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A hybrid multi-objective evolutionary approach for Optimal Path Planning of a Hexapod Robot

A preliminary study

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Abstract.
Hexapod robots are six legged robotic systems, which have been widely investigated in the literature for various applications including exploration, rescue, and surveillance. Designing hexapod robots requires to carefully considering a number of different aspects. One of the aspects that require careful design attention is the planning of leg trajectories. In particular, given the high demand of fast motion and high energy autonomy it is important to identify proper leg operation paths that can minimize energy consumption while maximizing velocity of the movements. In this frame, this paper presents a preliminary study on the application of a hybrid multi-objective optimization approach for the computer-aided optimal design of a legged robot. To assess the methodology, a kinematic and dynamic model of a leg of a hexapod robot is proposed as referring to the main design parameters of a leg. Optimal criteria have been identified for minimizing the energy consumption and efficiency as well as maximizing the walking speed and the size of obstacles that a leg can overtake. We evaluate the performance of the hybrid multi-objective evolutionary approach to explore the design space and provide a designer with optimal setting of the parameters. Our simulations demonstrate the effectiveness of the hybrid approach by obtaining improved Pareto sets of trade-off solutions as compared with a standard evolutionary algorithm. Computational costs show an acceptable increase for an off-line path planner.

Keywords: Multi-objective Optimization, Robot design, Legged robots, Hexapod robots.

1 Introduction

Hexapod walking robots (HWR) are six legged robots having a degree of autonomy that can range from partial autonomy, including teleoperation, to full autonomy without active human intervention [1][2]. HWR usually have as high stability, low footprint, fault tolerant locomotion features [3]. They can also overcome obstacles that are comparable with the size of the robot leg [4]. These main characteristics make hexapod walking robots a suitable choice in several application scenarios such mine fields [5], planets exploration [6], search and rescue operations [7], forests harvesting [8]. Despite the above referenced advantages and applications many challenges remain in the field of hexapod locomotion. In fact HWR are still complex and slow machines, consisting of many actuators, sensors, transmissions and power supply hardware.

During the last years the field of legged robots has been strongly influenced by the development of efficient optimization techniques, which coupled with low-cost and fast computational resources, have allowed for the resolution of such optimization problems. Nevertheless, challenges remain in the field of many legged robot locomotion such as Hexapods. Hexapods are walking that are, in fact, complex and slowly machines, consisting of many actuators, sensors, transmissions and supporting hardware.

One of the approaches that need more investigation in the field of is multi-objective optimization (MOO), which involves minimizing or maximizing multiple objective functions subject to a set of constraints. Indeed, optimizing the design of a hexapod robot includes analysing and selecting design trade-offs between two or more conflicting objectives.

In the area of MOO, Multi-Objective Evolutionary Algorithms (MOEAs) demonstrated to be well-suited for solving several complex multi-objective problems [9, 10]. These algorithms adopt the same basic principles of the single-object evolutionary algorithm by emulating the evolutionary process on a set of individuals (solutions), i.e. an evolutionary population, by means of the so-called evolutionary operators (fitness assignment, selection, crossover, mutation and elitism). In general, MOEAs differ on the fitness assignment method, but most of them are part of a family, called Pareto-based, which use the Pareto dominance concept as the foundation to discriminate solutions to guide their search [10]. For examples, the interested reader can refer to several surveys of multi-objective optimization methods, such as for engineering [11][12], for data mining [13–15], for bioinformatics [16], for portfolio and other financial problems [17].

A previous attempt of using an MOEA to optimize the design of a leg mechanism has been presented in [18], where the authors compared the performance with that of an earlier study and in all cases the superiority and flexibility of the EMO approach was demonstrated. The MOEA used in this previous study was NSGA-II [19].

In this paper, we use a hybrid approach to extend and improve the previous result, which, at the best of our knowledge, is the only attempt of using a MOO approach to solve the problem of the design optimization of a robotic leg.

2 Material and methods

In this section we briefly present the material and methods used in this work. For the brevity required by a conference paper, we are only presenting the main characteristics of the algorithms and of the robotic platform used. The interested reader should refer to the cited publications in the provided reference list for more details.

