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Multicriteria Optimal Humanoid Robot Motion Generation

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1. Introduction

Humanoid robots, because of their similar structure with humans, are expected to operate in hazardous and emergency environments. In order to operate in such environments, the humanoid robot must be highly autonomous, have a long operation time and take decisions based on the environment conditions. Therefore, algorithms for generating in real time the humanoid robot gait are central for development of humanoid robot.

In the early works, the humanoid robot gait is generated based on the data taken from human motion (Vukobratovic et al. 1990). Most of the recent works (Roussel 1998, Silva & Machado 1998, Channon 1996) consider minimum consumed energy as a criterion for humanoid robot gait generation. Roussel (1998) considered the minimum consumed energy gait synthesis during walking. The body mass is concentrated on the hip of the biped robot. Silva & Machado (1998) 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 (1996). 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 (Capi et al. 2001) and a real time gait generation (Capi et al. 2003). In addition of minimum consumed energy (MCE) criteria, minimum torque change (MTC) (Uno et al. 1989, Nakano et al. 1999) was also considered. The results showed that MCE and MTC gaits have different advantages. Humanoid robot motion generated based on MCE criterion was very similar with that of humans. Another advantage of MCE criterion is the long operation time when the robot is actuated by a battery. On the other hand, MTC humanoid robot motion was more stable due to smooth change of torque and link accelerations.

Motivated from these observations, it will be advantageous to generate the humanoid robot motion such that different criteria are satisfied. This belongs 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.

The multiobjective problem is almost always solved by combining the multiple objectives into one scalar objective using the weighting coefficients. Therefore, to combine different

objectives in a single fitness function, an a-priori decision is needed about the relative importance of the objectives, emphasizing a particular type of solution. These techniques often require some problem-specific information, such as total range each objective covers. In complex problems, such as humanoid robot gait generation, this information is rarely known in advance, making the selection of single objective weighting parameters difficult. In addition, there is no rational basis of 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 (Becerra & Coello). 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-optimat 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 (MOEA) (Coello 1999, Herrera et al. 1998) 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 environment conditions. In out method, the basic idea is to encode the humanoid robot gait parameters in the genome and take the parameters of the non-dominated optimal gaits in the next generation. The specific questions we ask in this study are: 1) whether MOEA can successfully generate the humanoid robot gait that satisfies different objective functions in a certain degree, 2) whether the humanoid robot gait optimized by MOEA in simulation can indeed be helpful in hardware implementation.

In order to answer these questions, we considered the MCE and MTC cost functions as criteria for "Bonten-Maru" humanoid robot gait synthesis. We employed a real number MOEA. Simulation and experimental results show a good performance of the proposed method. The non-dominated optimal Pareto optimal solutions have a good distribution and humanoid robot gait varies from satisfying each of both considered objectives to satisfying both of them. Therefore, as a specific contribution of proposed method is that in a single run of MOEA are generated humanoid robot gaits with completely different characteristics, making it possible to select the appropriate gait based on our preferences. 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 of 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 Multiobjective Optimization Problem

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:

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

where $x = (x_1,\ldots\ldots x_m) \in X$, $y = (y_1,\ldots\ldots y_n) \in Y$ 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:

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

The decision vector a is called Pareto-optimal if and only if a is nondominated regarding the whole parameter space X. 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. The set of objective vectors corresponding to a set of Pareto-optimal parameter vectors is called "Pareto-optimal front".

In extending the ideas of SOEAs to multiobjective cases, two major problems must be addressed: -- How to accomplish fitness assignment and selection in order to guide the search towards the Pareto-optimal set? -- 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 an 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 Nondominated Sorting Genetic Algorithm

NSGA was employed to evolve the neural controller where the weight connections are encoded as real numbers. Dias & Vasconcelos (2002) compared the NSGA with four others multiobjective evolutionary algorithms using two test problems. The NSGA performed better than the others did, showing that it can be successfully used to find multiple Pareto-optimal solutions. In NSGA, before selection is performed, the population is ranked on the basis of domination using Pareto ranking, as shown in Fig. 1. All nondominated individuals are classified in one category with a dummy fitness value, which is proportional to the population size (Srivinas, & Deb 1995). After this, the selection, crossover, and mutation usual operators are performed.

