Evolutionary discovery of self-stabilized dynamic gaits for a soft underwater legged robot

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Abstract*—In recent years a number of robotic platforms have been developed, that are capable of robust locomotion in presence of a simple open loop control. Relying on the self-stabilizing properties of their mechanical structure, morphology assumes a crucial role in the design process, that is, however, usually guided by a set of heuristic principles falling under what is commonly known as embodied intelligence. Despite many impressive demonstrations, the result of such a methodology may be sub-optimal, given the dimension of the design space and the complex intertwining of involved dynamical effects. Encouraged by the growing consensus that embodied solutions can indeed be produced by bio-inspired computational techniques in a more automated manner, this work proposes a computer-aided methodology to explore in simulation the design space of an existing robot, by harnessing computational techniques inspired by natural evolution. Although many works exist on the application of evolutionary algorithms in robotics, few of them embrace this design perspective. The idea is to have an evolutionary process suggesting to the human designer a number of interesting robot configurations and embodied behaviors, from whose analysis design hints can be gained to improve the platform. The focus will be on enhancing the locomotion capabilities of a multi-legged, soft, underwater robot. We investigate for the first time the suitability of a recently introduced open-ended evolutionary algorithm (novelty search) for the intended study, and demonstrate its benefits in the comparison with a more conventional genetic algorithm. Results confirm that evolutionary algorithms are indeed capable of producing new, elaborate dynamic gaits, with evolved designs exhibiting several regularities. Possible future directions are also pointed out, in which the passive exploitation of robot's morphological features could bring additional advantages in achieving diverse, robust behaviors.

I. INTRODUCTION

In order to operate in real, challenging, environments, robots should be endowed with robust and efficient locomotion, allowing them to negotiate rough terrains. From an engineering perspective several different approaches are possible in order to pursue this objective, and engineers indeed managed to produce very elaborate solutions to accomplish this task [1]. Nonetheless, despite many remarkable successes made possible by human invented computational techniques (e.g. motion planning), the animal kingdom still represent an excellent source of inspiration for what concerns robotic locomotion. As opposed to approaches that require substantial computational efforts, bio-mechanical studies hypothesized that the remarkable capabilities of some running animals may be in fact the result of self-stabilizing mechanical properties, in presence of a simple feed-forward periodic actuation [2]. Inspired by this observation, a number of bio-inspired robotic platforms have been developed in the last years, such as the RHex [3] and the Sprawl [4] robots. PoseiDRONE [5], an octopus-inspired soft-bodied ROV recently developed at The BioRobotics Institute of SSSA as a successor of the more renowned OCTOPUS [6], also falls in this category. The robot, featuring a simple design and passively compliant silicone limbs, exhibits a number of different gaits in presence of a simple open-loop control by exploiting its self-stabilized body dynamics. It thus represents a good example of the possibility to exploit the dynamical coupling between robot's morphology and the environment (embodiment [7]) for locomotion.

The key to exploit body dynamics and self-stabilization capabilities lies in a proper design of robot's morphology. Even though the aforementioned robotic platforms were designed following a bio-inspired approach to benefit from embodiment, their design was conceived by humans, often following qualitative heuristic principles [8]. As a consequence, the result of such an approach may be in general sub-optimal for a given task and environment: on one hand for the complex intertwining of physics effects, on the other because of the dimension of the design space spanned by morphological parameters, that can be remarkably big also for a simple robot (and thus difficult to manage for a human designer).

The idea that embodiment can emerge from biologically-inspired reproductive processes is more and more accepted in the robotics community, as indicated by several examples in the field of evolutionary robotics [9]. These approaches require to generate several possible robot morphologies and test them (usually in simulated environments) with respect to the task they are expected to accomplish. The best performing robots are then combined to produce even better ones based on an evolution-inspired algorithm (e.g. genetic algorithms [10]). Although the possibility to exploit these techniques to automatically design and fabricate robots is highly appealing, research in this direction still has to cope with some technological and practical limitations [9]. Simulations based on evolutionary techniques can nevertheless provide some insights for what concerns the design of a robotic platform.

In this work a computer-aided methodology is proposed to explore the design space of a bio-inspired robot with respect to its locomotion capabilities. PoseiDRONE is used as a case study: a mathematical model of the robot has been extended with respect to previous work [19], and exploited to investigate in simulation possible alternative designs. The objective is to discover several self-stabilized gaits relying on morphological

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properties, and derive design indications that could guide the development of novel, improved versions of the robot. Among these indications, we expect to observe interesting morphological configurations, as well as complex dynamics effects that can be passively exploited to achieve locomotion.

