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Engineering morphological development in a robotic bipedal walking problem: An empirical study

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ABSTRACT

In living beings, the natural development of the body has been shown to facilitate learning. The application of these natural developmental principles in robotics have been considered in different robotic morphologies and scenarios, leading to mixed results. Development was found to be beneficial for learning in some instances, but also irrelevant or detrimental in others. This mix of results and scenarios has allowed researchers to extract some notions about the conditions that must be fulfilled or set to apply morphological development successfully. Notions that we have organized to set a series of design conditions to successfully apply morphological development. Thus, in this article, we are going to focus on the study of one of them that has been frequently addressed by researchers in their studies in very general terms. It can be described as the need to achieve a suitable synergy among the different components involved in the development and learning process: morphological development strategy, controller, task, and learning algorithm. In particular, we have concentrated on empirically determining the influence of five developmental strategies, implemented in different ways, applied at different speeds and deployed in different orders and combinations, over the problem of a NAO robot controlled by an artificial neural network obtained through a neuroevolutionary algorithm learning a bipedal walking task. The results obtained permit providing a more detailed description of what a suitable synergy implies and how it can be utilized to design more successful morphological developmental processes to improve robot learning.
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1. Introduction

Humans and animals undergo morphological development processes from infancy to adulthood that have been shown to facilitate learning [1,2]. Within the field of robotics, some of the developmental principles observed in nature have been applied to different robot morphologies with the goal of improving their learning performance and adaptation capabilities. However, the application of these morphological development principles has led to mixed results depending on the type of experiment that was carried out. Thus, morphological development has been found to be helpful [3–6], irrelevant [7,8], or even detrimental [8,9] for learning. In fact, the underlying mechanisms through which morphological development may influence learning and, in particular, how to engineer these processes, are still not very well understood although some researchers have provided some indications of what may be going on. For example, in a case that contemplates a three-finger hand morphology learning to grasp different geometric objects, Bongard [5] relates task complexity with the influence of morphological change when learning. The more complex the task, the more advantageous morphological development is for learning. That is, as the number of different objects to be grasped increases, morphological changes became more relevant for learning, compared to learning with a fixed morphology. The argument about task complexity is also supported by Bongard and Buckingham [10] in a four-wheel robot. In this case, morphological changes are performed by modifying the characteristics of the simulator, from a less realistic to a more realistic one, considering more morphological parameters in the simulation, like wheel radius, motor gain, or the wheel friction coefficient. They find that such morphological changes only influence learning when task complexity increases and when enough time is left for the robot to learn.

From another viewpoint, it has been found that abrupt changes in morphology also tend to condition learning. In a locomotion learning experiment with a quadruped and a hexapod robot, Bongard [9] found that an abrupt change in the controller-morphology relationship decreases the learning performance. He hypothesizes

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that the learning algorithm needs time to adapt the controller to the new morphology. Similar conclusions were reported by Lungarella and Berthouze [11] in a bipedal mechanism held by its shoulders that was learning to swing under an external perturbation. In this case, morphological changes were achieved through an abrupt developmental mechanism that implied freezing and freeing degrees of freedom (DOF). This led to instabilities in the system, making it harder to find an adequate robotic swinging behavior.

Another factor that has been found to possibly influence learning is the order of the morphological changes involved in the development process. In nature, development often follows a predefined cephalocaudal and proximodistal sequence [12]. However, in robotics there is a lot more freedom to establish a developmental sequence, which also complicates finding the right one. In this line, Ivanchenko and Jacobs [8], in a task of learning a predefined arm trajectory, found that freeing and freezing DOF following a proximodistal development sequence helps to improve learning performance over the non-development case, but in the case of the inverse sequence development becomes detrimental for learning. The same types of results were obtained by Vujovic et al. [6]. In a joint Evolutionary and Developmental (Evo-Devo) experiment with quadruped morphologies evolved in the real world, they showed how learning performance was improved when following a specific developmental sequence, being irrelevant in other cases and also how the development of certain morphological parameters was irrelevant. This conclusion was also reached by Savastano and Nolfi [7] in an iCub robot experiment. They found that an improvement of the learning performance was achieved when development was applied over the motor system of the robot, being irrelevant when it was applied over the sensor system.

The speed at which the morphological changes happen, or the time at which development takes place also seem to influence the performance of the learning algorithm. In a developmental 2D soft-voxel robot, Nadizar et al. [13] found that fast and early development of the morphology led to an improvement of the learning results, while a continuous growth (slow development), which even ends in a bigger morphology, does not imply any difference with respect to no development. Kriegman et al. [14] also found a relationship between development in the early phases of evolution and the learning performance in an Evo-Devo 3D voxel experiment, indicating that short periods of development at the beginning of evolution help to improve learning.

Finally, the initial conditions of the morphology also appear to influence morphological development, even considering the same type of morphological development. Using a "starfish" simulated soft robot with 6 tentacles in a 2D world that learns to move, Benureau & Tani [15] have shown how the same morphological development strategy (starting the muscle development of the robot with different sizes) leads to different learning outcomes. In addition, these learning outcomes are accompanied by different robot behaviors, which may or may not arise easily depending on the selected development parameters. Given this variety of often complex and hard to compare experimental setups, leading to partial and sometimes contradictory results, in previous work by our team [16–18] we sought to address the influence of morphological development on the learning process under simple and controlled experimental conditions, to avoid uncontrolled parameters that could distort the results. To this end, we performed a series of experiments with different morphologies seeking to produce a set of principles related to how morphological development could be engineered and how they can lead to improvements in learning performance and justify the effort involved in development. These general conditions, can be summarized as:

1. The problem must be complex enough: As many authors, such as Bongard [5], Bongard and Buckingham [10], Deimel et al. [19], have already mentioned, the learning problem must be complex enough to justify the need for morphological development. Otherwise, traditional algorithms can achieve correct results and it is not worth the effort to apply development. In this context, problem complexity is understood as the difficulty for the learning algorithm to find the optimal solution, meaning that the problem cannot be easily solved by directly applying some naive optimization strategy.
2. Seek a simplified morphology that facilitates the initial stages of learning: Learning with the initial morphology must be simpler than learning with the final one, simplifying the problem at the early stages of development. This allows developing a scaffolding learning methodology to gradually increase the complexity of the learning task through the different developmental stages achieving the maximum complexity with the final morphology. This was pointed out by Zhu et al. [20], Naya-Varela et al. [21] and Benureau & Tani [15].
3. Availability of optimal solutions at the beginning of the process. To avoid misleading learning, we consider that optimal solutions must be available from the beginning of the learning process or that a clear sequential non-deceptive path of local optima in each stage of development should lead to the final optimum. Although a morphological development strategy that reduces the solution search space could help to find the optimal solution due to the simplification of the problem, it can also make the task of finding the optimum harder if the reduced area of the search space does not contain it. Some comments in this line were already presented by Lungarella and Berthouze [22] and Naya-Varela et al. [16].
4. Guarantee a suitable synergy between the morphological development process, the task and the learning system: It is necessary to have an adequate synergy between the morphology, the controller, the learning strategy, and the selected developmental strategy. Especially, the developmental strategy must be in accordance with the capacity of the controller to adapt to morphological changes and also the learning algorithm must be able to adjust the controller of the robot to each morphological change in a timely manner. Hints towards this are provided by Vujovic et al. [6], Ivanchenko and Jacobs [8], Lee et al. [23], Natale et al. [24] and Nadizar et al [13].

The first three conditions were already discussed and commented in other papers, including [21] where they were contemplated in the case of a biped robot learning to walk. This paper is an extension of that work and it is devoted to the analysis of the fourth condition. To this end, we will analyze the influence of different morphological development strategies in the case of a specific morphology and task, to provide some basic notions about the concept of synergy between morphological development, the task and the learning system. It will be performed by carrying out a series of experiments to demonstrate the influence of different elements related to these morphological changes and learning processes on the final learning result. In this paper, we again consider the problem of learning to walk in a bipedal robot, a quite difficult problem for exploring the search space of possible controllers (a needle in a haystack type of problem), leading to the robots falling down in a very high percentage of cases. Thus, making the computational cost of a developmental strategy worth it.

In fact, although there are numerous examples of bipedal-legged robots in the literature [25–28], walking in bipedal robots is still a complex task and only a few cases of robots have been shown to perform well independently of the environment

[27,28]. In fact, most of these robots are programmed to walk, they do not learn to walk. As mentioned before, adaptive robots that can modify their morphology and adapt it to the environment and task conditions belong to an incipient field and are still proof of concept [29,30]. There are few examples that study how to learn to walk in bipedal robots from a developmental perspective. Lungarella and Berthouze [11,22] analyzed the influence of morphological development by freezing and freeing the DOF of a bipedal robot in the already mentioned case under an external perturbation, but also without it. Hardman et al. [31] compared the performance of learning utilizing an annealing optimization algorithm with and without morphological changes in a two-legged robot with four links. They showed how two selected morphological development strategies outperform learning without them: developing the length of the foot and increasing the mass and inertia of the body of the robot. Zhu et al. [20] showed how morphological development based on starting with a long body that can serve as a tripod can bootstrap the learning ability of a genetic algorithm, gradually reducing the body size and increasing the leg length. However, they also pointed out the necessity of a suitable match between the task and the selected procedures, because they also reported worse results when other procedures are applied.