2.1 A hybrid multi-objective evolutionary approach

The MOEA we considered for our experiments is a controlled elitist genetic algorithm, which is a variant of the well know and widely used NSGA-II [19]. An elitist GA always favours individuals with better fitness value (rank) whereas, a controlled elitist GA also favours individuals that can help increase the diversity of the population even if they have a lower fitness value. In our application domain, it is very important to maintain the diversity of population for convergence to an optimal Pareto front. This is done by controlling the elite members of the population as the algorithm progresses. A non-dominated rank is assigned to each individual using the relative fitness. Individual *a* dominates *b* (*a* has a lower rank than *b*) if *a* is strictly better than *b* in at least one objective and *a* is no worse than *b* in all objectives. This is same as saying *b* is dominated by *a* or *a* is non-inferior to *b*. Two individuals *a* and *b* are considered to have equal ranks if neither dominates the other. The distance measure of an individual is used to compare individuals with equal rank. It is a measure of how far an individual is from the other individuals with the same rank. For the rest, the standard process of evolutionary algorithms still applies. It works on a population using a set of operators that are applied to the population. A population is a set of points in the design space. The initial population is generated randomly by default. The next generation of the population is computed using the non-dominated rank and a distance measure of the individuals in the current generation.

To increase the performance of the MOEA we used a hybrid scheme to find an optimal Pareto front for our MO problem. In fact, a MOEA can reach the region near an optimal Pareto front relatively quickly, but it can take many further function evaluations to achieve convergence. For this reason, a commonly used technique is to run the MOEA for a relatively small number of generations to get near an optimum front. Then the Pareto set solution obtained by the MOEA is used as an initial point for another optimization solver that is faster and more efficient for a local search. We used the Goal Attainment Method [20] as the hybrid solver, which reduces the values of a linear or nonlinear vector function to attain the goal values given in a goal vector. The method used is a sequential quadratic programming (SQP), which represent the state of the art in nonlinear programming methods [21]. The slack variable γ is used as a dummy argument to minimize the vector of objectives simultaneously; goal is a set of values that the objectives attain. In our case, the goals were set as 0, while the starting point was the Pareto set obtained by the MOEA.

In our experiments, we used the MATLAB 2015a implementation for both algorithms, further details can be found in the software documentation.

2.2 Measures for comparing the quality of the results

The main performance measure we considered is the *hypervolume* [22], that is the only one widely accepted and, thus, used in many recent similar works. This index measures the hypervolume of that portion of the objective space that is weakly dominated by the Pareto set to be evaluated. The estimation is done through 10^6 uniformly distributed random points within the bounded rectangle. We took as bounding point vector [1000, 100], because these are the maximum realistic values we allowed for the design of the hexapod robot [23].

Pareto *dominance* is equal to the ratio between the total number of points in Pareto-set P that are also present in a reference Pareto-set R (i.e., it is the number of non-dominated points by the other Pareto-set). In this case a higher value obviously corresponds to a better Pareto-set. Using the same reference Pareto-set, it is possible to compare quantitatively results from different algorithms.

The reference Pareto was obtained in the following way: first, we combined all approximations sets generated by the algorithms under consideration, and then the dominated objective vectors are removed from this union. At last, the remaining points, which are not dominated by any of the approximations sets, form the reference set. The advantage of this approach is that the reference set weakly dominates all approximation sets under consideration [12, 24].

We also calculated the *computational efficiency* calculated as the total time spent by the MATLAB routines for each run of one approach divided by the number of generations for that run. This has been preferred to the simple computation time because for each run of the MOEA a different number of generations were employed by the algorithm for obtaining the Pareto set. The computational efficiency allows a direct comparison of all the runs. The tests have been done on an Intel® Core™ i7-3770 3.40GHz using 4 parallel threads.

2.3 The Cassino Hexapod robot

In a recent past, research activities have been undergoing at LARM, Laboratory of Robotics and Mechatronics of Cassino and Southern Lazio University, for developing six-legged robots within the so called "Cassino Hexapod" series (for more details see [25–28]. The main features of the proposed design solutions have been the use of low-cost mechanism architectures and user friendly operation features. Cassino Hexapod is legged waling robot, whose intended main application task is the inspection and analysis of historical sites. In particular, the robot should be able to move inside archaeological and/or architectural sites by carrying surveying devices and by avoiding damage to the delicate surfaces or historical items of the site. Additionally, the robot should be able to operate also in environments that cannot be reached or that are unsafe for human operators.