In the ranking procedure, the nondominated individuals in the current population are first identified. Then, these individuals are assumed to constitute the first nondominated front with a large dummy fitness value (Srivinas, & Deb 1995). The same fitness value is assigned to all of them. In order to maintain diversity in the population, a sharing method is then applied. Afterwards, the individuals of the first front are ignored temporarily and the rest of population is processed in the same way to identify individuals for the second nondominated front. A dummy fitness value that is kept smaller than the minimum shared dummy fitness of the previous front is assigned to all individuals belonging to the new front. This process continues until the whole population is classified into nondominated

fronts. Since the nondominated fronts are defined, the population is then reproduced according to the dummy fitness values.
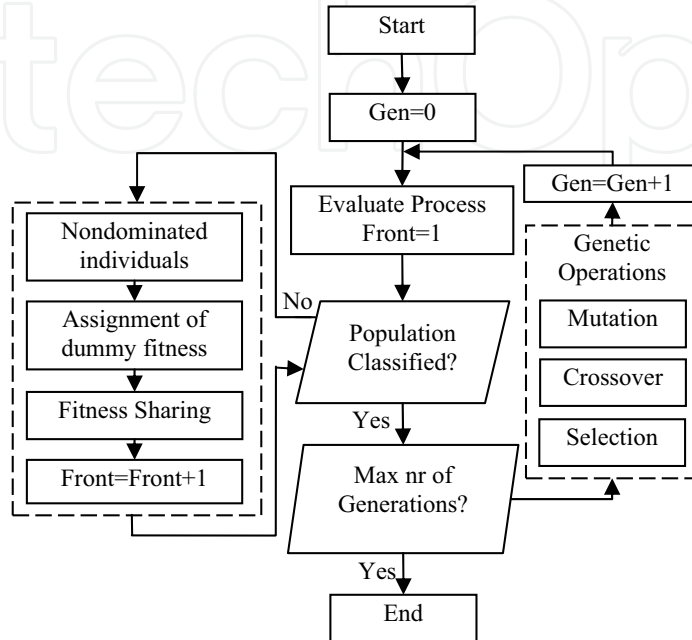

Fig. 1. Flowchart of NSGA.

Fitness Sharing: In genetic algorithms, sharing techniques aim at encouraging the formation and maintenance of stable subpopulations or niches (Zitzler et al. 2000). This is achieved by degrading the fitness value of points belonging to a same niche in some space. Consequently, points that are very close to, with respect to some space (decision space X in this paper), will have their dummy fitness function value more degraded. The fitness value degradation of near individuals can be executed using (3) and (4), where the parameter d_{ij} is the variable distance between two individuals i and j, and σ_{shared} is the maximum distance allowed between any two individuals to become members of a same niche. In addition, df_i is the dummy fitness value assigned to individual i in the current front and df_i is its corresponding shared value. N_{pop} is the number of individuals in the population. The sharing function (Sh) measures the similarity level between two individuals. The effect of this scheme is to encourage search in unexplored regions. For details about niching techniques, see Sareni et al. (1998).

$$Sh(d_{ij}) = \begin{cases} 1 - \left(\dfrac{d_{ij}}{\sigma_{shared}} \right)^2, & \text{if } d_{ij} < \sigma_{shared} \\ 0, & \text{if } d_{ij} \geq \sigma_{shared} \end{cases} \tag{3}$$

$$df_i^{'} = df_i \left[\sum_{j=1}^{Npop} Sh(d_{ij}) \right]^{-1} \tag{4}$$

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 Fig. 2. 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:

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

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, $\overline{x}_i$ and $\overline{z}_i$ are the coordinates of the mass particle "i" with respect to the $O_1X_1Z_1$ coordinate system, $\ddot{\overline{x}}_i$ and $\ddot{\overline{z}}_i$ 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, $\overline{x}_i, \overline{z}_i$, and acceleration, $\ddot{\overline{x}}_i, \ddot{\overline{z}}_i$, 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 $\ddot{\overline{x}}_3, \ddot{\overline{z}}_3$ are functions of $l_3, \theta_3, \dot{\theta}_3, \ddot{\theta}_3$, 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.