Thus, as indicated above and continuing the work done by Naya-Varela et al., in the following sections we are going to address the fourth point mentioned by the authors. Specifically, we will discuss what a suitable synergy may mean when engineering morphological development processes as well as provide some empirical evidence on the importance of these synergies and their implications when applying morphological development, especially in terms of the developmental strategy. To achieve these goals, the article is structured as follows: Section 2 describes the formalization of morphological development approach we use in this paper. Section 3 is devoted to the methodological aspects of the experimental setup constructed in order to show what a suitable synergy among the morphology, control system, and learning algorithm means, and what it involves. The results of the experiments carried out with different morphological development strategies and implementations are presented in Section 4. A discussion of the results obtained and how the different morphological development strategies have influenced learning and the obtained insights about how to apply them over different morphologies are presented in Section 5. Finally, a series of conclusions of this work consisting on how an adequate synergy can influence learning and how it can be deployed are commented in Section 6.

2. Morphological development functions

Following the formalization proposed in [32], we define morphological development as a function, *MD(t)*, that describes the morphology of the robot throughout its lifetime. Thus, we consider that a robot morphology is made up of a set of *l* links $L=\{l_1, l_2, \ldots, l_l\}$, a set of *j* joints $J=\{j_1, j_2, \ldots, j_j\}$, which can be actuated or not, and a set of *s* sensors $S=\{s_1, s_2, \ldots, s_s\}$. This morphology runs during time $t \in [0, T]$, where t = 0 is the beginning of the robot lifetime and t = T is the end. The links, joints and sensors have sets of properties (^{L}P, ^{J}P and ^{S}P) with a cardinality of $\times$,*y* and *z*, respectively. These property sets can be expressed as:

$$^{L}P = \begin{bmatrix} lp_{11} & \cdots & lp_{1l} \\ \vdots & \ddots & \vdots \\ lp_{x1} & \cdots & lp_{xl} \end{bmatrix}$$

$$^{J}P = \begin{bmatrix} jp_{11} & \cdots & jp_{1j} \\ \vdots & \ddots & \vdots \\ jp_{y1} & \cdots & jp_{yj} \end{bmatrix} \tag{1}$$

$$^{S}P = \begin{bmatrix} sp_{11} & \cdots & sp_{1s} \\ \vdots & \ddots & \vdots \\ sp_{z1} & \cdots & sp_{zs} \end{bmatrix}$$

Therefore, a robot morphology can be defined as the set of links, joints and sensors that make up the robot and their properties:$\mathfrak{M} = \{L, J, S, \ ^{L}P, ^{J}P, ^{S}P\}$. This leads to the general formal definition of morphological development as a non-stationary function *MD(t)* that describes the evolution in time of the values for the properties in these property sets for the lifetime of the robot:

$$MD(t) = \{ \ ^{L}P_t, ^{J}P_t, ^{S}P_t\} \forall t \in [0, T] \tag{2}$$

Therefore, when contemplating morphological development, the morphology of the different robots can be specified at the beginning of their lifetime as $\mathfrak{M}_0 = \{L, J, S, \ ^{L}P_0, ^{J}P_0, ^{S}P_0\}$ and by $\mathfrak{M}_T = \{L, J, S, \ ^{L}P_T, ^{J}P_T, ^{S}P_T\}$ at the end. Development can be carried out over any or all of these property sets. For instance, if we only consider growth based morphological development, which only affect the links, the values of the properties represented by ^{J}P and ^{S}P remain constant throughout the lifetime of the robot and the only ones that change are those corresponding to ^{L}P, leading to:

$$MD(t) = \{ \ ^{L}P_t\} \quad \forall t \in [0, T] \tag{3}$$

Where ^{L}P specifies the parameters for each link of the robot, such as their length or mass. This growth based morphological development approach is the one considered in this paper. In general, as most of the parameters are kept constant, and only a few specific ones are changed during the lifetime of the robot, *MD(t)* is expressed as a combination of the morphological parameters that vary.

From an engineering perspective, the problem becomes how to construct an *MD(t)* function that is appropriate for facilitating the solution of the problem that needs to be addressed. This has two implications. On the one hand, it is necessary to select the most effective parameters to modify during the lifetime of the robot. On the other hand, a decision must be made on how to modify these parameters along time so that they facilitate the desired learning result. This is not an easy task and it is clearly problem dependent in the sense that depending on the characteristics of the task or set of tasks the robot needs to learn, the *MD(t)* that is constructed may be quite different. In other words, starting from an initial morphology $\mathfrak{M}_0$ a specification of *MD(t)* as a function of the modifications that are going to be carried out over each parameter and their schedules must be provided. We are going to express this as a sum of the modifications in time (expressed as Δ) over the different parameters that are considered. Thus, where *n* represents either a Link *L*, a Joint *J*, or a Sensor *S*, and *m* the parameters undergoing development:

$$MD(t) = \mathfrak{M}_0 + \sum_{n,m} \Delta \ ^{n}P_m(t) \tag{4}$$

Each modification function corresponding to one parameter provides a definition of when the parameter starts its development, when it ends and how it is modified during this time interval. It is important to note that there are an infinite number of possible development functions for a parameter. In some cases, it can be modified continuously in a given interval, starting from the value of the initial morphology to that of the final one (depending on the size of the interval the change will be faster or slower).

In others it may go brusquely or in discrete steps from the initial morphology to the final one. Anyway, whatever the path followed by the development of each individual parameter; it is also important to note that the positioning of the intervals at which each is modified implicitly leads to a global morphological development schedule that makes up the whole morphological development process. This schedule establishes which changes occur concurrently or sequentially and this may have a strong bearing on the results. Summarizing, starting from an initial morphology, which, following the indications of previous papers, should be a morphology that makes learning much easier, a *MD(t)* function that determines when and how each parameter changes must be established. However, as mentioned by several authors [6,23] for this function to be effective, it should be synergic with the learning algorithm (defined by is adaptation capabilities) and the task to be carried out (defined by its difficulty). Starting from the formalization made here, in the following section we will address the specific problem of bipedal walking with a NAO type robot as a practical prototype case and empirically study what these synergies may involve.

3. Materials and methods

To address the study of the implications of different morphological development strategies, in this paper we have chosen a hard task in a complex morphology, in particular the problem of an adaptation of the NAO robot learning to walk, as a prototypical example to study the engineering of a morphological development process.

3.1. Robot and simulator

The robot morphology is based on a commercial NAO bipedal robot [33]. This robot is 58 cm tall, weighs around 4.5 kg and has 25 degrees of freedom (DOF). All the experiments were carried out in the CoppeliaSim simulator [34], which already has a native model of it. In order to make the robot able to develop, we have modified this native model (Fig. 1), specifically in the legs and feet to simplify the simulation model and also to allow the development of the morphology:

- *Upper link*: The upper part of the legs was changed from a single mesh to two cuboids, both with the same dimensions and weight, 8x8x7.2 cm. They are joined by a prismatic joint, which allows the extension of the upper part of the leg, with a maximum force of 50 N. The maximum extension of the prismatic joint is 4.0 cm, which is almost a third of the size of the upper link when not extended. When fully contracted, the leg matches the original dimensions of the NAO. The mass of the upper link has been increased with respect to the original mass of the NAO. Furthermore, the mass of the legs may vary in the different developmental stages, while preserving the size of the cuboids invariant.
- *Lower link*: The lower part of the legs was also changed to two different cuboids. The upper cuboid is 8x8x3 cm and the lower one is 9x8x3 cm. Again, the properties of the cuboids and their geometric orientation were selected to preserve the original NAO design and their mass is also dependent of each developmental stage. The prismatic joint has the same functionality and properties as the prismatic joint of the upper link: a maximum force of 50 N and a maximum extension of 4.0 cm.
- *Feet*: The foot size and weight have also been modified with respect to the native design of the NAO robot in CoppeliaSim. The simulation model was simplified, reducing the number of cuboids that constitute the original foot of the NAO. Now, each foot is 18.4x10x1.5 cm and weights 0.276 kg. Furthermore, both the size and the weight of the foot change during development.

The main insight of morphological development is that to learn an effective controller for a given final morphology and task in situations where learning this controller directly is very difficult, it is better to start with a much simpler morphology that facilitates learning a controller for the task and then establish a morphological development path that allows adapting the controller to the final morphology. Consequently, to achieve a successful morphological development process towards the final morphology, the first thing that must be chosen is an initial morphology for the developmental process that facilitates learning the controller.

