ARTICLE IN PRESS

Computers & Operations Research xx (xxxx) xxxx–xxxx

Contents lists available at ScienceDirect

Computers & Operations Research

journal homepage: www.elsevier.com/locate/caor

Static force capability optimization of humanoids robots based on modified self-adaptive differential evolution

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ARTICLE INFO

Keywords:
Optimization metaheuristic
Differential evolution
Constrained optimization
Humanoid robot
Static force capability

ABSTRACT

The current society requires solutions for many problems in safety, economy, and health. The social concerns on the high rate of repetitive strain injury, work-related osteomuscular disturbances, and domestic issues involving the elderly and handicapped are some examples. Therefore, studies on complex machines with structures similar to humans, known as humanoids robots, as well as emerging optimization metaheuristics have been increasing. The combination of these technologies may result in robust, safe, reliable, and flexible machines that can substitute humans in multiple tasks. In order to contribute to this topic, the static modeling of a humanoid robot and the optimization of its static force capability through a modified self-adaptive differential evolution (MSaDE) approach is proposed and evaluated in this study. Unlike the original SaDE, MSaDE employs a new combination of strategies and an adaptive scaling factor mechanism. In order to verify the effectiveness of the proposed MSaDE, a series of controlled experiments are performed. Moreover, some statistical tests are applied, an analysis of the results is carried out, and a comparative study of the MSaDE performance with other metaheuristics is presented. The results show that the proposed MSaDE is robust, and its performance is better than other powerful algorithms in the literature when applied to a humanoid robot model for the pushing and pulling tasks.

1. Introduction

A humanoid robot can be seen as a complex redundant manipulator that contains upper and lower limbs and a base located at the feet. In order to achieve a humanoid robot that is capable of operating in everyday life environments, a dynamically stable and efficient motion is required. The research on humanoid robots has been a worldwide topic in the past decades by virtue of the continuous improvement in both hardware and software.

The development of robots that could replicate human movements is a relevant topic in scientific research and industrial development and could be useful for numerous applications in the real world: the world stage of ergonomic and musculoskeletal disorders can be reduced by replacing humans with machines. First, the elderly may live safely and in a more comfortable way with assistance of humanoid robots (see comments in [1–3]). In addition, unsafe and unhealthy works (in general) can be avoided by humans by employing humanoid robots. Furthermore, humanoid robots can also provide assistance to people with some kind of physical incapacity [4]. Humanoid robots are expected to play an important role in assisting human activities because of their flexibility and friendly appearance. Therefore, the topic about humanoid robots is one of the most important and challenging in the field of robotics.

Worldwide, there are a number of humanoid robots that have been recently built such as the prototypes HRP-2W [5], Honda [6], WABIAN [7], Bonten–Maru [8], Johnnie [9], and HanSaRam [10]. However, there are few studies such as [11] that deal with the static force capability of these machines, which is necessary to estimate the limits supported by the mechanism and ensure the accomplishment of a particular task, specifically in high load situations. In case of humanoid robots as the model optimized in [12,13] (see Section 2 for details), with kinematics and actuation redundancy, the equations that define the force capability are nonconvex and nonlinear. For a humanoid, there are four equivalent solutions (multimodality) by only reversing the positioning of the left and right limbs. Taking into account the gravitational forces, the complexity increases and thus obtaining the

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http://dx.doi.org/10.1016/j.cor.2016.10.011
Received 7 November 2015; Received in revised form 20 October 2016; Accepted 24 October 2016
Available online xxxx
0305-0548/

robot's force capability becomes a global optimization problem [11–13].

Global optimization problems frequently arise in almost every field of engineering design and other scientific applications. Optimization metaheuristics related to evolutionary algorithms allow designers to tackle global optimization problems by iteratively trying to improve a candidate solution population with regard to a given measure of quality. Although optimization metaheuristics do not guarantee a convergence, they are still capable of detecting quality solutions that can be of interest to users. Moreover, the combination of optimization metaheuristics and robotics has shown satisfactory results in most diverse applications [14–16], including the humanoid robots [12,13,17]. This is the reason why many researchers have employed metaheuristics such as genetic algorithms (GA), differential evolution (DE), and particle swarm optimization (PSO), among others, for robotic optimization problems. In fact, the DE has outperformed other multiple metaheuristics in optimization competitions and robotic applications [13,18–20].

In the last decade, the DE has emerged as an efficient and powerful population-based stochastic search approach for real-valued functions. Because of its performance when applied to numerous constraints and large-scale real-world problems, it is evident that this technique is flexible and efficient enough to be chosen instead of other state-of-the-art algorithms [20]. Its advantages are its simple structure, ease of use, and execution speed. In addition, the DE algorithm is found to be robust and able to provide the same results consistently over several trials [19,21].