Fig. 1. The Cassino Hexapod II

3 Kinematic model of one leg

The kinematic model of one leg can be established by considering two links in a 3R configuration as shown in Fig. The 3 R revolute joints have parallel rotation axes. The first and second revolute joints are connected to the first and second link, respectively. The third revolute joint is allowing the rotation of a wheel relative to the second link. The kinematic path planning task consists of identifying proper values of the revolute joint angles θ_1 and θ_2 as function of time. Typically a robot controller will updated the values of the joint angles θ_1 and θ_2 at a fixed clock speed rate that can be assumed as equal to 10 milliseconds. Values of joint angles are often obtained in path planning techniques by search algorithms or by means of interpolation equations such as 5th order polynomials, as proposed for example by Frankovský et al. [29]. Accordingly for the joint angles θ1 and θ2 one can write

$$\theta_1(t) = a_1\, t^5 + a_2 t^4 + a_3\, t^3 + a_4\, t^2 + a_5\, t + a_6 \tag{1}$$

$$\theta_2(t) = b_1\, t^5 + b_2 t^4 + b_3\, t^3 + b_4\, t^2 + b_5\, t + b_6 \tag{2}$$

Specific boundary conditions can help in simplifying the required models by reducing the number of parameters to be searched or set-up in Eqs. (1) and (2). For example, one can assume that a leg motion starts from the fully straight leg configuration having θ_1 and θ_2 equal to zero. Additionally, the initial and final angular speed and acceleration can be assumed as equal to zero at the beginning and at the end of a leg motion. Based on the above boundary conditions one can set up the following parameters in Eqs. (1) and (2)

$$\begin{aligned}
\theta_1(t=0) &= 0 \rightarrow a_6 = 0\\
\theta_2(t=0) &= 0 \rightarrow b_6 = 0\\
\dot{\theta}_1(t=0) &= 0 \rightarrow a_5 = 0\\
\dot{\theta}_2(t=0) &= 0 \rightarrow b_5 = 0\\
\ddot{\theta}_1(t=0) &= 0 \rightarrow a_4 = 0\\
\ddot{\theta}_2(t=0) &= 0 \rightarrow b_4 = 0
\end{aligned}$$

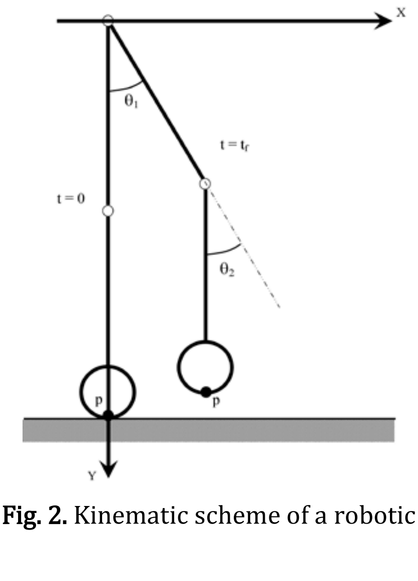


Fig. 2. Kinematic scheme of a robotic leg,

Accordingly, the kinematic path planning of a leg requires identifying the parameters in Eqs. (1) and (2). These parameters can be obtained by using search scripts in optimization algorithms.

4 Dynamic model of one leg

Dynamic effects play a significant role in the operation of a leg especially as referring to energy consumption and operation speeds. Accordingly, a basic dynamic model has been established by referring to the basic double pendulum architecture of a leg as shown in (**Fig. 2**). Accordingly, dynamic equations can be established by referring to the Euler-Lagrange formulation in the form

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q}_1}\right) - \frac{\partial L}{\partial q_1} = \tau_I \qquad (3)$$

in which

$i = 1,2 \ldots n$
L = Lagrangian = $T - U$
T = total kinetic energy of the system
U = Potential energy of the system
q_i = generalized coordinates of manipulator
$\dot{q}_i$ = time derivatives of the generalized coordinates
τ_i = generalized force (torque) that is needed at the *i*-th joint for moving the link l_i
The inverse dynamic problem can be written by referring to Eq. (3) in terms of the torques τ_i that are needed to obtain the prescribed movement of the leg. Inputs are the prescribed θ_1 and θ_2 versus time as obtained from Eqs. (1) and (2).