Thus, in the case we considered here, a very simple analysis of why this problem is so hard when trying to achieve it directly with the final morphology shows that the main problem is stability. Most candidates fall and thus provide no or very little information to the learning algorithm in terms of walking. Consequently, it seems that a good choice for an initial morphology would be one that does not fall easily. To this end, we have decided to simplify the robot morphology and have chosen an extremely stable initial morphology. The main differences of this initial morphology with respect to the final one with the aim of making it more stable are:

- *Increased Foot Size (FS)*: The foot size is increased with the aim of augmenting the contact area between the morphology and the ground.
- Lowered robot center of gravity: Lowering the center of gravity of the robot allows increasing its stability. This also makes a higher number of walking gaits accessible to the robot without falling. This lowering of the robot center of gravity is achieved by acting on:
  - *Leg Length (LL)*: which implies a reduction of the robot size.

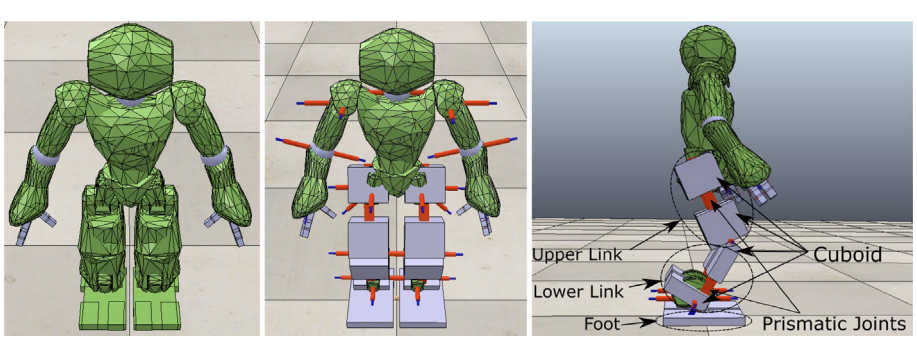

Fig. 1. Left: frontal view of the original NAO robot model in CoppeliaSim. Middle: frontal view of the developmental model of the NAO robot. In green, the defaults meshes of the original robot. In grey, the modified parts. Right: side view of the NAO model where its different parts are indicated.

- *Leg Mass (LM)*: which contemplates a redistribution of the total mass of the legs, gaining weight in their lower parts and thus, reducing the gravity center.
- *Arm Development (AD)*: starting without arms, the gravity center is not only lowered, but also the instability produced by dynamic swinging movements is also reduced.
- *Hip Width (HW)*: Increasing the distance between the two hip joints, thus widening the space between legs, allows the robot to increase its stability.

Obviously, starting from this initial morphology, the developmental process should be able to take us to the final one. Consequently, the morphological development function should contemplate acting over the five parameters that were modified to obtain the initial morphology. Following the notation indicated in the previous section, the morphology of the robot for a given instant of time t can be given as:

$$MD(t) = \mathfrak{M}_0 + \Delta LL(\mathrm{t}) + \Delta LM(\mathrm{t}) + \Delta FS(\mathrm{t}) + \Delta HW(\mathrm{t}) + \Delta AD(\mathrm{t}) \forall t \in [0, T] \# \tag{5}$$

3.2. Developmental functions

There are infinite developmental functions that could be used. In this paper, the objective is to provide a series on insights on the effects of different strategies for the construction of this function contemplating a series of individual strategies for the development functions for each of the parameters as well as different approaches to their combination/scheduling. It is important to note here that in order to contemplate different options, we have allowed continuous values for three of the parameters ($\Delta LL(\mathrm{t})$, $\Delta \mathrm{LM}(\mathrm{t})$, and $\Delta \mathrm{HW}(\mathrm{t})$) and only discrete values for the other two ($\Delta FS(\mathrm{t})$ and $\Delta \mathrm{AD}(\mathrm{t})$). In fact, in this paper, arm development is only allowed at discrete points in which the upper arm, the elbow, the forearm, the wrist and the hands appear abruptly.

In the following we describe a series of prototypical *MD(t)* functions that we have created in order to analyze their effects on learning.

3.2.1. No development

There is no development, and the morphology is permanently at the final morphology. Thus:

$$MD_{node\,v}(\mathrm{t}) = \mathfrak{M}_{\boldsymbol{T}} \forall t \in [0, T] \# \tag{6}$$

Abrupt change of the morphology ($MD_{abrupt}(t)$):

We define a time where an abrupt transition from the initial morphology to the final morphology occurs. Thus:

$$MD_{abrupt}(t) = \begin{cases} \mathfrak{M}_0, if t < T_f \\ \mathfrak{M}_{\boldsymbol{T}}, if t \geq T_f \end{cases} \# \tag{7}$$

where T_f if the time when the robot achieves the final (adult) morphology. Throughout this section, and unless otherwise specified T_f has been defined as the midlife time ($T/2$) of the robot, and t covers the whole life $\forall t \in [0, T]$.

Linear change of the morphology ($MD_{linear}(t)$):

One of the most straightforward ways of applying development between two morphologies is to apply linear development. Thus, as a baseline approach, we have decided to implement the morphological changes linearly on the parameters that are continuous: leg length, leg mass and hip width. Thus, the development at a given time can be calculated by $\Delta LL(\mathrm{t})$, $\Delta \mathrm{LM}(\mathrm{t})$, and $\Delta \mathrm{HW}(\mathrm{t})$ according to the following equation:

$$\Delta parameter(t) = \begin{cases} \frac{\max(\Delta parameter)}{T_f} * t, if t < T_f \\ \max(\Delta parameter), if t \geq T_f \end{cases} \# \tag{8}$$

For the discrete variables, we define 5 transition points where there is a sudden change of the morphology. The final morphology is achieved at the midlife time ($T/2$) as in the previous case and, therefore, each discrete transition between morphologies is applied at $T/10$ time intervals until $T/2$. The formalization of the morphological development functions for $\Delta FS(\mathrm{t})$ and $\Delta \mathrm{AD}(\mathrm{t})$ can be found in the Appendix (see equations A(1) and A(2)) due to their size.

Thus, we define a specific *MD(t)* called $MD_{linear}(t)$ as the morphology at time t by using equation (5), where equation (8) is used to obtain the $\Delta LL(\mathrm{t}), \Delta \mathrm{LM}(\mathrm{t}), \mathrm{and} \Delta \mathrm{HW}(\mathrm{t})$, and equations A(1) and A(2) for the $\Delta FS(\mathrm{t})$ and $\Delta \mathrm{AD}(\mathrm{t})$ respectively.

For this type of experiment, the time when the robot reaches the final morphology, T_f, has been initially selected to be the midlife time ($T/2$) as in the previous experiment. In addition, in order to consider the effect of different development speeds, we have considered other cases where T_f corresponds to $T/4$, $T/6$, $T/10$ and $2T/3$.

Several discrete changes of morphology ($MD_{discrete}(t)$):

For several discrete changes of morphology, we discretize the continuous parameters (leg length, leg mass and hip width) and we use the same 5 transition points that were used for the discrete parameters. Thus,

$$MD_{discrete}(t) = \begin{cases} \mathfrak{M}_0, if t < \frac{T_f}{5} \\ \mathfrak{M}_1 = MD_{linear}\left(\frac{T_f}{5}\right), if \frac{T_f}{5} \geq t < \frac{2T_f}{5} \\ \mathfrak{M}_2 = MD_{linear}\left(\frac{2T_f}{5}\right), if \frac{2T_f}{5} \geq t < \frac{3T_f}{5} \\ \mathfrak{M}_3 = MD_{linear}\left(\frac{3T_f}{5}\right), if \frac{3T_f}{5} \geq t < \frac{4T_f}{5} \\ \mathfrak{M}_4 = MD_{linear}\left(\frac{4T_f}{5}\right), if \frac{4T_f}{5} \geq t < T_f \\ \mathfrak{M}_{\boldsymbol{T}}, if t \geq T_f \end{cases} \# \tag{9}$$

where $\mathfrak{M}_1$, $\mathfrak{M}_2$, $\mathfrak{M}_3$, and $\mathfrak{M}_4$ are arbitrary morphologies between the initial ($\mathfrak{M}_0$) and final morphology ($\mathfrak{M}_{\boldsymbol{T}}$).