3.1 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 (Capi 2002).
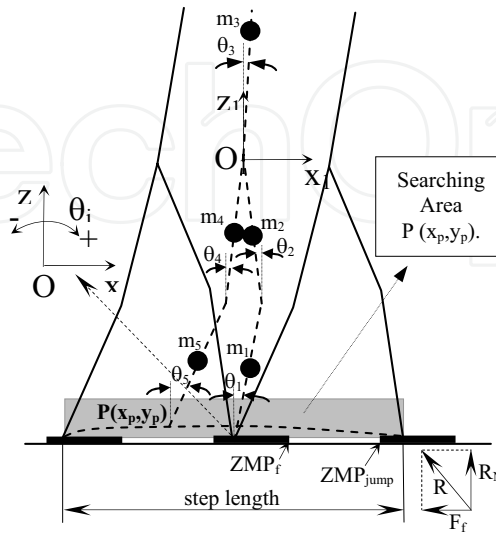
Fig. 2. Five-link humanoid robot.

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

$$J = \frac{1}{2}(\int_0^{t_f} \tau^T \tau dt + \Delta\tau_{jump}^2 \Delta t + \int_0^{t_f} C dt), \tag{6}$$

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 constraint function, given as follows:

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

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 :

$$J(\theta)\ddot{\theta} + X(\theta)\dot{\theta}^2 + Y\dot{\theta} + Z(\theta) = \tau . \tag{7}$$

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 (Uno 1989, Nakano 1999) 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:

$$J_{torquechange} = \frac{1}{2}(\int_0^{t_f}\left(\frac{d\tau}{dt}\right)^T\left(\frac{d\tau}{dt}\right)dt + \left(\frac{\Delta\tau}{\Delta t}\right)^2 + \int_0^{t_f}Cdt).$$ (8)

4. Boundary Conditions and GA Variables

To have a continuous periodic motion, the humanoid robot posture has to be the same at the beginning and at the end of the step. Therefore, the following relations must be satisfied:

$$\theta_{10} = \theta_{5f},\ \theta_{20} = \theta_{4f},\ \theta_{1f} = \theta_{50},\ \theta_{2f} = \theta_{40},\ \theta_{30} = \theta_{3f}.$$ (9)

In order to find the best posture, the optimum value of θ_{10}, θ_{20} and θ_{30} must be determined by GA. For a given step length, it is easy to calculate θ_{40} and θ_{50}. When referring to Figure 2, it is clear that links 1, 2, 4 at the beginning of the step and links 2, 4, 5 at the end of the step, change the direction of rotation. Therefore, we can write:

$$\dot{\theta}_{10} = \dot{\theta}_{20} = \dot{\theta}_{40} = \dot{\theta}_{2f} = \dot{\theta}_{4f} = \dot{\theta}_{5f} = 0.$$ (10)

The angular velocity of link 1 at the end of the step and link 5 at the beginning of the step is considered to be the same. In order to find the best value of angular velocity, we consider it as one variable of GA, because the rotation direction of these links does not change. GA will determine the optimal value of the angular velocity of the body link, which is considered to be the same at the beginning and at the end of the step. The following relations are considered for the angular acceleration:

$$\ddot{\theta}_{10} = \ddot{\theta}_{5f}, \ddot{\theta}_{20} = \ddot{\theta}_{4f}, \ddot{\theta}_{1f} = \ddot{\theta}_{50}, \ddot{\theta}_{2f} = \ddot{\theta}_{40}.$$ (11)

In this way, during the instantaneous double support phase, we don't need to apply an extra torque to change the angular acceleration of the links. To find the upper body angle trajectory, an intermediate angle θ_{3p} and its passing time t_3 are considered as GA variables.

To determine the angle trajectories of the swing leg, the coordinates of an intermediate point $P(x_p, z_p)$ and their passing time t_p, are also considered as GA variables. The searching area for this point is shown in Figure 2. Based on the number of constraints, the degree of the time polynomial for $\theta_1, \theta_2, \theta_3, \theta_4$ and θ_5 are 3, 3, 7,6 and 6, respectively.

	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

Table 1. "Bonten-Maru" humanoid robot link parameters.

5. Results

5.1 "Bonten-Maru" Humanoid Robot

In the simulations and experiments, we use the the "Bonten-Maru" humanoid robot (Nasu et al. 2002, Takeda et al. 2001). The parameter values are presented in Table 1 and the robot is shown in Fig. 3(a). The "Bonten-Maru I" humanoid robot is 1.2 m high and weights 32 kg, like an 8 years old child. The "Bonten-Maru I" is a research prototype, and as such has undergone some refinement as different research direction are considered. During the

design process, some predefined degree of stiffness, accuracy, repeatability, and other design factors have been taken into consideration. The link dimensions are determined such that to mimic as much as possible the humans. In the "Bonten-Maru" humanoid robot, a DC motor actuates each joint. The rotation motion is transmitted by a timing belt and harmonic drive reduction system. Under each foot are four force sensors, two at the toe and two across the heel. These provide a good indication of both contact with the ground, and the ZMP position. The head unit has two CCD cameras (542x492 pixels, Monochrome), which are connected to the PC by video capture board. A Celeron based microcomputer (PC/AT compatible) is used to control the system.

