground was also small.

6. **Conclusions.**

This paper proposed a new method for humanoid robot gait generation based on several objective functions. The proposed method is based on multiobjective evolutionary algorithm. In our work, we considered two competing objective functions: MCE and MTC. Based on simulation and experimental results, we conclude:

- Multiobjective evolution is efficient because optimal humanoid robot gaits with completely different characteristics can be found in one simulation run.
- The nondominated solutions in the obtained Pareto-optimal set are well distributed and have satisfactory diversity characteristics.
- The optimal gaits generated by simulation gave good results when they were tested in the real hardware of "Bonten-Maru" humanoid robots.
- The optimal gait reduces the energy consumption and increases the stability during the robot's motion.

In the future, it will be interesting to investigate if the robot can learn to switch between different gaits based on the environmental conditions.

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