Development of a single parameter ($MD_{only_x}(t)$)

To test the influence of each developmental parameter isolated from the rest, we have performed five experiments where only one parameter develops, being all the other parameters set at the final morphology values throughout the learning process. Thus, we can generate 5 developmental functions:

$$MD_{only_LL}(t) = \mathfrak{M}_0 + \Delta LL(\mathrm{t}) + \Delta LM(\mathrm{T}) + \Delta FS(\mathrm{T}) + \Delta HW(\mathrm{T}) + \Delta AD(\mathrm{T}) \# \tag{10}$$

$$MD_{only_LM}(t) = \mathfrak{M}_0 + \Delta LL(\mathrm{T}) + \Delta LM(\mathrm{t}) + \Delta FS(\mathrm{T}) + \Delta HW(\mathrm{T}) + \Delta AD(\mathrm{T}) \# \tag{11}$$

$$MD_{only_FS}(t) = \mathfrak{M}_0 + \Delta LL(\mathrm{T}) + \Delta LM(\mathrm{T}) + \Delta FS(\mathrm{t}) + \Delta HW(\mathrm{T}) + \Delta AD(\mathrm{T}) \# \tag{12}$$

$$MD_{only_HW}(t) = \mathfrak{M}_0 + \Delta LL(\mathrm{T}) + \Delta LM(\mathrm{T}) + \Delta FS(\mathrm{T}) + \Delta HW(\mathrm{t}) + \Delta AD(\mathrm{T}) \# \tag{13}$$

$$MD_{only_AD}(t) = \mathfrak{M}_0 + \Delta LL(\mathrm{T}) + \Delta LM(\mathrm{T}) + \Delta FS(\mathrm{T}) + \Delta HW(\mathrm{T}) + \Delta AD(\mathrm{t}) \# \tag{14}$$

Sequential development ($MD_{sequence_x}(t)$)

Another possibility consists in applying a sequential development approach. Instead of developing all the parameters at the same time, we can develop one parameter and, once that development finishes, continue the development with another parameter. This process is repeated until all the parameters are developed. In this case, there are five different morphological parameters and there will be 5!=120 different possible permutations. We will just consider two of these permutations: A sequence of foot size, arm,

leg mass, hip width and leg length development and its opposite (leg length, hip width, leg mass, arm and foot size development). Each of these individual developmental intervals last $T_f/5$ of time. The continuous variables are linearly developed during an interval of duration $T_f/5$ and the discrete variables are developed in 5 discrete steps, each applied every $T_f/25$ instants of time. Thus:

$$MD_{FS_AD_LM_HW_LL}(t) = \mathfrak{M}_0 + \Delta FS(\mathrm{t}) + \Delta AD\left(\mathrm{t} - \frac{T_f}{5}\right) + \Delta LM\left(\mathrm{t} - \frac{2T_f}{5}\right) + \Delta HW\left(\mathrm{t} - \frac{3T_f}{5}\right) + \Delta LL\left(\mathrm{t} - \frac{4T_f}{5}\right)\# \tag{15}$$

$$MD_{LL_HW_LM_AD_FS}(t) = \mathfrak{M}_0 + \Delta LL(\mathrm{t}) + \Delta HW\left(\mathrm{t} - \frac{T_f}{5}\right) + \Delta LM\left(\mathrm{t} - \frac{2T_f}{5}\right) + \Delta AD\left(\mathrm{t} - \frac{3T_f}{5}\right) + \Delta FS\left(\mathrm{t} - \frac{4T_f}{5}\right)\# \tag{16}$$

where $\Delta LL(t)$, $\Delta LM(t)$ and $\Delta HW(t)$ are defined as:

$$\Delta parameter(x) = \begin{cases} 0, if x < 0 \\ \frac{\max(\Delta parameter)}{\left(\frac{T_f}{5}\right)} * x, if x < \frac{T_f}{5} \\ \max(\Delta parameter), if x \geq \frac{T_f}{5} \end{cases} \# \tag{17}$$

Being x the developmental time of each of the parameters.

The formalization of the morphological development functions for the discrete parameters $\Delta FS(\mathrm{t})$ and $\Delta \mathrm{AD}(\mathrm{t})$ can be found in the Appendix (see equations A(3) and A(4)).

A schematic representation of both developmental strategies is shown in Fig. 2, where the discrete development is indicated as thin vertical lines and the linear development of parameters as horizontal arrows.

3.3. Morphological development

As explained in the previous section, there are five different features that we develop on the NAÓs morphology. This section provides a detailed description on how we apply the development on the robot model. Both legs are developed at the same time and, thus, the same parameters control properties for both sides of the robot. This is also the case for the feet and arms.

- **Leg Length (LL):** The prismatic joints of the lower and upper links are fully contracted in the initial morphology ($\mathfrak{M}_0$) and they are fully extended in the final one ($\mathfrak{M}_T$). Both prismatic joints are controlled simultaneously by the same parameter, Δleg_length. $\max(\Delta leg_length)$ is 4 cm, which matches with the maximum extension of the prismatic joints.
- **Leg Mass (LM):** The mass of the cuboids of the legs is reduced during development. There are four cuboids in each leg, and they are controlled by 3 parameters: $\Delta mass_UL$ for the mass of both cuboids of the upper link, $\Delta mass_LLLC$ for the mass of the lower link lower cuboid, and $\Delta mass_LLUC$ for the mass of the lower link upper cuboid. The values for $max(\Delta mass_UL)$, $max(\Delta mass_LLLC)$ and $max(\Delta mass_LLUC)$ are −0.2913, −0.2842 and −0.308 kg respectively. When changing the mass of the cuboids, their inertia moments are changed accordingly.
- **Foot Size (FS):** Both the width and the length of the foot are reduced during development. This is controlled by two parameters $\Delta foot_width$ and $\Delta foot_length$. The $\max(\Delta foot_{width})$ and $\max(\Delta foot_{length})$ are −0,01 m and −0,016 m respectively. The density of the foot does not change and, therefore, the mass also changes when length and width change. The inertia moments of the foot are changed accordingly.
- **Hip Width (HW):** The distance between the two hip joints is reduced during development. The hip joints are located symmetrically with respect to the mid-sagittal plane of the robot. Development is controlled by parameter Δhip_width, where the $\max(\Delta hip_width)$ value is −0.025 m.
- **Arm Development (AD):** The development of the arm happens in 5 discrete steps. In the initial morphology, the arm only contains the body of the shoulder. In the first development step, the upper arm is added. At the second development step, an elbow (spheric body) is added. Later, the forearm is developed. In the fourth development step, the wrist and hand are added. Finally, the fingers are added in the final development step. All the bodies of the arm are the same as in the native model of the NAO robot.

To illustrate how the robot develops, we have created Table 1, where the main parameters that change during development are reported for the initial and final morphologies, and at four intermediate steps as defined in Section 3.2 for the $MD_{discrete}(t)$ development function. For simplicity due to the limited space of the table, the parameter configuration of the arm size is specified by the initial letter of each part of the body that constitutes the arm at that developmental stage: Shoulder (S); Upper Arm (UA); Elbow (E); Forearm (F); Wrist and Hand (WH); Fingers (Fi). These morphological developmental stages are shown in Fig. 3.

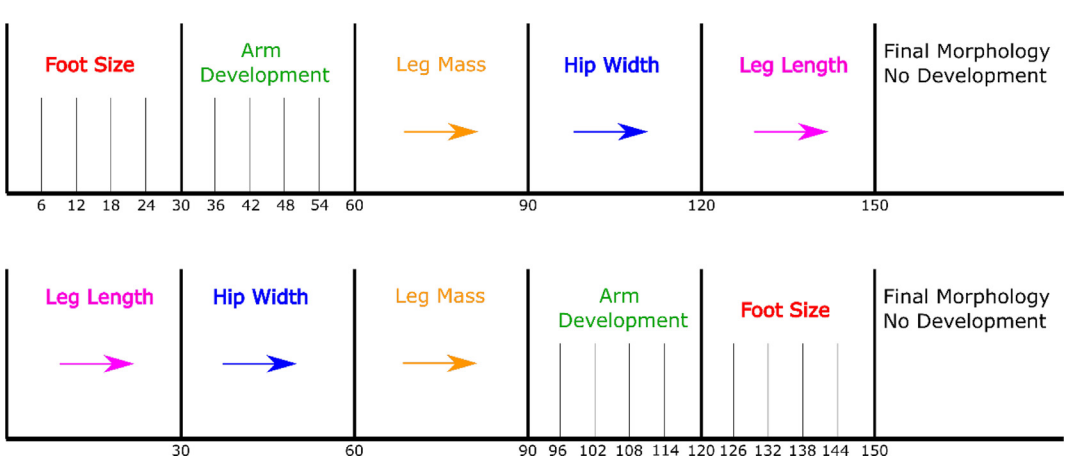

Fig. 2. The $MD_{FS_AD_LM_HW_LL}(t)$ (top) and for $MD_{LL_HW_LM_AD_FS}(t)$ (bottom) developmental sequences for a robot with a lifetime T of 300 learning generations.

Table 1
Parameter configuration for the different morphologies at each developmental stage.