Although a lot of research has been carried out in which evolutionary algorithms are applied in robotics [9], a design perspective such as the one here adopted, in a bio-inspired, embodied framework is not common. Also, our robot and setting offer a number of interesting features to investigate the passive exploitation of morphology to achieve diverse behaviors. Related works following a similar approach usually evolve the control to achieve quasi-static gaits for fully actuated, rigid, kinematically complex, terrestrial robots, with a predefined morphology [11] [12] [13] [14]. Our setting is different in many respects. First, we focus on morphology evolution (open-loop control is present, but it is remarkably simple) for a soft, under-actuated, quadruped robot, featuring passively compliant limbs in an underwater environment. The underwater setting offers additional challenges (e.g. with respect to modeling) but also intriguing opportunities. Highly dynamic gaits can be discovered that exploit a combination of terrestrial locomotion and swimming. Second, given the stressed interaction with the fluid environment, focusing on morphology is particularly interesting, as slight morphological changes can induce very different behaviors that can be exploited to achieve an effective locomotion (a concept that is related to the broader one of morphological computation [15]). Third, the evolutionary algorithm here proposed for this study is adopted for the first time (to the best of our knowledge) for this intended purpose. We suggest and investigate the adoption of novelty search [16], an open-ended evolutionary algorithm that explicitly maximizes a novelty metric to produce a variety of different solutions to a problem. Applied in several settings in the context of evolutionary robotics and artificial life, its adoption is proposed here for the first time to explore the design space of a real robot. In this context, benefits are highlighted in the comparison with a conventional objective-based genetic algorithms. The proposed methodology has the potential to become a new, general design paradigm to mix bio-inspired robot design and artificial evolution, merging strengths of both worlds.

II. REFERENCE ROBOT

In this section the robotic platform that we want to improve is briefly described. The PoseiDRONE robot [5] is made of three main components (Fig. 1): a legged module comprising four legs, a floating module, and a jet-pulsed swimming module (not relevant for this work).

The legged module comprises four legs, each of which is formed by a silicone cone embedding a thin central core of steel (a flexible, cylindrical beam with a diameter of 1.5 mm). Each leg is actuated via a dedicated three bars mechanism (Fig. 1a, Fig. 2): when the crank m rotates (Fig. 1a$_1$, Fig. 2), a pseudo-elliptical loop is induced in the distal part of the leg (Fig. 1a$_2$), as shown in [17] [18]. When the leg touches the ground this particular loop induces a pushing or pulling force (depending on the crank's clockwise or anti-clockwise rotating direction) that enable the robot to move.

The floating module has a key role in robot's locomotion, and this is a peculiar aspect of our setting. It can be inflated and deflated to different extents: by passively changing robot's stance, it greatly affects the way legs push/pull the ground. When completely deflated (Fig. 1b), the robot is sprawled onto the ground, and moves by using a crawling gait as described in [17]. The mean speed in this configuration is of 0.13 body lengths per second (BL/s). By placing the floating module in the rear part of the robot and partially inflating it (Fig. 1c), the robot assumes a suitable posture for bipedal walking [19]. The mean speed in this configuration is of 0.37 BL/s, with an increase factor up to 2.9 with respect to crawling locomotion. Finally, by further inflating the floating module, the robot is almost neutral in water: by activating the legs in this configuration, slow movements can still be observed due to the hydrodynamic forces, as shown in Fig. 1d and studied in [20]. Although the robot exhibited in previous studies self-stabilizing locomotion, this work will demonstrate that, by playing with the same morphological structure and working principle, it may be capable of more dynamic, multi-modal gaits.

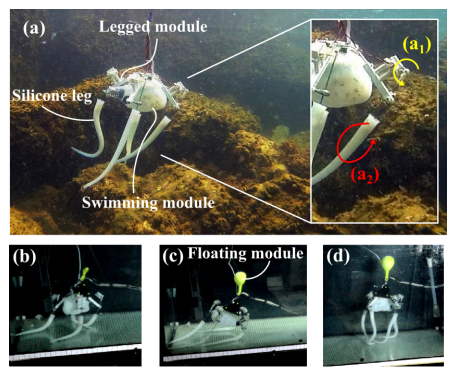

Fig. 1. Robot components (a) and different qualitative behaviors observed in tank experiments as the mean robot density of the robot was varied, by changing the inflation state of the floating module: crawling (b), running (c) and sculling (d).

III. SAGITTAL MODEL

In order to explore the design space of our robot, in the following we will use a general, parametric, mathematical model. The mathematical details are not reported here: the interested reader can refer to [19], in which the basic formulation was described in detail and exploited to describe the behavior of the current version of the robot. However, being the model generalized, extended, and widely exploited for the present work, a description of relevant parameters (Fig. 2, Tab. I) and of its most salient features is reported.

The locomotion of the robot is mostly planar, thus a sagittal model was sufficient to describe its dynamics. The model features three degrees of freedom (DoF), identifying robot's position (x and y, positions on the horizontal and vertical axis, respectively) and orientation ϑ in the space (Fig. 2). With respect to [19] (where only the frontal legs were actuated to study bipedal locomotion), all the legs can be actuated. Cranks rotates at a speed of $\dot{\vartheta}_r$, with a resulting frequency $f = \dot{\vartheta}_r/2\pi$ (frontal and hind legs are in fact allowed to rotate at two different frequencies $f_{front},\ f_{rear}$). Moreover, an inter-leg phase shift $\phi_{interleg}$ can now exist between the

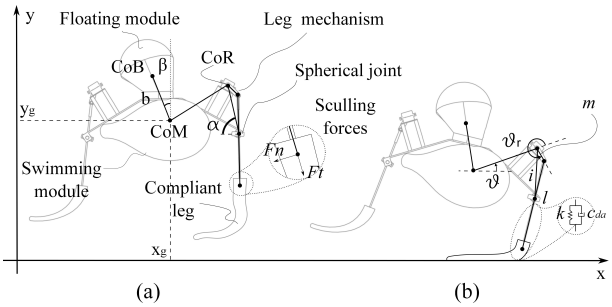

Fig. 2. Schematic representation of the model, superimposed onto the current design of the robot during flight phase (a) and during contact phase (b). Highlighted are the most relevant variables and parameters. Leg mechanism's components are highlighted only for one of the frontal legs. The three bars mechanism is composed of segments i, m, l.

two legs of each pair (front and hind pairs), as well as a front to rear phase shift $\phi_{frontRear}$. From a dynamic point of view legs are described as mass-less spring-damper systems as in [21]: each leg exerts to the ground elastic and damping forces proportional to the stiffness k and damp coefficient c_{da}.