In the classical DE used for solving optimization problems, the control parameters and mutation strategies are user-specified and kept fixed during the run. However, recent studies indicate that the performance of the DE is very sensitive to the parameter setting and the choice of the best control parameters is dependent on the optimization problem. Therefore, it is not always an easy task to adjust these parameters [21]. The choice of control parameters (i.e., mutation control parameter, F, crossover control parameter, CR, and population size, NP) and mutation strategies directly affect the convergence performance of the DE in satisfying the evolution requirement and balancing its exploitation ability of the previous experience and global exploration of the search space in the evolutionary process. For details, the readers can refer to the three surveys of DE in [18–20], and the references therein.

Some research studies propose adaptation schemes during the search process of the DE in order to accelerate its convergence. These adaptive DE variants have shown promising results in the DE literature. Examples given are the DE [22], self-adaptive differential evolution [23,24], self-adaptive DE with neighborhood search [25], generalized adaptive DE [26], composite DE [27], adaptive DE with optional archive (JADE) [28], ensemble of mutation strategies and control parameters in DE [29], success-history based adaptive DE [30], DE with self-adaptive population resizing mechanism [31], self-adaptive DE [21], PM-AdapSS-DE (probability matching-based adaptive strategy selection) [32], generalized adaptive DE (GaDE) [33], DE with fitness-based area-under-curve bandit (F-AUC-Bandit) [34], among others.

Qin et al. [23] developed a self-adaptive DE (SaDE) algorithm for the constrained real-parameter optimization, in which both the trial vector generation strategies and associated control parameter values were gradually self-adapted according to the learning experiences. Moreover, it introduces probabilities to adjust the mutation parameter (or scaling factor) and crossover rate. Later, the authors extended the SaDE algorithm to solve unconstrained optimization problems [35], and further experiments demonstrated that the SaDE algorithm outperforms the conventional DE and several state-of-the-art metaheuristics [24]. Nevertheless, this algorithm can still be improved, and therefore, the proposed DE approach presented in this study can be viewed as a modified variant of the SaDE [24], referred to as MSaDE, for short.

In the SaDE, four different strategies (combining mutation and crossover) are employed; the mutation control parameter is generated by a normal distribution with both the mean value and standard deviation constant (0.5 and 0.3, respectively), and the crossover rate is generated by a normal distribution with constant standard deviation (0.1) and adaptive mean value. The MSaDE keeps the SaDE main structure; however, the strategy "DE/current-to-rand/1" has been replaced by the one called "DE/current-to-gr_best/1," which has been proposed in [36], and has shown excellent performance when compared with the original DE algorithm, SaDE, JADE and others. In order to improve both exploration and exploitation ability, the scaling factor has been modified to become an adaptive mechanism based on the succeeded trials. Furthermore, the crossover rate and the scaling factor are generated by Cauchy distribution [28], which presents less dispersed values compared with the normal distribution of probability.

The remainder of this paper is organized as follows. Section 2 describes the humanoid model, its features, and the optimization problem design. Section 3 presents the framework of the DE and SaDE and the proposed modified version of the SaDE algorithm (MSaDE). Next, Section 4 contains the experimental results and their analysis. Finally, Section 5 presents some concluding remarks and suggestions for further research.

2. Humanoid robot model and the optimization problem

Simulating the behavior of a humanoid robot is fundamental in several real-world applications. An effective simulation of the humanoid robot and the possibility to predict the contact forces that the robot will develop with external-world objects is crucial to establish the effectiveness of the robot control system in order to prevent the robot to compromise its own integrity and to test the safety of the human–robot interaction [17]. This section describes the physical characteristics, kinematics, and static balance of the humanoid robot presented in this study.

2.1. Mechanical characteristics

The humanoid robot adopted in this research [4] contains twelve revolute joints, each with one degree of freedom and nine links, as shown in Fig. 1. The limbs (arms and legs) are composed of three joints and two links, and the trunk connects all the limbs. The robot's neck and head are drawn only for representation.

The physical characteristics of the motors that compose the robot determine the maximum torque that each joint supports. Moreover, the links have predefined weights and lengths and it is supposed that the links can support any load (in a structural meaning). The joint and link features are shown in Table 1, where the units are written generically. Furthermore, it is assumed that the joints in contact with the environment (ankles and fists) cannot produce any torque.

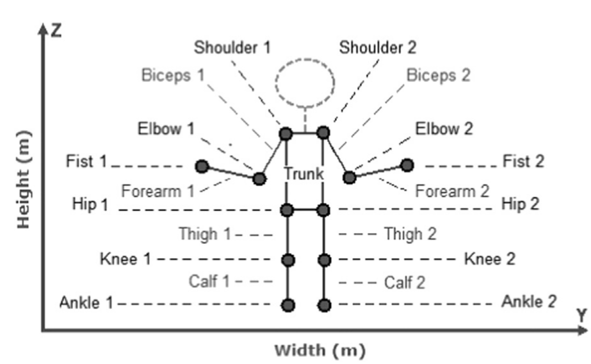

Fig. 1. Humanoid model.