		Morphologies					
Feature	Parameters	$\mathfrak{M}_0$	$\mathfrak{M}_1$	$\mathfrak{M}_2$	$\mathfrak{M}_3$	$\mathfrak{M}_4$	$\mathfrak{M}_T$
Leg Length	Lower and upper leg length (m)	0.144	0.152	0.16	0.168	0.176	0.184
Body Mass	Upper Link – Both Cuboids (kg)	0.75	0.69174	0.63348	0.57522	0.51696	0.4587
	Lower Link - Lower Cuboid (kg)	0.5	0.44316	0.38632	0.32948	0.27264	0.2158
	Lower Link - Upper Cuboid (kg)	0.5	0.4384	0.3768	0.3152	0.2536	0.192
Foot Size	Length (m)	0.2	0.1968	0.1936	0.1904	0.1872	0.184
	Width (m)	0.11	0.108	0.106	0.104	0.102	0.1
	Weight (kg)	0.35	0.3381	0.3252	0.3056	0.2864	0.276
Hip Width	Width (m)	0.075	0.07	0.0648992	0.06	0.0547984	0.049748
Arm Development	Bodies in the arm	S	S + UA	S + UA + E	S + UA + E + F	S + UA + E + F + WH	S + UA + E + F + WH + Fi

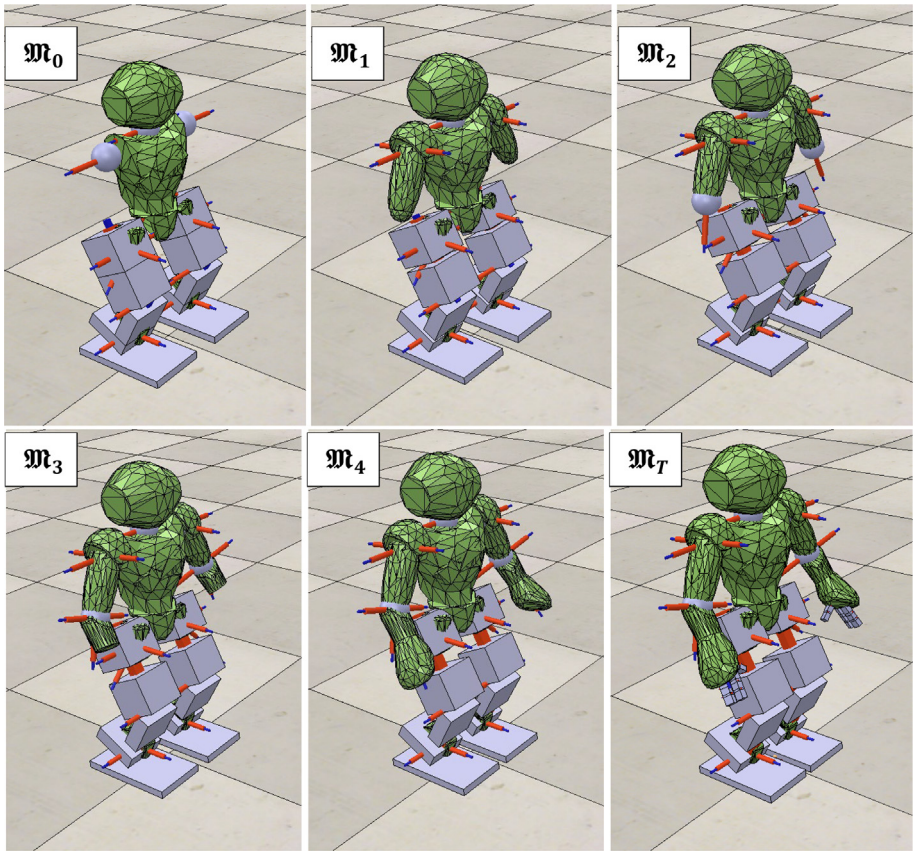

Fig. 3. Different morphological development stages of the NAO morphology. Image $\mathfrak{M}_0$ and $\mathfrak{M}_T$, are the initial and final morphologies respectively, while $\mathfrak{M}_1$, $\mathfrak{M}_2$, $\mathfrak{M}_3$ and $\mathfrak{M}_4$ are the reference intermediate developmental stages.

3.4. Controller and learning algorithm

Regarding the control system, the robot controller considered is an Artificial Neural Network (ANN) with 3 inputs plus one bias and 14 outputs. The remaining degrees of freedom (11/25), among which are those corresponding to the head, are not considered by the controller, and keep their initial positions fixed. This has been done to avoid increasing the size of the neural network, and thus the search space, too much, as we consider that these degrees of freedom are not especially relevant. Each output controls the actuation of one revolute joint. These joints are:

- 3 joints for the hip on each side: hip yaw, hip roll, and hip pitch for the left and right hip.
- 3 joints for each leg: knee, ankle pitch, and ankle yaw for the left and right leg.
- 1 joint for each shoulder. The shoulder actuation allows balancing the body through arm movements.

The inputs to the ANN are sinusoidal functions that generate periodic signals with a specific pattern. This methodology has been used by other authors [35] and in our previous work [32]. These sinusoidal functions have an amplitude of 2.0 rad and a frequency 1.21π rad/s, with phases of 0, $\pi/3$, and $\pi/5$ rad respectively. Three inputs with the same frequency but different phase have been selected to provide the ANN with various pattern generators. Thus, the ANN can combine them to produce gait patters that could be different or not from those provided by the inputs. The outputs of the ANN are denormalized to the Range of Motion (ROM) available for each joint, as shown in Table 2. Initially, the ANN starts without any hidden neurons or recursive connections, and it is fully connected. The synaptic weights and the topology of the

Table 2
Denormalized values of the outputs of the ANN. These values correspond to the ROM available for each joint.

Joint	ROM
Right Shoulder Pitch	[-20.0, 50.0]
Right Ankle Roll	[-30.0, 30.0]
Right Ankle Pitch	[-65.0, -5.0]
Right Knee Pitch	[25.0, 85.0]
Right Hip Pitch	[-50.0, 10.0]
Right Hip Roll	[-20.0, 20.0]
Right Hip Yaw Pitch	[0.0, 0.0]
Right Shoulder Pitch	[-20.0, 50.0]
Left Ankle Roll	[-30.0, 30.0]
Left Ankle Pitch	[-65.0, -5.0]
Left Knee Pitch	[25.0, 85.0]
Left Hip Pitch	[-50.0, 10.0]
Left Hip Roll	[-20.0, 20.0]
Left Hip Yaw Pitch	[0.0, 0.0]

Table 3
Basic configuration parameters of the MultiNEAT algorithm.

MultiNEAT parameter	Value
Population Size	50
Generations	300
Minimum Species Size	1
Maximum Species Size	3
Survival Rate	0.2
Crossover Rate	0.5
Mutate Weights Probability	0.1
Elite Fraction	0.01
Mutate Add Neuron Probability	0.1
Mutate Add Link Probability	0.2
Recurrent Probability	0.01

ANN are optimized through the NEAT neuroevolutionary algorithm [36], concretely the MultiNEAT implementation [37]. The basic configuration parameters of the NEAT algorithm are displayed in Table 3. It is important to point out that although NEAT measures the optimization time in generations, these generations correspond to the lifespan of an individual, and there is not evolution of the morphology here. Neuroevolution is the optimization mechanism to find the adequate robot controller at a given point in time. Recurrent connections are allowed, although their implementation on the ANN depends on the evolutionary process. Note that the addition of two sinusoidal signals of different amplitudes and phases but with the same frequency, produces a new sinusoidal signal of the same frequency with a different amplitude and phase. Thus, the ANN can produce sinusoidal outputs of different amplitudes and phases by adjusting the weights of the synapses. In addition, the recurrent connections of the ANN can be seen as another input signal with a small delay with respect to the other basic inputs, thus opening the possibility of generating new extra behaviors.

3.5. Evaluation

All the controllers were tested in the CoppeliaSim simulator, with the ODE physical engine [38]. Each individual was evaluated for 5 s with a simulation time-step of 50 ms, which implies a total of 100 time-steps of simulation, and a physics engine time-step of 5 ms. For every simulation step, the controller was used to set the target of the joints. After loading the model of the robot, before starting the simulation, the different parameters of the robot that are being developed are modified based on the corresponding *MD(t)* and they are fixed during the evaluation time. That is, there is no morphological change during the evaluation of an instance. The morphology changes between generations, once the whole population on the neuroevolutionary algorithm has been evaluated.

The objective is for the NAO to travel the longest possible distance in a straight line (over the X-axis, which is the one in the direction of the NAO's initial orientation). As we want to analyze the relevance of the developmental process with respect to the learning algorithm in bipedal walking, the distance traveled will only be taken into account when the robot performs bipedal walking. The distance traveled is not considered if the robot falls and keeps moving on the ground. We consider that there is a fall when the head of the NAO is lower than 0.3 m above the floor. If the NAO does not fall, the fitness is calculated as the distance traveled in a straight line over "X" in meters. However, if the NAO falls, the simulation is stopped, and we take the distance traveled 16-simulation time steps before the moment the NAO fell as the fitness value. It was obtained empirically that 16-time steps before falling the NAO is generally still in a stable upright position.

3.6. Experiments and statistical analysis

To quantitatively analyze the adequacy of the developmental process to the ability of the learning algorithm to adapt the controller to the physical changes of the robot while learning to walk, all the different morphological development functions, MD(t), defined in Section 3.2 have been tested. For each *MD(t)*, a total of 40 independent runs were carried out for each experiment with the objective of gathering relevant statistical data. For each independent run, the NEAT algorithm optimizes a population of 50 individuals for 300 generations.

For each experiment, we generate evolution graphs. If not stated in the text, the evolution graphs for each experiment display the median of the best fitness obtained in 40 independent runs (solid lines) and the 75 and 25 percentiles are indicated by shaded areas.