Constant forces included in the model consist of gravity and buoyancy forces. The former depends on the mean density of the whole system (ρ_r), deriving from the material properties as well as from the inflation state of the floating module. A peculiar aspect of our model lies in decoupling the center of buoyancy or CoB (where the buoyancy force is applied) from the center of mass or CoM (where the gravity force is applied). The resulting momentum can induce peculiar effects that can be exploited for locomotion. Particularly, the CoB is placed at a distance b with respect to the CoM and it is oriented of β with respect to the medial plane.

A quadratic drag model was adopted, and the contribution of the central body was decoupled from the one of each leg. While the body drag was already described in [19], the introduction of a resistive fluid drag model accounting for leg's sculling effects is an addition of this work. By taking as reference works on the sculling movement of conical arms [20] [22], the contributions in the tangential and normal direction of each leg are, respectively, $F_t = -\lambda_t v_t |v_t|$ and $F_n = -\lambda_n v_n |v_n|$ (Fig. 2), where λ_t and λ_n are the tangential and normal drag coefficient, and v_t, v_n are the tangential and normal speeds of the leg. For the sake of simplicity, instead of discretizing each leg with several segments as in [20], a single segment approximation is adopted. Moreover, the sculling forces of each leg are applied only when they move freely in water, without touching the ground. As for the drag of the central body, the main difference with respect to [19] is that the body is approximated with a spherical shape of radius R. The resulting drag is isotropic in the x and y directions, and can be computed easily also when varying the dimensions of the robot as $F_{drag} = -(1/2)C_d \rho_w \pi R^2 |v| v$, where $C_d = 0.47$ is the drag coefficient of a sphere, $\rho_w = 1000\ kg/m^3$ is the water density, R is the radius of the sphere, and v is the speed in the considered direction. The spherical approximation is particularly convenient for the present study also to compute other quantities consistently, such as the body inertia ($J = (2/5)MR^2$, where M is the mass of the robot and depends on ρ_r and R) and the added mass of the robot ($M_{added} = (2/3)\pi \rho_w R^3$).

One last improvement introduced in this work consists of a second order foot slipping model. Each foot can slip independently from the others: when the slipping condition $|F_x| > c_{sf} F_y$ is verified for a foot, the force exerted by the leg is considered to be $F_x = -sgn(v_x) c_{df} F_y$ as described in [2], where v_x is the speed of the slipping foot. The new contact point is then computed by using a second order model: in order to do so, the total mass M of the robot is uniformly distributed among the legs and the central body ($M/5$ is thus the resulting mass attributed to each slipping leg). The model has been implemented in MATLAB® and solved using its ordinary differential equations solver ODE45.

IV. OPTIMIZATION SETUP

The model described in Sect. III is used to explore the design space of the robot in simulation by adopting evolutionary techniques (i.e. genetic algorithms). First, a standard objective-based genetic algorithm is adopted, for comparison. Then, novelty search [16] is used to better explore the design space, by maximizing a novelty metric in a properly defined behavioral space. The optimization setup will now be described.

A. Encoding and parameters

The genome is the same for both the objective-based and novelty-based settings. It embeds the geometric, actuation, and material parameters described in Tab. I, for a total of 24 genes[1]. Direct encoding was adopted, i.e. relevant quantities directly appear in the genome. The reader can observe that some parameters are expressed as multipliers of other quantities. This is done in order to directly embed some necessary constraints among the parameters into the genome, without the need to explicitly specify them: having only bound constraints a simpler implementation of genetic algorithms is needed. With respect to the model presented in Sect. 2, the most relevant constraints are $i + m < l$, $m < i$, $m < R$, $c_{df} < c_{sf}$.

B. Experimental details

In order to evaluate each genome, the model is allowed to run for $t_e = 25\ s$. The first $10\ s$ are discarded when evaluating the resulting locomotion in order to get rid of the transient behavior. All robots start from a suitable initial condition so that the distance between the ground and the closest foot is the same for each of them, independently from their size. Fall is declared every time the robot experiences not modeled contacts with the ground, i.e. when it touches the ground with parts of the body other than feet. If a robot falls, the event is detected and the simulation is stopped. All the processing was performed using MATLAB 2013b (The MathWorks Inc., Natick, MA). Each execution of the genetic algorithm ran in parallel over 12 cores of a Workstation (Intel Xeon 3.07 GHz, 48GB RAM), for a total execution time of $\sim$ 48 h.