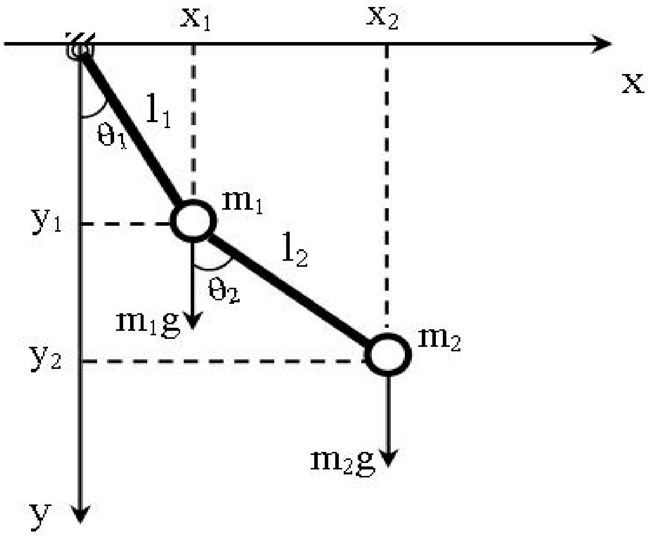


Fig. 3. Scheme of control architecture

Using the above mentioned values of θ_1 and θ_2 and referring to the model in Fig. 3 one can calculate the coordinates of the leg joints in the form

$$x_1 = l_1 \,\text{sen}\theta_1; y_1 = -l_1 \cos\theta_1; \\ x_2 = l_1 \,\text{sen}\theta_1 + l_2 \,\text{sen}\theta_2; y_2 = -l_1 \cos\theta_1 - l_2 \cos\theta_2 \quad (4)$$

The time derivatives of Eq.(4) can be written as

$$\dot{x}_1 = l_1 \cos\theta_1 \cdot \dot{\theta}_1 \qquad \dot{y}_1 = l_1 \,\text{sen}\theta_1 \cdot \dot{\theta}_1 \\ \dot{x}_2 = l_1 \cos\theta_1 \cdot \dot{\theta}_1 + l_2 \cos\theta_2 \cdot \dot{\theta}_2 \quad \dot{y}_2 = l_1 \,\text{sen}\theta_1 \cdot \dot{\theta}_1 + l_2 \,\text{sen}\theta_2 \cdot \dot{\theta}_2 \quad (5)$$

Eq.(5) can be also used to write

$$\dot{x}_1^2 + \dot{y}_1^2 = l_1^2 \cos^2\theta_1 \cdot \dot{\theta}_1^2 + l_1^2 \text{sen}^2\theta_1 \cdot \dot{\theta}_1^2 = l_1^2 \cdot \dot{\theta}_1^2 \quad (6)$$

Eq.(5) can be also rewritten as follows

$$\dot{x}_2^2 = l_1^2 \cos^2\theta_1 \cdot \dot{\theta}_1^2 + l_2^2 \cos^2\theta_2 \cdot \dot{\theta}_2^2 + 2 l_1 l_2 \cos\theta_1 \cos\theta_2 \dot{\theta}_1 \dot{\theta}_2 \\ \dot{y}_2^2 = l_1^2 \text{sen}^2\theta_1 \cdot \dot{\theta}_1^2 + l_2^2 \text{sen}^2\theta_2 \cdot \dot{\theta}_2^2 + 2 l_1 l_2 \,\text{sen}\theta_1 \text{sen}\theta_2 \dot{\theta}_1 \dot{\theta}_2 \quad (7) \\ \dot{x}_2^2 + \dot{y}_2^2 = l_1^2 \cdot \dot{\theta}_1^2 + l_2^2 \cdot \dot{\theta}_2^2 + 2\, l_1 l_2 \dot{\theta}_1 \dot{\theta}_2 \cos(\theta_1 - \theta_2)$$