The statistical results are represented by a series of boxplots. Each boxplot represents the median and the 75 and 25 percentiles in the last generation for 40 independent runs of each of the different types of experiments. The whiskers are extended to 1.5 of the interquartile range (IQR). Single points represent values that are out of the IQR. Statistical analyses based on a two-tailed Mann-Whitney *U* test [39] were carried out to test for the statistical significance of the developmental experiments. Specifically, all the developmental experiments were compared against the no-development one and in some cases different developmental experiments were also compared to each other. A p-value of 0.05 is taken as the significance value for accepting or rejecting the null hypothesis. All the p-values shown have been adjusted using the Bonferroni correction [40]. To make the figures clearer, in the case of comparison among developmental experiments, only the statistically significant results are presented.

4. Results

The results are shown in six different groups. The first one, corresponds to the results of the learning process when applied directly to the morphologies at each developmental stage, including the initial and final morphology, without any morphological development. These results permit comparing the relative difficulty of the problem for the different intermediate morphologies. The rest consider the different development functions defined in Section 3.2: the discrete developmental experiments, the combined linear and discrete development, the sequential development, the development of just one parameter, and how the

morphological development speed influences the learning performance.

4.1. Problem difficulty

To concentrate on the fourth design condition out of those we mentioned in the introduction (a suitable synergy), we must first ensure that the remaining design conditions are met. To this end, and in order to test whether learning bipedal walking with a simple controller is worth addressing through morphological development, a first attempt was made to produce ANN-based walking controllers using the NEAT algorithm with the 6 fixed morphologies presented in Fig. 3. Specifically, we tested the initial morphology ($\mathfrak{M}_0$) and the final morphology ($\mathfrak{M}_T$) as well as the four intermediate morphologies defined by $MD_{discrete}(t)$): $\mathfrak{M}_1$, $\mathfrak{M}_2$, $\mathfrak{M}_3$, and $\mathfrak{M}_4$. The results of the learning process throughout the neuro-evolutionary process are displayed in Fig. 4.

In the case of the final morphology ($\mathfrak{M}_T$), and as commented before, the robot can only walk a median of less than 0.4 m after 300 generations of NEAT (Fig. 4, dotted gray line), which is a poor result regarding the best performances obtained in Naya-Varela et al. [21] in similar experimental conditions. In addition, if we analyze the population of the controllers during learning, we can observe that most of them fall at the beginning of the learning phase. Thus, in view of the results, it seems that the first design condition is fulfilled and the problem seems to be hard enough to merit trying to address it through morphological development.

The second design condition mentions that to properly design a morphological development problem, learning with the initial morphology must be simpler than learning with the final one. As reported in Fig. 4, the results show a progressive increase in difficulty in performing the task as the morphologies get closer to the final one (the fitness achieved at the end of learning is lower than that of the previous morphology). Only morphology $\mathfrak{M}_2$ slightly outperforms the fitness achieved by morphology $\mathfrak{M}_1$ at the end of learning. Clearly, the easiest to learn is the robot with the initial morphology $\mathfrak{M}_0$(with a median of 1.27, and 1.5 and 1.07 for percentile 75 and 25 respectively). Note that the best fitness is achieved by morphologies which are shorter and heavier than the final morphology. This indicates that the difference in fitness is caused by the difficulty to learn the controller and not by limitations of the final morphology. Thus, it seems that the selected initial morphology and the design hypotheses that have led to its design meet the criteria established in the second design condition.

Finally, the third design condition (availability of optimal solutions from the beginning of the process) is met by not establishing any limitation on the robot's motor system, allowing it to perform any action given by the ANN controller at any time during learning, unlike what happens with certain strategies of morphological development, as is the case of freezing and freeing DOF.

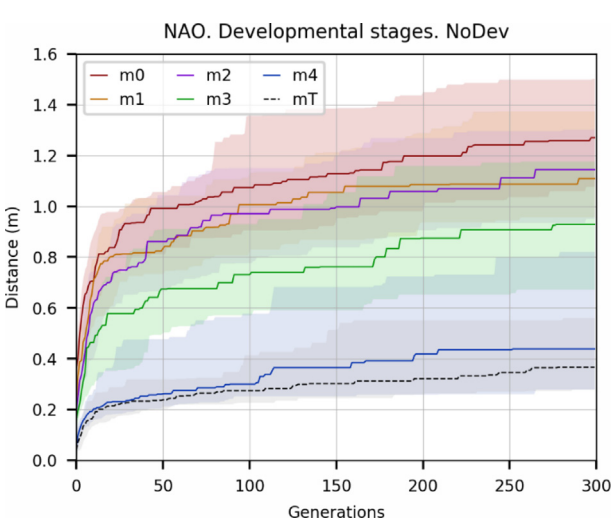

Fig. 4. Learning process for the different morphologies shown in Fig. 3 without any developmental process. The lines represent the median of the fitness value of the best controllers obtained in 40 independent executions.

4.2. Discrete development

Now, concentrating on the objective of this paper, that is, addressing the fourth design condition, and as stated in Section 3.2, there are many ways to implement a development function, even when the final and initial morphologies are set. The first naïve approach to apply development is to use one or several discrete transitions from the initial to the final morphology. Thus, as a first experiment we decided to perform a single development transition from the initial morphology to the final one at a specific moment of the learning process, $MD_{abrupt}(t)$. This was done at the midlife time ($T/2$), in generation 150. A second approach would be to create a discrete path of development, $MD_{discrete}(t)$, that goes from the initial to the final morphology through discrete transitions that lead to a series of intermediate morphologies, $\mathfrak{M}_1$, $\mathfrak{M}_2$, $\mathfrak{M}_3$, and $\mathfrak{M}_4$ (Fig. 3). Thus, development happens abruptly in generations 30, 60, 90, 120 and 150 where the final morphology is reached. After each transition the robot learns for 30 generations. The developmental path was established by adding complexity to the morphology, such as raising the center of gravity, increasing the balancing behavior by adding arm elements, reducing the size of the feet, etc.

The results of how the learning process evolves for the two discrete morphological development strategies can be seen in Fig. 5 left. Fig. 5 right displays the statistical significance of the developmental experiments based on the Mann-Whitney U test. All developmental experiments were compared to the no-development one and between them, but they are not statistically different. Thus, this approach has not led to an improvement in learning when compared to learning directly with the final morphology. Thus, the two developmental strategies cannot be considered different. They show how such simple morphological development strategies are far from being suitable to improve the learning performance of the final morphology.

Based on these results, it seems that to achieve a successful morphological development from an initial morphology to a final morphology, it is not enough to select an initial morphology that facilitates learning at the beginning and at some point, develop abruptly to the final morphology. It is also necessary to establish an adequate morphological development path from the initial morphology to the final one in order to achieve the adequate synergy between the different elements involved in the problem. In this line, the $MD_{discrete}(t)$ experiment provides a developmental path, but this path is not effective to achieve better results than no development.

The poor results of these types of developmental strategies may be explained by the characteristics of the problem to learn bipedal walking. Learning bipedal locomotion is a problem that depends strongly on the robot's stability, which implies that robot movements should be very precise and well-coordinated to avoid poor behaviors that may end up with the robot falling. In this situation, any small perturbation to the robot may imply a loss of stability or coordination, with the possibility of causing a dramatic change in the robot's behavior. In this case, such perturbations in the NAO are caused by the abrupt change in the morphology-control relationship originated by development transitions. In other words, the learning algorithm is not fast enough to adapt to the changing

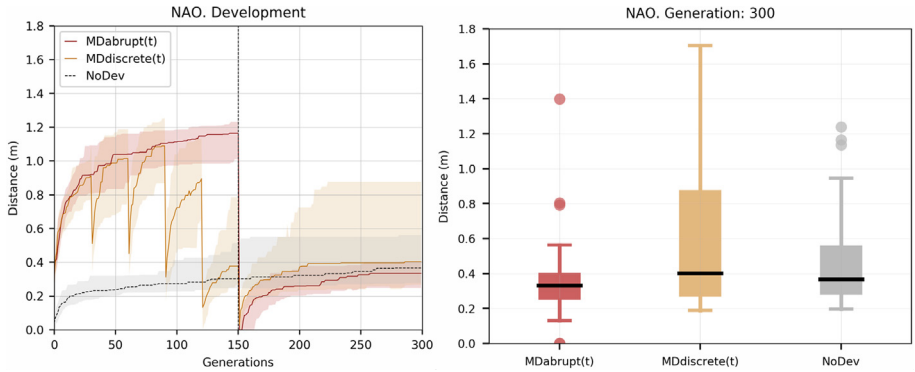

Fig. 5. Left: Comparative results in the case of learning with the final morphology (gray), with an abrupt transition from the initial to the final morphology (red) and with several discrete morphological developments (yellow). Right: box plot comparing the results of the three experiments at the end of learning.

morphology in these brusque transitions involving many parameters. Furthermore, as can be seen in Fig. 5, these disturbances become more pronounced the more developed the robot is. Although the sudden changes in the initial phases of development cause disturbances in the morphology-controller relationship leading to a decrease in the fitness value, the intrinsic initial stability of the system allows the fitness to recover its previous value quickly. In other words, there are still controllers that allow the robot to walk without falling and provide information to the learning algorithm. However, as development progresses, the stability of the morphology decreases, making it increasingly difficult for the learning algorithm to adapt the controller to the new state of development. Hence, at the end of development, fitness drops are more pronounced, and it is not possible to recover the fitness value obtained in previous stages of development because very few, if any, individuals are able to walk, and the learning algorithm lacks information that can help to adapt the controller.