C. Objective-based setting

The first experiment is performed by using a conventional objective-based genetic algorithm. An implementation from MATLAB's Global Optimization Toolbox was used (linear

[1] In Tab. I 'x2' denotes the existence of two parameters of the described type, related to the frontal and rear leg mechanisms

TABLE I. MODEL PARAMETERS AND CORRESPONDING BOUNDS

Parameter	Description	Bounds
	Geometry	
R	Radius of the central spherical body	$[0.05, 0.30]\ m$
β	Inclination of the CoB with respect to the medial plane	$[-90, +90]^\circ$
bR_{mul}	Multiplier determining the distance b between CoB and CoM $b = bR_{mul} \cdot R$	$[0, 2]$
$lMul$	x2 - Multiplier determining the length of the legs l $l = lMul \cdot (m + i)$	$[1, 2]$
$mMulI$	x2 - Multiplier determining the length of the cranks $m = min(mMulI \cdot i, mMulR \cdot R)$	$[0.01, 0.95]$
$mMulR$	x2 - Multiplier determining the length of the cranks (see above row)	$[0.01, 0.95]$
i	x2 - Distance of crank's CoR from the spherical joint	$[0.01, 0.40]\ m$
α	x2 - Inclination of leg's mechanisms	$[0, 120]^\circ$
	Actuation	
f	x2 - Rotation frequency of the cranks (sign encodes the direction)	$[-3, 3]\ Hz$
$\phi_{interleg}$	Phase shift between legs of the same pair	$[0, 360]^\circ$
$\phi_{frontRear}$	Phase shift between frontal and rear legs	$[0, 360]^\circ$
	Materials	
λ_t	Tangential drag coefficient of the legs	$[0, 0.04]\ kg/m$
λ_n	Normal drag coefficient of the legs	$[0, 0.15]\ kg/m$
k	Stiffness of the legs	$[50, 400]\ N/m$
dr	Damping reduction factor $c_{da} = dr \cdot 2\sqrt{k\ M}$	$[0.1, 1.5]$
c_{sf}	Static friction coefficient	$[0.1, 1]$
c_{dfmul}	Dynamic friction coefficient multiplier ($c_{df} = c_{dfmul} \cdot c_{sf}$)	$[0.1, 0.9]$
ρ_r	Robot density	$[1010, 1400]\ \frac{kg}{m^3}$

constrained solver, in which only bound constraints were imposed). Tab. II summarizes the most relevant settings, that are common also to the novelty-based experiments. In MATLAB the optimization is expected to be a minimum problem: thus, in order to maximize the distance traveled by the robot, the fitness was defined as $fitness = -|spaceTraveled|\ /BL$, where $BL = l_{front} + l_{rear}$ is the characteristic body length that is used to normalize the space traveled. Falling robots receive a fixed positive penalty of 100, plus an additional penalty that depends on how much time they managed not to fall (the less, the higher the penalty): $P_{fall} = \lceil 100 + 5 \cdot (t_e - t_{fall}) \rceil$, where t_e is the total expected execution time and t_{fall} is the falling time.

TABLE II. GENETIC ALGORITHM SETTINGS

Option	Value
$GenomeSize$	24
$PopulationSize$	800
$CrossoverFraction$	0.7
$EliteCount$	4
$TimeLimit$	Inf
$Generations$	70
$CreationOperator$	$gacreationuniform$
$SelectionOperator$	$gaselectionstochunif$
$CrossoverOperator$	$crossoverscattered$
$MutationOperator$	$mutationgaussian$

D. Novelty search setting

Novelty search [16] is a recently proposed approach to evolutionary computation inspired by the open-ended essence of natural evolution. Rather than proceeding towards a specific goal, natural evolution perpetually discovers novel solutions to meet the challenges that biological creatures have to cope with. Novelty search works in the very same way: instead of maximizing an explicit, task-based objective function (like traditional evolutionary algorithms do), it tries to maximize some notion of *novelty*. For example, in this work, novelty search will be applied to maximize some notion of behavioral novelty, as quantified by a novelty metric that operates in a space of behavioral features (behavior space). Even in an objective-based problem, novelty search completely ignores the objective. Positive reward (i.e. high fitness) is not attributed to individuals performing *well* but, instead, to individuals performing *differently*. Nevertheless, it has been shown that this algorithm manages to maximize the unknown objective, often finding far better solutions with respect to objective-based algorithms. Proposers of the algorithm argue that this may be due to the fact that while objective-based algorithms tend to greedily exploit solutions that immediately appear as promising, novelty search may reward (as long as they appear novel) counter intuitive intermediate solutions that may later provide far better solutions [16].

Here we propose the application of novelty search to explore the design space of a robot. In addition to the possible algorithmic advantages, the algorithm's tendency to explicitly encourage diversity has a couple of attractive consequences. First, it has the potential to produce a number of diverse designs at once, possibly suggesting more than just one locomotion modalities that the robot can exploit to face different situations. This is particularly appealing in case the robot has the ability to control (to some extent) morphological changes once deployed in the real world. Another major benefit that could arise is related to the so called reality gap problem [9], a well known issue in evolutionary robotics: a design evolved in simulation is most likely to fail when tested in the real world due to the inevitable discrepancies between simulation and reality. In this regard, while conventional genetic algorithms tend to converge to a specific solution (with a consequently high chance of failure), novelty search has the advantage of producing several options to choose from.

From an implementation point of view it is not difficult to switch from an objective-based search to a novelty-driven one. In this work the simple genetic algorithm setting explained in the previous setting was modified to work in a novelty-driven fashion, and a custom MATLAB implementation of the algorithm was developed based on the public C++ code by Joel Lehman [23].