Considering the effects of gravity, in terms of mass and inertia in Eqs. (4)-(6) one can write the potential energy U as

$$U = m_1 g y_1 + m_2 g y_2 = -m_1 g l_1 \cos\theta_1 + m_2 g (l_1 \cos\theta_1 + l_2 \cos\theta_2) \quad (8)$$

The kinetic energy T can be written as

$$T = \frac{1}{2} m v^2 = \frac{1}{2} m (\dot{x}^2 + \dot{y}^2) = \frac{1}{2} m_1 (\dot{x}_1^2 + \dot{y}_1^2) + \frac{1}{2} m_2 (\dot{x}_2^2 + \dot{y}_2^2) \quad (9)$$

Substituting Eqs. (6) and (7) into Eq. (9) one can write

$$T = T_1 + T_2 = \frac{1}{2} m_1 l_1^2 \dot{\theta}_1^2 + \frac{1}{2} m_2 l_1^2 \dot{\theta}_1^2 + \frac{1}{2} m_2 l_2^2 \dot{\theta}_2^2 + \frac{1}{2} m_2 \left(2 \dot{\theta}_1 l_1 \dot{\theta}_2 l_2 \cos(\theta_1 - \theta_2)\right) \quad (10)$$

The Lagrangian can be finally written by using Eqs. (8) and (10) in the form

$$L = T - U = \frac{1}{2} (m_1 + m_2) l_1^2 \dot{\theta}_1^2 + \frac{1}{2} m_2 l_2^2 \dot{\theta}_2^2 + m_2 l_1 l_2 \dot{\theta}_1 \dot{\theta}_2 \cos(\theta_1 - \theta_2) + \quad (11) \\ + (m_1 + m_2) g l_1 \cos\theta_1 + m_2 l_2 \cos\theta_2$$

Substituting Eq.(11) in Eq.(3) leads to the calculation of the required input torques τ_i that are needed to obtain the prescribed movement of the leg in the form

$$\tau_1 = (m_1 + m_2) l_1^2 \ddot{\theta}_1 + m_2 l_1 l_2 \ddot{\theta}_2 \cos(\theta_1 - \theta_2) + m_2 l_1 l_2 \dot{\theta}_2^2 \,\text{s en}(\theta_1 - \theta_2) + \\ + g l_1 (m_1 + m_2) \,\text{sen}\theta_1 \quad (12) \\ \tau_2 = m_2 l_2^2 \ddot{\theta}_2 + m_2 l_1 l_2 \ddot{\theta}_1 \cos(\theta_1 - \theta_2) - m_2 l_1 l_2 \dot{\theta}_1^2 \,\text{s en}(\theta_1 - \theta_2) + l_2 m_2 g \,\text{sen}\theta_2$$

A formulation for optimal path planning problem

The path planning task for a hexapod leg with n DoFs can be described using m knots in the trajectory of each *k*-th joint of a manipulator. The prescribed task can be given by the initial and final points P_0 and P_m of the trajectory. The movement of the leg can be obtained by the simultaneous motion of the n joints in order to perform the prescribed task. Among the many available criteria, one can assume the energy aspect as one of the most significant performance in order to optimize the manipulator operation, since the energy formulation can consider simultaneously dynamic and kinematic characteristics of the performing motion. It should also be considered that a maximization of the operation speed of a leg corresponds to a maximization of the amplitude of the movement, when time is fixed.

An optimality criterion concerning with energy aspects of the path motion can be conveniently expressed in terms of the work that is needed by the actuators. In particular, the work by the actuators is needed for increasing the kinetic energy of the system in a first phase from a rest condition to actuators states at which each actuator is running at maximum velocity. In a second phase bringing the system back to a rest condition, the kinetic energy will be decreased to zero through the actions of actuators and brakes. The potential energy of the system will contribute to size the necessary work by the actuators and friction effects in the joints can be assumed as negligible as compared to the actions of actuators and brakes. Thus, we have considered convenient to use the work W_{act} done by the actuators in the first phase of the path motion as an optimality criterion for optimal path generation as given by the expression

$$W_{act} = \sum_{k=1}^{3} \left[\int_0^{t_k} \tau_k \ \dot{\alpha}_k \ dt \right] \tag{13}$$

in which τ_k is the *k*-th actuator torque; $\dot{\alpha}_k$ is the *k*-th shaft angular velocity of the actuator; and t_k is the time coordinate value delimiting the first phase of path motion with increasing speed of the *k*-th actuator.