The dof are presented in Fig. 3(b). The high number of dof gives the "Bonten-Maru I" humanoid robot the possibility to realize complex motions. The hip is a ball-joint, permitting three dof; the knee joint one dof; the ankle is a double-axis design, permitting two. The shoulder has two dof, the elbow and wrist one dof. The DC servomotors act across the three joints of the head, where is mounted the eye system, enabling a total of three dof. The distribution of dof is similar with the dof in human limbs.

(a)   (b)
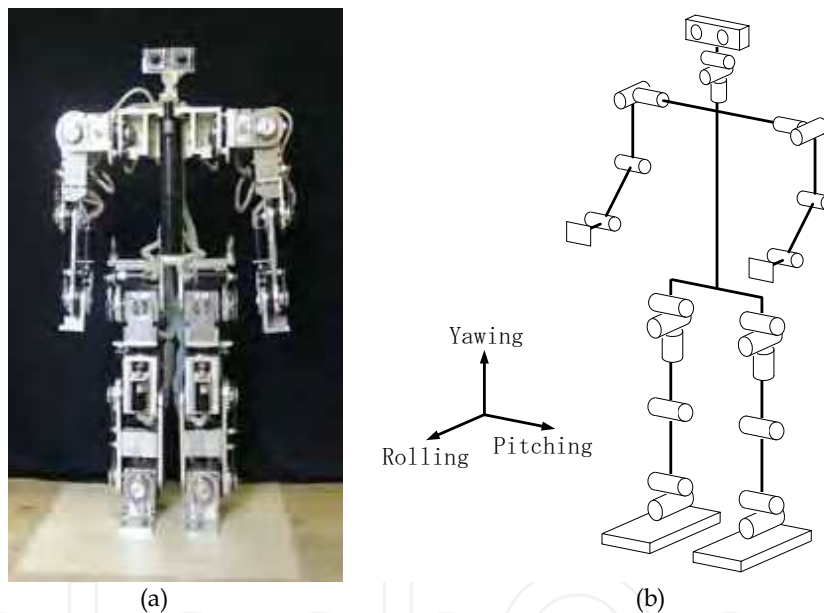
Fig. 3. "Bonten-Maru" humanoid robot.

5.2 Simulation and Experimental Results

Due to difficulties of binary representation when dealing with continuous search space with large dimension, real coded GA (Herrera 1998) 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. On all optimization runs, 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.
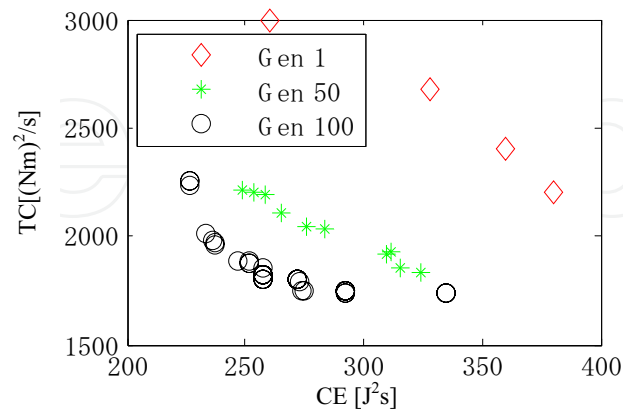
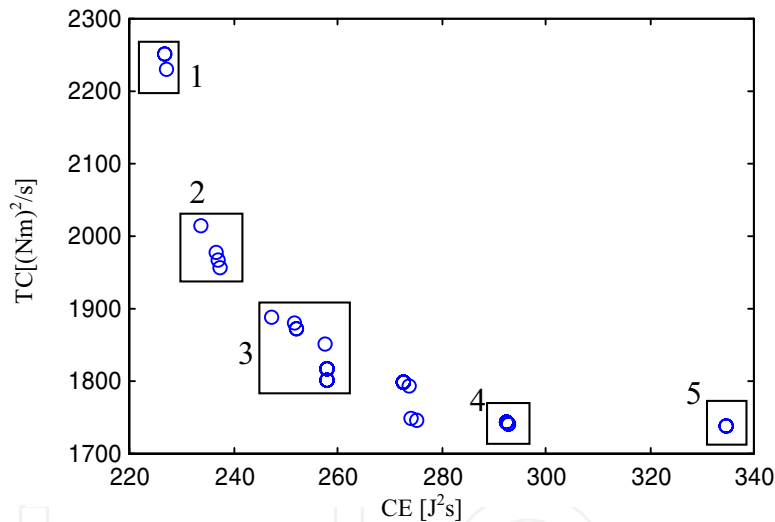Fig. 4. Pareto optimal solution for different generations.