First of all, the behavior space in which the search for novelty will operate should be defined. This is done by characterizing the behavior of each robot design (encoded in a genome $\boldsymbol{g}$) with a vector $\boldsymbol{x}$ of behavioral features $(f_1, \ldots f_n)$. This point is crucial: the behavioral characterization should be done in such a way that by encouraging diversity in this space all the potentially interesting behaviors can be discovered. Being interested in locomotion, the behavior vector was defined as $\boldsymbol{x} = (\overline{s}_x, \overline{s}_y, \overline{\delta_{front}}, \overline{\delta_{rear}}) \in \Re^4$. The quantities $\overline{s}_x$ and $\overline{s}_y$ are, respectively, the normalized space traveled in the x and y direction: normalization is performed by dividing the space traveled in t_e for the characteristic body length BL as in Sect. IV-C. It should be noted that although the

space traveled is present into the features vector, there is no pressure towards maximizing it. The pressure is towards producing individuals exhibiting a *different* space traveled. As an example, a slow individual will get a high novelty score if most of the individuals evolved so far move fast. The quantities $\overline{\delta_{front}}, \overline{\delta_{rear}}$ denotes the mean duty factor of front and rear legs (percentage of time in which a foot touches the ground). Each generated robot design is characterized with a vector $\boldsymbol{x}$ of this type. As for falling robots, only the first two features are computed by considering the behavior preceding the fall: other features are set to 0.

Having defined the behavior space, we need a way to quantify how much novel an observed behavior is with respect to the already seen ones. This is done by computing a novelty score, that is the scalar quantity actually optimized by the genetic algorithm. In order to compute the novelty score we need 1) to keep track of behaviors discovered during the evolutionary process 2) to actually quantify novelty in behavior space. Point 1) is solved by novelty search by maintaining a novelty archive where the most novel behaviors of each epoch can be stored for future comparison. As for point 2), the novelty ρ of a given individual $\boldsymbol{x}$ in behavior space can be easily implemented as a sparseness measure such as the average distance to the k-nearest neighbors

$$\rho(\boldsymbol{x}) = -\frac{1}{k}\sum_{i=0}^{k} ||\boldsymbol{x} - \boldsymbol{\mu_i}||$$

where k is an experimentally determined parameter, $\boldsymbol{\mu_i}$ is the i-th nearest neighbor and $||.||$ denotes the Euclidean distance (the preceding minus sign is inserted here to formulate the problem as a minimization). It is to be noted that when computing novelty scores the algorithm compares each individual with all the others present both in the novelty archive and in the current population, as these two sets forms a more comprehensive sample of the search space visited so far.

An appropriate feature scaling may be needed when applying this approach: otherwise, given that the novelty computation resorts to Euclidean distance, the algorithm may be biased toward exploring the novelty space of variables with a bigger magnitude and overlook the ones with a smaller one. In order to ensure a proper feature scaling the following normalization is applied to each behavior vector before computing the novelty score (at the end of each epoch): $\overline{\boldsymbol{x}} = (\boldsymbol{x} - \boldsymbol{x_{min}})/(\boldsymbol{x_{max}} - \boldsymbol{x_{min}})$, where $\overline{\boldsymbol{x}}$ is the normalized behavior vector, $\boldsymbol{x_{min}}, \boldsymbol{x_{max}}$ are vectors containing, respectively, the minimum and maximum values for each feature (computed by considering the full space embracing both the novelty archive and the current population), and the division is intended as an element by element vector operation. This ensures that all the features are in the range $[0, 1]$, so that the scale does not affect the comparison[2].

At the end of each epoch, the most novel individuals enter the novelty archive. In the original formulation of the algorithm [16], this mechanism is handled by a number of adaptive thresholds. In our setting this aspect was simplified in order to reduce the number of parameters to be arbitrarily chosen: the N_{add} most novel individuals of each generation are added to the novelty archive ($N_{add} = 0.025 \cdot PopulationSize$). Having defined the fitness value of the genetic optimization (i.e. the novelty score) we are now able to run the genetic algorithm, with the same settings of the fitness-based experiments (Tab. II).

[2]The implementation should guarantee that vectors normalized differently (e.g. normalized in two different epochs) are never compared. In our setting, behavior vector are stored not normalized, and every time the novelty is to be computed everything is normalized on the fly.

V. RESULTS AND DISCUSSIONS

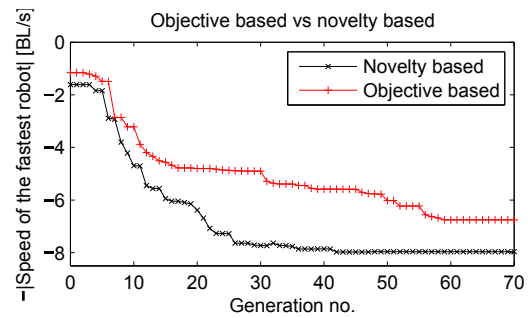

Fig. 3. Speed of the fastest individual of each generation. Comparison of the objective-based and novelty-based genetic algorithm: note that while optimizing the speed is the explicit goal of the objective-based algorithm, novelty search is completely agnostic of this objective.