Therefore, minimizing W_{act} has the aim to size at the minimum level the design dimensions and operation actions of the actuators while generating a path between two given extreme positions. Indeed, in general once the actuator work is minimized, energy consumption of the system operation will be optimized consequently.

The other factor to optimize is the average speed, which is as follows:

$$v_{avg} = \frac{x_2 - x_1}{t_f - t_0} \tag{14}$$

in which x_1 and x_2 are the coordinates at the beginning (t_0) and at the end (t_f) of the movement. Note that, in this work, we assumed (y_2 - y_1) = (x_2 - x_1) due to the symmetry of the model that has been proposed in Fig.3.

The two optimal criteria that have been considered are conflicting, because an increase in the speed will result in higher energy consumption. Therefore, it can be established a multi-criteria optimization problem as follows:

$$min_{\mathbf{d}}(W_{act}(\mathbf{d}), \frac{1}{v_{avg}(\mathbf{d})}) \quad (15)$$

where **d** is the vector of design variables: [a_1 a_2 a_3 b_1 b_2 b_3].

5 Experimental Results

Using the experimental setup described in Section 2, we ran both standard MOEA and the hybrid MOEA twenty-one times with different random seed. Identical parameter setting is used for the MOEAs: population size = 300; Tournament selection, size = 4; number of individuals in the Pareto set = 100; Elite count = 15; individual recombination (crossover) probability = 0.8; Gaussian mutation function. The MOEA stopped when the average change in the spread of the Pareto front over last 100 generations is less than 10^{-4}.
Median values for performance indicators are presented to represent the expected (mid-range) performance. For the analysis of multiple runs, we compute the quality measures of each individual run, and report the median and the standard deviation of these. Since the distribution of the algorithms we compare are not necessarily normal, we use the Mann-Whitney U test (a.k.a. Wilcoxon rank sum test) test [30] to indicate if there is a statistically significant difference between distributions. We recall that the significance level of a test is the maximum probability *p*, assuming the null hypothesis, which the statistic will be observed, i.e. the null hypothesis will be rejected in error when it is true. The lower the significance level the stronger the evidence. In this work we assume that the null hypothesis is rejected if $p < 0.01$.
Considering all the runs, the median number of generations was 229 (standard deviation = 102, minimum = 10; maximum = 544).