Fig. 5. 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.
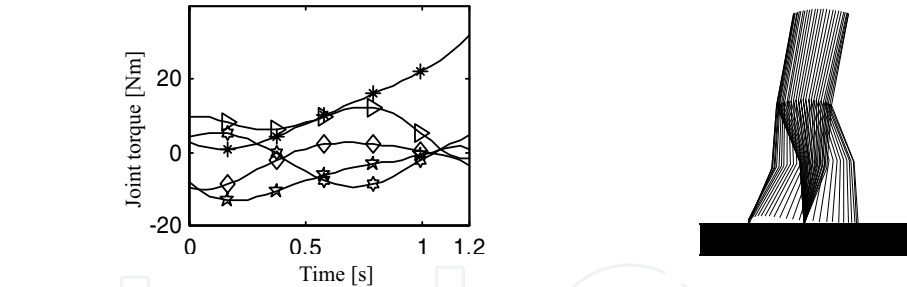
Fig. 4 shows the Pareto optimal front for generations 1, 50 and 100. During the first 50 generations there is a great improvement on the quality and distribution of Pareto optimal solutions. From this figure, it can be deduced that the MOEA is equally capable of finding the best solution for each objective when two conflicting objectives are considered simultaneously.
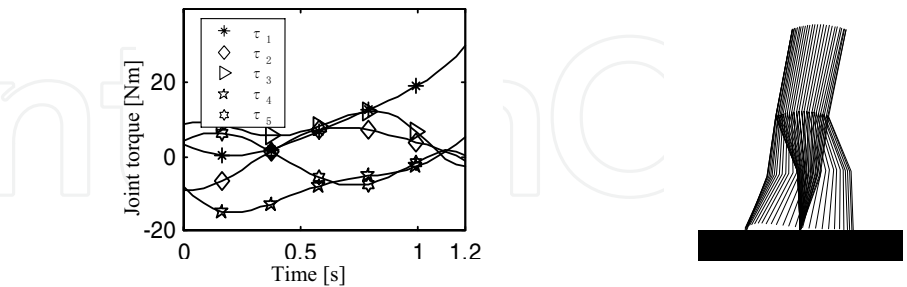
(a)   Box 1 result (MCE).
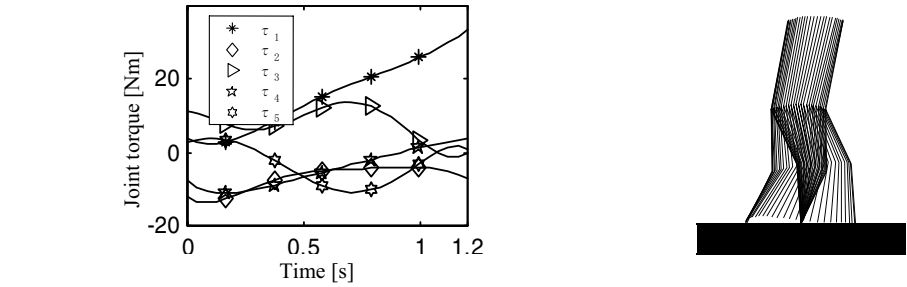
(b)   Box 5 result (MTC).

(c)   Box 3 results.

Fig. 6. Different results from Pareto-front solutions.