A. Objective-based experiments

Results of the objective-based optimization are discussed in this paragraph. The algorithm chooses rather quickly one specific design, that is then refined until the algorithm is stopped having reached the maximum allowed number of generations (Fig. 3). The best performing robot evolved by the objective-based genetic algorithm runs at $6.755\ BL/s$, a remarkably higher speed with respect to the one currently exhibited by the robot ($< 1BL/s$), that is also consistent with the one of state of the art robotic platforms (e.g. RHex [3], Sprawl [4]). It is to be noted that we are able to reach this speed in an underwater setting, in which the robot has to cope with fluid resistance. The algorithm converged towards a bipedal design optimized to run backwards, where the frontal legs almost disappeared (Fig. 4). This is consistent with the biological model from which inspiration was drawn to design the robot, whose fastest legged gait is the bipedal one [24]. The central body has a radius $R = 0.067\ m$, robot's density is $\rho_r \approx 1300\ kg/m^3$ for a resulting mass $M = 1.6\ kg$. Hind legs are $l_{rear} = 0.12\ m$ long, and their spring and damping constants are $k = 387.6\ N \cdot m$, $dr = 1.45$, respectively. Their tangential drag coefficient is almost negligible while the normal one is relevant ($\lambda_t = 0.0008\ N \cdot s^2/m^2$, $\lambda_n = 0.07\ N \cdot s^2/m^2$), like in animals featuring webbed feet. Moreover, feet have a very good grip on the ground ($c_{sf} = 0.98$), so that slipping is very rare. As for actuation, the genetic algorithm managed to design a robot that can exploit almost the highest allowed frequency ($F_{rear} = 2.97\ Hz$). A very special symmetry can be observed in the evolved design, with the two rear cranks being out of phase by almost π ($\phi_{interleg} = 177\ °$). Fig. 4 reports y, ϑ, F_{ytot} and the gait diagram for this individual. The latter highlights a bipedal gait with a prolonged flight phase. The two hind legs both have a duty factor $\delta_{R1} \approx \delta_{R2} \approx 0.1$, while the front legs never touch the ground. By analyzing in detail the locomotion of the

robot, a very sophisticated behavior could be observed, that exploits all the features that evolution could benefit of in order to produce an effective gait. The robot's stance (depending on several factors, such as the buoyancy momentum and the swimming forces), the geometrical configuration and the actuation are calibrated by the algorithm in a way that ensures that each leg impacts the ground with an angle of $\approx 45°$. The two hind legs impact the ground alternatively, determining an impulsive force that propels the robot (Fig. 4). The detachment from the ground is fast, and a negative peak force due to leg's drag is observed: the resulting momentum is exploited to quickly bring back the robot (unbalanced toward the rear due to the impact with the ground) in a stance suitable for the next impact. Remarkably, the genetic algorithm finds a balance (and a temporal synchronization) among the actuation and the passive dynamics of the body, that exploits all the features that evolution had at disposal: this is an example of an embodied solution produced by a bio-inspired computational process. This experiment thus suggests a small, relatively heavy robot featuring a bipedal design, webbed feet with high grip with the substrate, springy, over-dumped legs out of phase by π, and a fast actuation.

B. Novelty-based experiments

In this section results of the novelty-based exploration of the design space are reported. Coherently with results achieved by novelty search in other settings [16] the algorithm – although being completely agnostic of the objective – outperforms the objective-based setting, showing a better convergence and producing faster robots every generation (Fig. 3). The fastest robot reaches a speed of $7.964\ BL/s$ ($\approx 18\%$ faster than the best produced by the objective based experiment). Interestingly, the evolved robot is actually a swimmer (Fig. 5): this suggests that robot's morphological structure and leg mechanism, originally designed for crawling and running, may be in fact also suitable for fast sculling-based swimming. In this case the algorithm suggested a completely different locomotion modality that was never exploited by the physical robot, but that could be very effective in an underwater scenario (e.g. to overcome an obstacle on the sea floor, or to quickly move from one site to another). The robot propels itself (both horizontally and vertically) with powerful down strokes of the two frontal legs (rear legs disappeared during evolution). Its dimensions are similar to the ones of the hopper produced by the objective-based setting ($R = 0.063\ m$), but this robot is lighter ($\rho_r = 1188\ kg/m^3$, resulting mass $M = 1.26\ kg$) and has longer legs ($l_{front} = 0.14\ m$) to improve its swimming capabilities. Evolution suggested (and exploited) a peculiar feature of the actuation mechanism: picking $m \approx i$ ($m_{front} = 0.38\ m$, $i_{front} = 0.04\ m$), high speeds are induced in the distal part of the leg, producing high swimming forces when the leg's drag coefficient are relevant ($\lambda_n = 0.39\ N \cdot s^2/m^2$, $\lambda_t = 0.009\ N \cdot s^2/m^2$). Again some symmetries can be observed. For example, the two frontal legs ($F_{front} = 2.99\ Hz$) are out of phase of $\phi_{interleg} \approx \pi/2$: this entails two strokes in rapid successions, tilting the robot up. Then follows a recovery phase, in which the robot's pitch is stabilized passively thanks to the decoupling between CoM and CoB ($b = 0.06\ m \approx R$) (Fig. 5).