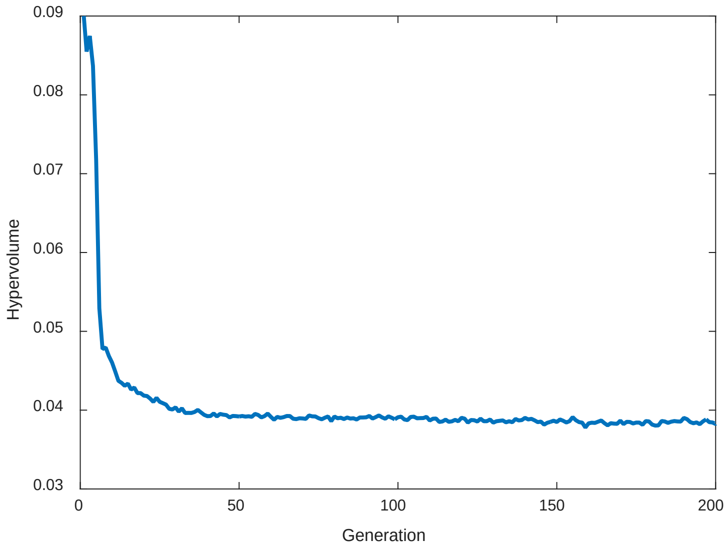


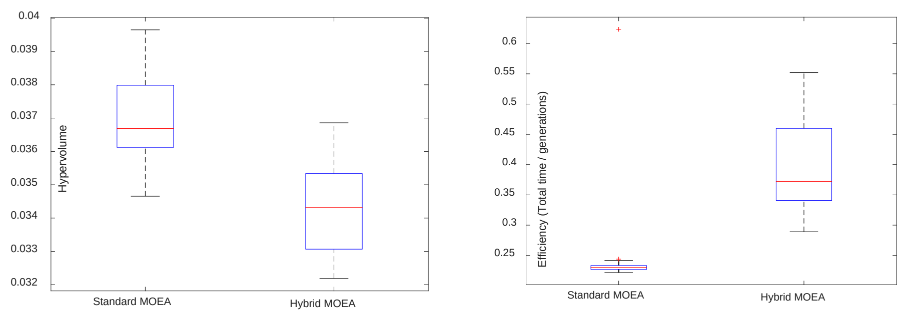
Fig. 4. Average hypervolume values over generations.

Fig. 4 shows the hypervolume values over generations. We can see that the stop condition (Pareto spread is lower than 10-4) still allows a quite high number of generations without significant improvements in terms of minimization of the hypervolume. This test confirms that we should not expect a significant increase in the performance with more generations.

Table 1 presents the experimental results on the three performance measures considered. For all measures, the Hybrid MOEA significantly outperforms the Standard MOEA. This is evidenced in **Fig. 5**, which reports the box plots for hypervolumes and efficiency comparison. It is evident from the figure the significant increase given by the hybrid approach used at the average cost of 0.1422 seconds for generation. This is confirmed by the statistical test which rejects the hypotheses that the distributions are the same in both cases.

Table 1. Multi-metric comparison of the Pareto sets obtained by the Standard and Hybrid MOEAs. Values are the medians of each distribution and the standard deviation is in parentheses. Statistical significance (*p*) has been evaluated with the Mann-Whitney U test (Hypervolume and Efficency: the lower the better; Reference and Dominance: the higher the better).

Measure	**Standard MOEA**	**Hybrid MOEA**	***p***
Hypervolume	*0.0367(0.0013)*	***0.0343 (0.0014)***	*<0.001*
Dominance (%)	*0.00 (0021)*	***4.39 (1.18)***	*<0.001*
Efficiency (sec/gen)	***0.2301 (0.0860)***	*0.3723 (0.0851)*	*<0.001*



(a) (b)

Fig. 5. Box plot comparisons: (a) hypervolumes of 21 runs of the standard and hybrid MOEA; (b) computational efficiency calculated as the total time divided by the number of generations (variable for each run).

Fig. 6 presents the cumulative Pareto Sets obtained merging the Paretos of each run of the two approaches. These graphically confirm the numerical results that the hybrid approach significantly increases the performance of the MOEA. In particular, comparing the two cumulative Pareto sets, we can see that the improvement is well spread along the objective space and the most significant results is achieved in the central area which is the most common selection for the designer.

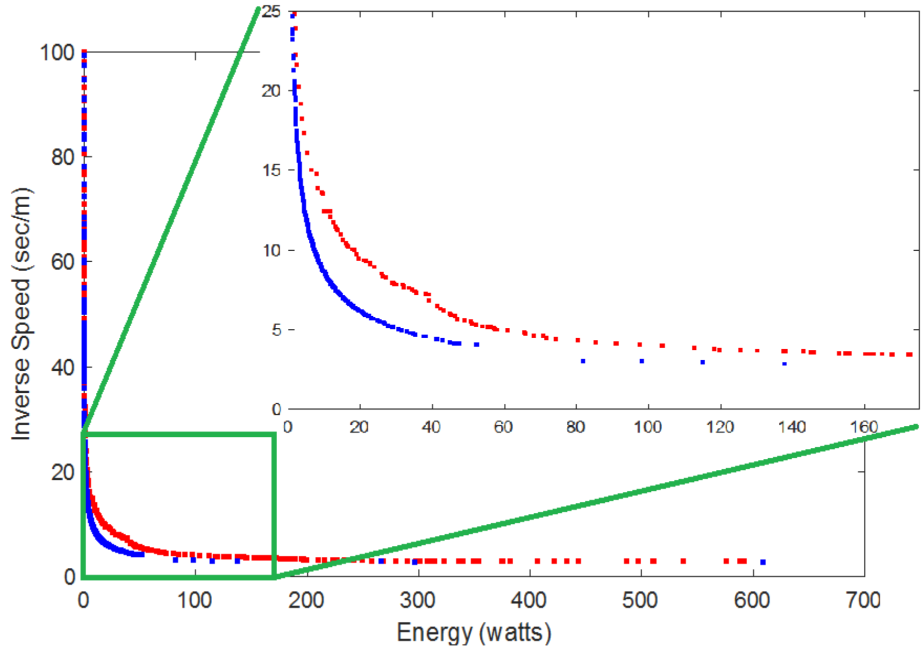


Fig. 6. Best Cumulative Pareto sets comparison: Standard MOEA Pareto set (red) and the Hybrid MOEA (blue). The central area of the figure is zoomed to highlight the difference.