Fig. 5 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 Fig. 4) at the expense of a less smoothens in the torque or choose some intermediate result. If we are interested for 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).
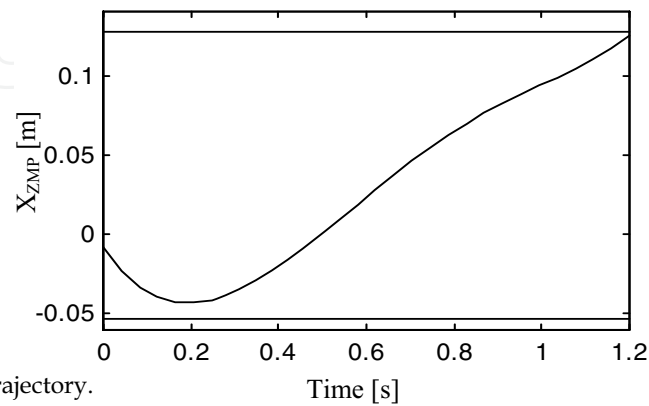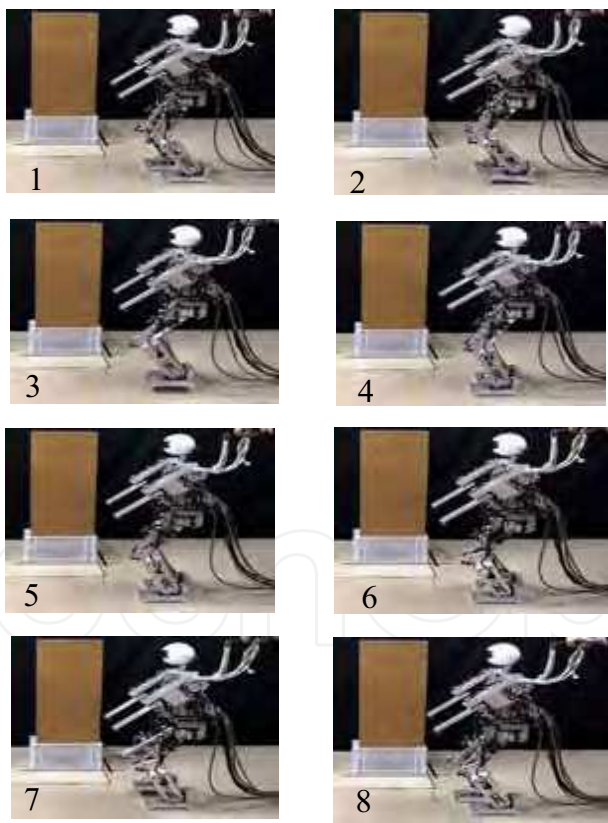

Fig. 7. ZMP trajectory.

Fig. 8. Video capture of robot motion.

The torque vector (τ_i) and the optimal gaits for different results of Pareto front solutions are shown in Fig. 6. The robot posture is straighter, similar to humans, for MCE cost function (Fig.6(a)). Torque value is low for MCE gait and the torques change smoothly for MTC gait (Fig. 6(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%.

The ZMP trajectory is presented in Fig. 7 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 Fig. 2. 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 transferred the optimal gaits that satisfy both objective functions on the "Bonten-Maru" humanoid robot (Fig. 8). The experimental results show that in addition of reduction in energy consumption, the humanoid robot gait generated by Box 3 solutions was stable. The impact of the foot with the ground was small.

6. Conclusion

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 performance when they were tested in the real hardware of "Bonten-Maru" humanoid robot.
- The optimal gait reduces the energy consumption and increases the stability during the robot motion.

In the future, it will be interesting to investigate if the robot can learn in real time to switch between different gaits based on the environment conditions. In uneven terrains MTC gaits will be more

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Humanoid Robots: New Developments

Edited by Armando Carlos de Pina Filho

For many years, the human being has been trying, in all ways, to recreate the complex mechanisms that form the human body. Such task is extremely complicated and the results are not totally satisfactory. However, with increasing technological advances based on theoretical and experimental researches, man gets, in a way, to copy or to imitate some systems of the human body. These researches not only intended to create humanoid robots, great part of them constituting autonomous systems, but also, in some way, to offer a higher knowledge of the systems that form the human body, objectifying possible applications in the technology of rehabilitation of human beings, gathering in a whole studies related not only to Robotics, but also to Biomechanics, Biomimmetics, Cybernetics, among other areas. This book presents a series of researches inspired by this ideal, carried through by various researchers worldwide, looking for to analyze and to discuss diverse subjects related to humanoid robots. The presented contributions explore aspects about robotic hands, learning, language, vision and locomotion.

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