As for the diversity of the final population, a comparison can be made with respect to the objective-based setup. As

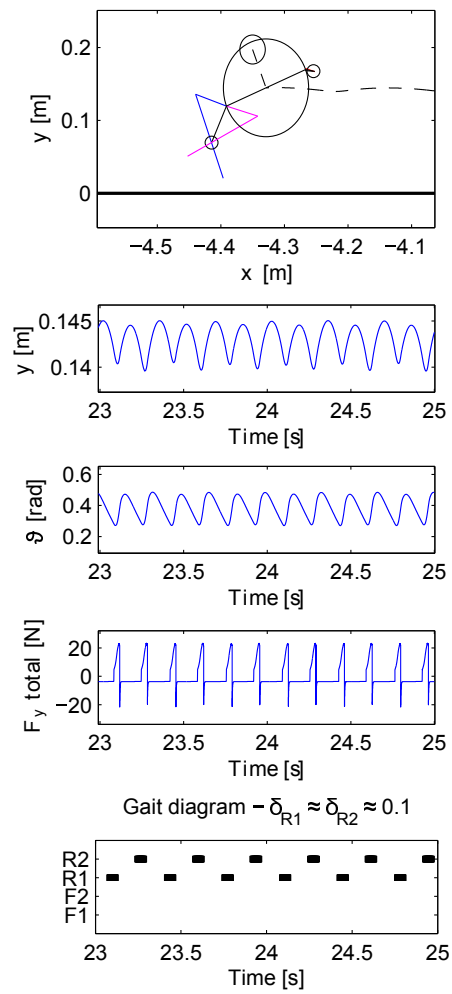

Fig. 4. The best performing robot evolved by the objective-based genetic algorithm. Several symmetries and optimized solutions can be identified in the design, as discussed in the text. The second graph shows the y position of the CoM. The oscillation is regular (the stability plot, here not reported for space limitations, highlights a double loop in the phase space $\dot{\vartheta}, \dot{x}, \dot{y}$). The third and fourth graphs depict ϑ and F_{ytotal}: note how negative peaks in the force plot (due to swimming forces) corresponds to the stabilization of ϑ. Finally the gait diagram (black segments denotes contact with the ground), highlighting a bipedal gait with an evident flight phase (R1, R2 are the two rear legs, F1, F2 the frontal ones).

highlighted by Fig. 6, the final population produced by novelty search exhibits a substantially higher behavioral and genotypic diversity with respect to the one produced by the objective-based setting. This suggests that novelty search better explored the design space, being capable of producing very different designs exhibiting a wide spectrum of behaviors. As a consequence, while the final population produced by the objective-based algorithm is homogeneous and constituted of just slight variations of the best individual, novelty search produced a diverse population of locomoting robots, characterized by different design solutions and performances. In addition to several bipedal hoppers similar to the one evolved in the objective-based setting, the algorithm managed to produce for example a number of quadrupedal designs. See for example the robot depicted in Fig. 7: although this small lightweight robot ($R = 0.06\ m$, $\rho_r = 1034\ kg/m^3$, $M = 0.9\ kg$) vaguely

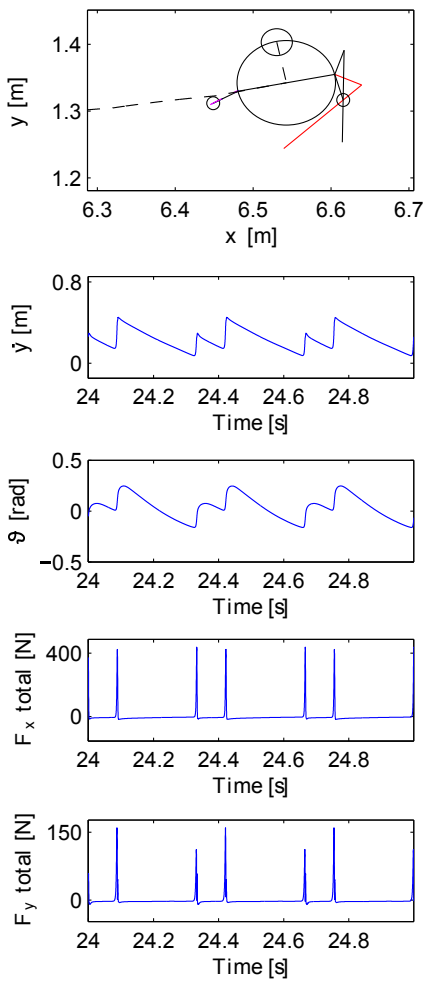

Fig. 5. Design of the best performing robot evolved by the novelty-based genetic algorithm. The second plot shows $\dot{y}$. The third plot highlights the pitch of the robot: tilted up during the swimming strokes, it passively recovers during the recovery phase due to the decoupled CoB. Force plots highlight very high impulsive forces arise from the high velocities of the distal part of the legs, induced by the peculiar configuration of leg's mechanism discovered by evolution ($i \approx m$) and high leg's drag coefficients. No gait diagram is reported given that the robot is a swimmer that never touches the ground

resembles some kind of fast terrestrial quadruped (e.g. antelopes), with its long legs and its posture, this design exploits several phenomena of the underwater setting. The robot is slightly tilted forward due to the CoB inclination ($\beta = 17°$), moreover the distance between CoM and CoB is relatively high ($b = 0.16\ m$) so that the buoyancy momentum helps in quickly stabilizing the pitch of the robot. Interestingly enough, this gait is a combination of swimming and running, as can be observed in Fig. 7. As a consequence of the long, springy, underdumped legs ($l_{front} \approx l_{rear} \approx 0.14\ m$ – note another symmetry discovered by the algorithm, $dr = 0.55$, $k = 100\ N \cdot m$) a ballistic trajectory starts after the impact: nevertheless, during the flight phase, hind legs determines a total of four swimming strokes that modify both the trajectory and the posture of the robot. Again the algorithm discovered that it is advantageous to have $m \approx i$ in order to exploit high velocities of the distal part of the leg for swimming. This trait is more pronounced in the