As a consequence of these results, in the next section we address different developmental strategies based on a linear development of those parameters that are continuous, with the aim to provide a smoother transition between morphological development stages that minimize the perturbations caused in the morphology-controller relationship.

4.3. Combining linear and discrete development

As explained in Section 3, we have three morphological development features that are continuous (leg length, hip width, and leg mass) and two that are discrete (foot size and arm development). In this section we analyze the effect of morphological development when these features develop at the same time but some of them develop linearly without discrete transitions and the others discretely. Note that all the experiments are characterized by having a discrete development of the foot and arms, while the development of the legs, hips, and mass can be linear or discrete, depending on the experimental configuration. Thus, there are 8 possible combinations considering 3 variables that can be linear or discrete.

The results of the learning process are presented in Fig. 6 top, while the statistical analysis is displayed in Fig. 6 bottom. The configuration of each experiment is displayed in Table 4. Notice that the case where all parameters are developed discretely, $MD_{discrete}(t)$, is the same as the one analyzed in the previous section, but it is included here for the sake of completeness. In this section, the linear development of the continuous features, $MD_{linear}(t)$, is called "Li: MLH. Di: AF" in the labels to maintain a coherent nomenclature. Furthermore, at generation 30, 60, 90, 120 and 150, the morphologies achieved are the same in all the experiments and correspond to those presented in Fig. 3. This allows comparing the results obtained using these developmental strategies among them and to those with abrupt transitions shown in Fig. 5.

In Fig. 6 bottom, only the experiments dealing with linear leg mass development (*Li: M. Di: HLAF*) and the linear development of the leg mass and leg length (*Li: ML. Di: HAF*) have been shown not to favor learning (p-value of 2.065 and 0.05725 respectively). The best results have been obtained in the experiments with the linear development of the leg mass, hip width, and leg length and the discrete one of the arms and feet, $MD_{linear}(t)$, (*Li: MLH. Di: AF*, p-value of 10^{-5}), followed by the linear development of the leg length, with discrete development of the rest of the parameters (*Li: L. Di: MHAF*, p-value of $3 * 10^{-5}$).

The linear development of some continuous features has led to several development strategies being able to improve the learning compared to the no development case. Interestingly, none of the features that are treated as continuous or discrete seem to have a decisive influence on the outcome. For example, there are experiments where in both cases a linear development of the legs has been applied and in one of them the learning improves the no development experiment, and in the other it does not. Furthermore, when analyzing the experiments which improve the no development experiment, no statistical difference can be found between them. Thus, none of the successful strategies seems better than others.

4.4. Sequential development

Until now, all the features have been developed at the same time (discretely or linearly). In this subsection, we will consider a sequential approach as defined by $MD_{sequence_x}(t)$ in Section 3.2. Thus, a single morphological developmental parameter is developed at each developmental stage, where each development stage lasts for 30 generations. Continuous parameters are developed linearly and discrete parameters discretely at the transition point. Fig. 7 top displays the learning process for the two developmental strategies described in Fig. 2, $\mathrm{MD}_{\mathrm{FS_AD_LM_HW_LL}}(t)$ and $\mathrm{MD}_{\mathrm{LL_HW_LM_AD_FS}}(t)$. Fig. 7 bottom shows how the learning results achieved with these morphological development strategies have improved learning compared to the no-development case. This is supported by the p-values obtained in the statistical analysis for the $\mathrm{MD}_{\mathrm{FS_AD_LM_HW_LL}}(t)$ development strategy with a p-value of 0.00108 and the $\mathrm{MD}_{\mathrm{LL_HW_LM_AD_FS}}(t)$ development one with a p-value less than 10^{-5}. Furthermore, comparing the developmental strategies between them, although one may think that $\mathrm{MD}_{\mathrm{LL_HW_LM_AD_FS}}(t)$ is better than $\mathrm{MD}_{\mathrm{FS_AD_LM_HW_LL}}(t)$, they are not statistically different (p-value of 0.5666).

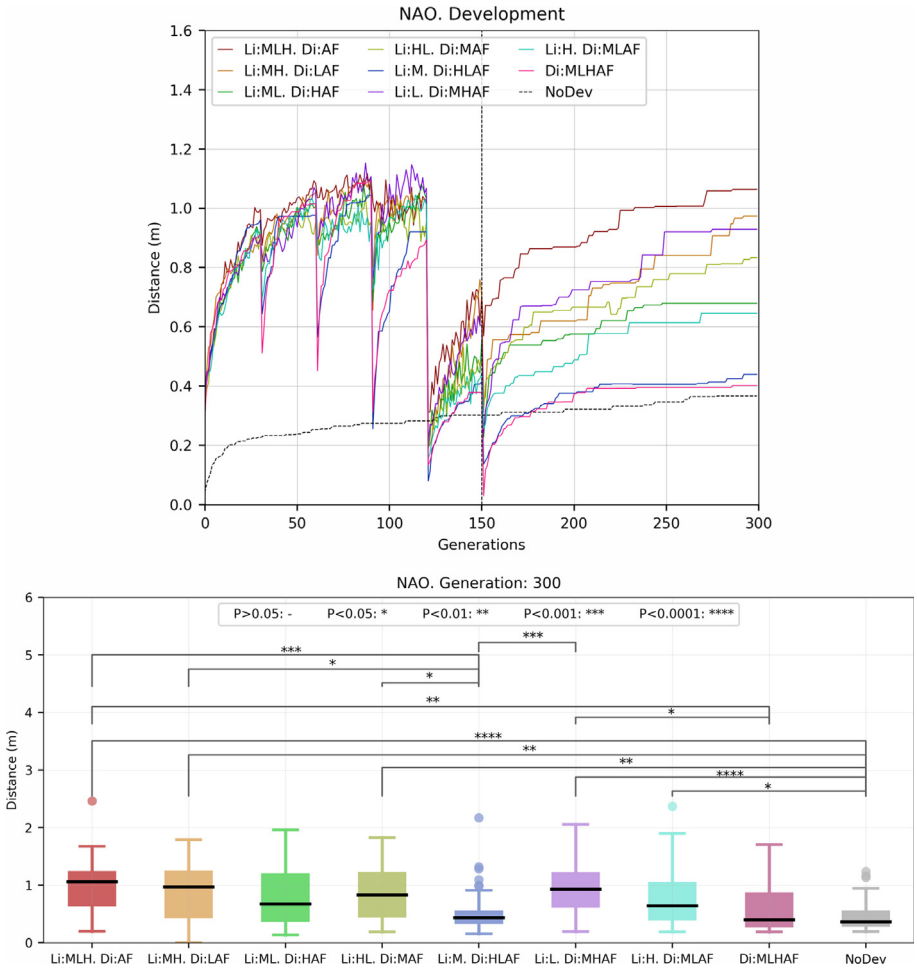

Fig. 6. Top: Median of several morphological development experiments considering the discrete developmental strategy (pink), the no-development (black) and different morphological development experiments with different developmental combinations. Bottom: Statistical analysis of the experiments combining discrete and linear development. Only statistically significant comparisons between experiments are shown.

Table 4
Developmental parameters and type of development in each of the experiments carried out. For simplicity, acronyms have been used to describe the type of development applied: Arm (A), Foot (F); Leg (L), Hip (H), Mass (M); Discrete development (Di); Linear development (Li).

	Arm	Foot	Mass	Hip	Leg
$\boldsymbol{MD_{discrete}(t)}$ =Di: MLHAF	Di	Di	Di	Di	Di
Li: L Di: MHAF	Di	Di	Di	Di	Li
Li: H Di: MLAF	Di	Di	Di	Li	Di
Li: LH Di: MAF	Di	Di	Di	Li	Li
Li: M Di: HLAF	Di	Di	Li	Di	Di
Li: ML Di: HAF	Di	Di	Li	Di	Li
Li: MH Di: LAF	Di	Di	Li	Li	Di
$\boldsymbol{MD_{linear}(t)}$ =Li: MLH Di: AF	Di	Di	Li	Li	Li

Based on our previous comments that abrupt changes in the morphology are less detrimental in the early stages of development due to the intrinsic stability of the morphology, $MD_{FS_AD_LM_HW_LL}(t)$ starts the morphological development process with two abrupt developmental strategies: foot development (from generation 0 to 30) and arm development (from generation 30 to 60). During both developmental sequences, the fitness value was around 0.8 m. This fitness value is maintained during the linear development of the mass. However, with the linear development of the hip and leg (from generation 90 to 120, and from 120 to 150 respectively), the fitness value starts to continuously decrease until reaching the final morphology. Although, intuitively, linear development in these phases of learning should help improve results, it seems that it makes the task of learning harder. This may be due to a combination of different factors: (1) The morphological development has guided the learning algorithm towards areas that may not be optimal in the adult morphology, such as those characterized by lateral displacements of the feet, which although they are solutions frequently found by the algorithm, narrowing the hip can be clearly limited; (2) The rapid speed of development for the morphological state in which they are found (with the other morphological parameters already developed), implies that the learning algorithm is not able to adapt to the changes required by the morphology-controller relationship; (3) Finally, with feet, arms and mass already developed, the morphology is more unstable, requiring more precise and controlled behaviors. Thus, any perturbation in the controller-morphology duo can cause a complete shift in the walking performance of the NAO using the same controller, which may go from optimal performance to falls.