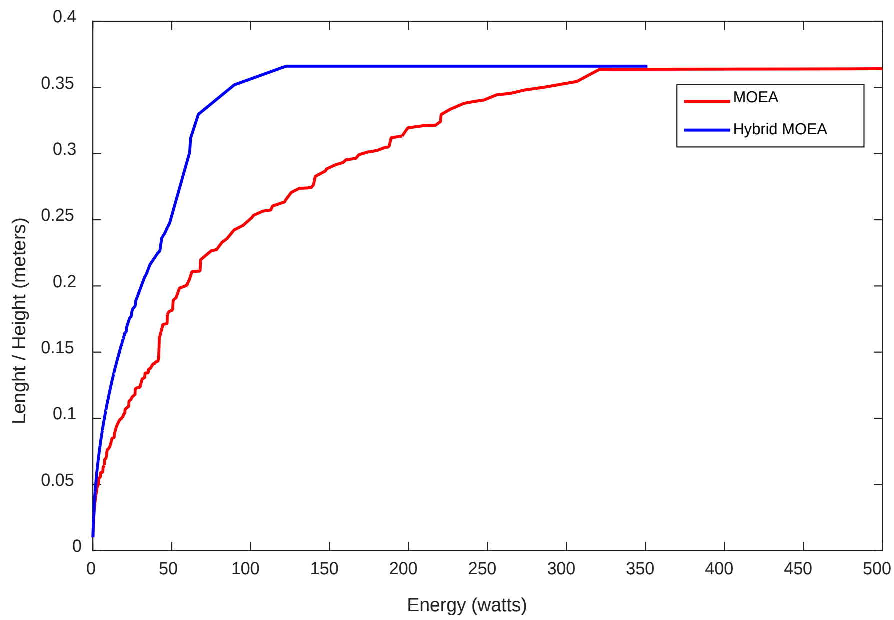


Fig. 7. Plot of Length and Height of the movement over Energy.

Indeed, from the designer point of view, the reader can clearly see the improvement given by the hybrid approach over the standard MOEA can be seen in **Fig. 7**, which plots the length and height of the movement over energy. Indeed, the possible designs obtained by the Hybrid MOEA can produce a movement of 0.3520 meters amplitude (length and height) consuming only 89.60 watts, while the matching solution of the standard MOEA requires 286.21 watts (3 times more) for the a similar amplitude (0.3502).
In terms of real applicability of the solutions, this result can allow to include smaller batteries and, thus, increase the available payload. Furthermore, one can note that the leg can reach about 3.5 times the link length (not considering the wheel radius) with energy values that can be even lower than 100 watts. These values can be seen as feasible also as compared to standards [1].

6 Conclusions

In this paper, we present a preliminary study on the use of a hybrid multi-objective evolutionary approach for the optimal path planning of a hexapod robot leg. To this end, we evaluated the performance of a hybrid multi-objective optimization approach to explore the design space and provide the designer with the optimal setting of the parameters. To preliminary assess the optimization approach, a kinematic and dynamic model of a leg of a hexapod robot has been proposed as referring to the main design parameters. Optimal criteria have been identified for minimizing the energy consumption and efficiency as well as maximizing the size of obstacles that the robot can overtake. In our simulations, the hybrid approach demonstrated to achieve statistically significantly better Pareto sets of trade-off solutions than the standard evolutionary algorithm with acceptable time increase. These solutions are also better in comparison with other non-evolutionary algorithms applied to similar design problems. Our future work will focus on the application of the hybrid MOEA approach to the optimized design of all the six legs of the robot, which is a constrained optimization problem with a larger design space to explore.

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