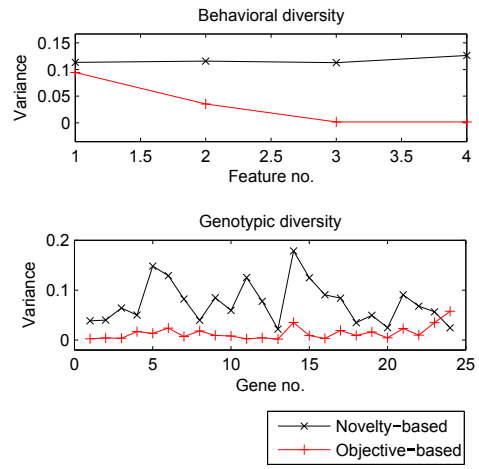

Fig. 6. Diversity of the final populations produced by the novelty-based and objective-based settings, as quantified by the variance of each feature (top) and of each gene (bottom) in the final population. Novelty search produces a more diverse population, better exploring both the design and the behavioral space.

hind pair in this case ($m_{front} = 0.042\ m$, $i_{front} = 0.059\ m$, $m_{rear} = 0.042\ m$, $i_{rear} = 0.046\ m$), that appear to have a different role with respect to the frontal ones (as also testified by duty factors, ≈ 0.1 for front legs, ≈ 0.05 for hind legs). Frontal legs are mostly used to absorb impacts with the ground, while rear legs are used to adjust the flight phase with swimming strokes. As for actuation, we observe another regularity, $F_{front} \approx F_{rear} \approx 1.4\ Hz$, while phase shift are $\phi_{interleg} = 40.4\ °$, $\phi_{frontRear} = 55\ °$. Results thus confirmed that novelty search is capable of producing fast, heterogeneous robots that suggest very different design solutions, each of which can provide several hints to the designer.

VI. CONCLUSIONS AND FUTURE WORK

In this paper the locomotion capabilities of a multi-legged underwater robot featuring compliant legs were investigated by means of evolutionary algorithms. A model inspired by a real robot was extended with respect to previous work. In addition to a conventional genetic algorithm, we proposed and demonstrated for the first time (to the best of our knowledge) the benefits of applying novelty search – an algorithm that explicitly searches for novel solutions – for exploring the design space of a real robot. In a considerably large design space, the proposed approach discovered very elaborated solutions, from whose analysis several insights were gained that will be useful for the design of the next prototypes. For example, the novelty setting suggested that the legged mechanism currently featured by the real robot may be in fact very suitable for sculling-based swimming, suggesting a completely different locomotion modality with respect to the one currently exhibited by the robot: this will of course affect future design choices. Based on the promising results achieved by considering our platform, we suggest this design methodology (merging bio-inspired embodied robot design and artificial evolution) as a general approach to design efficient robots that can fully benefit from the intrinsic dynamics of their body and from a rich interaction with the environment. The next natural step will be to test

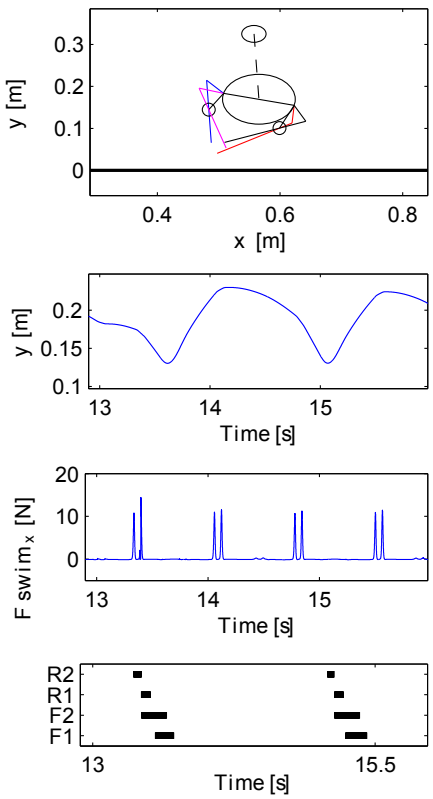

Fig. 7. Quadruped design evolved by novelty search. The gait exhibited by this individual is a peculiar combination of running and swimming. Plots report the y position, swimming forces and the gait diagram for this robot.

some of the technical solutions evolved in simulation into the real world. In this regard the adoption of novelty search is highly beneficial: providing several options to choose from, the chances that some of the designs evolved in simulation will actually maintain their qualitative behavior also in the real world are higher with respect to conventional approaches, that tend to converge to a specific solution. In future work we will refine the simulation setup, by modeling energy consumption and optimize energy efficiency in addition to locomotion speed. Also, we will explore the possibility of condensing more than one of the evolved designs into a single robot, capable of adapting its morphology online in order to exploit several self-stabilized gaits such as the ones described in this paper, switching smoothly among them. We expect that the insights gained through this kind of analysis will greatly contribute to the identification of the most relevant morphological and control parameters that will guide the design of such a robot.

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