On the other hand, the $MD_{LL_HW_LM_AD_FS}(t)$ experiment starts with the linear development of the legs and hip (from generation 0 to 30 and from 30 to 60 respectively) being followed by a linear development of the mass (from generation 60 to 90). This developmental phase allows maintaining the fitness value of the NAO in the [0.8, 1.0] interval. Once the linear development ends and the abrupt ones start, there are two drastic falls in the fitness value,

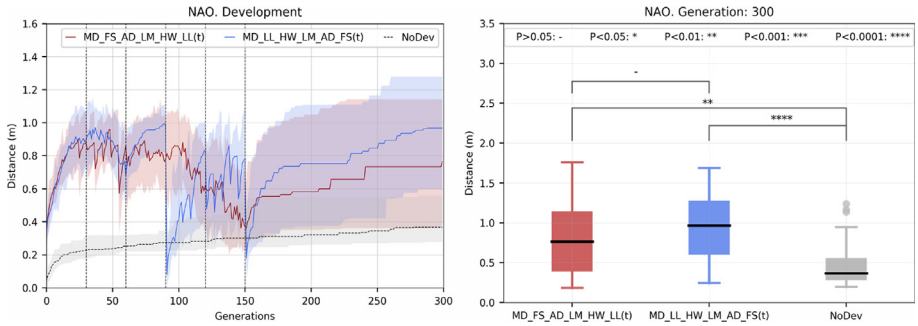

Fig. 7. Top: Learning process for each sequential developmental strategy and no development. The vertical dashed lines represent generations 30, 60, 90, 120 and 150. Bottom: Statistical comparison between the sequential experiments and the no development one, as well as between the two sequential ones.

which even go below the fitness value of the no-development experiment in those generations. However, unlike what happened with the no-development case, or what happened in the abrupt transition experiment, the fitness value quickly recovers its previous value to end at generation 300 with a fitness value very close to 1.0. This may be because, although the sudden changes in morphology affect the morphology-controller relationship, they occur at a learning stage in which the learning algorithm has been able to guide the solutions of the problem towards the optimum area in the solution space, and the controller only needs to make small changes to adapt to the new conditions of the morphology. Something that occurs neither in the case of no-development nor in the case of an abrupt discrete transitions, where the learning algorithm has been presented with a problem that is so difficult to learn from the beginning, that it has not been able to move its population towards the areas of the optimum. Another factor to highlight is the fact that sudden changes in morphology occur every 6 generations. Being the time intervals so small that there is no stagnation and/or trapping of the learning algorithm in suboptimal areas for a certain state of development. This does not happen in the case of no-development, where stagnation of the learning curve is observed, making it difficult to extract the learning algorithm from those areas for the new development state.

The results of Fig. 6 support the hypothesis that a smooth morphological development allows preserving an adequate synergy between the controller and the morphology, avoiding sudden changes in behavior. Although in the experiments of Fig. 7 the linear development of the hip and leg parameters was also taken into account, in this occasion the development is much faster, it only lasts 30 generations, while in Fig. 6 it lasts 150, which may be too high a speed for the learning algorithm to be able to adapt to the conditions of this problem. Thus, these slow changes in the morphology allow the learning algorithm to be able to keep the controller within the zone of optimal solutions found in the current morphological development stage. The controller is only disturbed by the sudden addition of the arm and foot in generation 120, presumably due to the increased stability of the NAO caused by the addition of the robot's wrist and hand, at the end of the arm. This morphological change can affect the rocking movement of the NAO, which, once the controller has adapted to this small but relevant change, leads to recovering fitness values that were seen prior to this morphological change.

On the other hand, from Fig. 6, something can be deduced that supports the main hypothesis raised in this document: for this specific case, an adequate synergy must be related to the capacity of the learning algorithm to adapt the controller to changes in the morphology. And this adaptation is closely related to the need to preserve the stability of the bipedal robot in all phases of learning. Thus, it can be seen how both the linear development of the hip and that of the mass, the others being discrete, do not provide sufficient advantage to the learning algorithm to improve in the case of abrupt transitions.

4.5. Developing only one feature

Until now, we have developed several features during the learning process, but we need to address whether they have the same influence over learning. In this subsection, we will analyze the results obtained from the development of a single morphological parameter without considering the development of any other ($MD_{only_x}(t)$), to view whether the development of one parameter is enough to achieve an adequate learning performance. This development is described in equations (10) to (14). The results of these experiments are displayed in Fig. 8. They show how only the linear development of just the legs improves the learning results compared to the no development case (p-value of 0.00023). Furthermore, we can observe how leg development by itself offers significantly better results than the other single param-

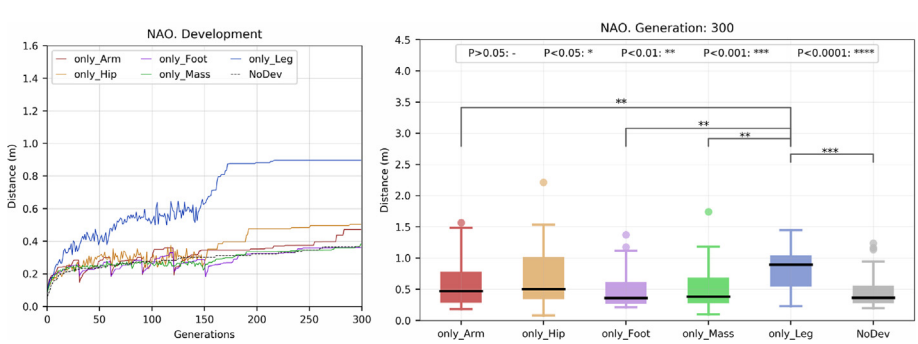

Fig. 8. Left: Learning results considering the development of a single parameter at a time. For clarity, only the medians of the best results are presented. Right: Statistical analysis of the different morphological development strategies.

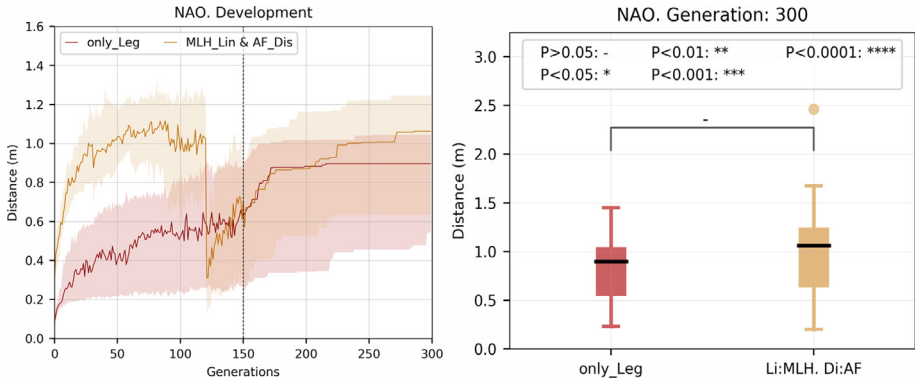

Fig. 9. Left. Learning process comparing the linear development of the leg by itself (red) to the linear development of the leg, mass, hip and the discrete one of the arm and foot (ochre). Right: Statistical comparison between both developmental strategies.

eter developmental strategies (p-value of 0.00508 with respect to only arm development, 0.0013 with respect to only feet development and 0.00323 with respect to only leg mass development) except for the development of just the hip with (p-value of 0.49445). On the other hand, the development of just the hip width has not shown statistical relevance with respect to the other developmental strategies.

Finally, comparing the results of the development of the legs to the best developmental strategy we have presented until now , $MD_{linear}(t)$, (Fig. 9), we can observe how the development of just the legs gives similar statistical results (p-value of 0.09889, which does not reject the null hypothesis), although the combined developmental strategy offers higher values in the median and the 25 and 75 percentiles. Thus, for these particular morphological configurations, it looks like the development of the legs by themselves allows the NAO to achieve high enough learning performance and it would probably not be necessary to combine the development of other parameters, although the results obtained considering them are slightly better. However, taking into account that the value obtained is close to being considered statistically relevant, more experiments should be carried out to check if the combined development really produces different results.

4.6. Developmental speed

Finally, we are going to address the relevance of the developmental speed for learning, as it was hinted in the analysis of the results of Fig. 7. To this end, the linear development of the leg, mass and hip, together with the discrete one of the arms and feet $MD_{linear}(t)$, (which turned out to be the developmental strategy that produced the best results), has been selected to be tested at five different developmental speeds. We define the developmental speed in relation to the time it takes the robot to achieve its final morphology T_f. As specified in Section 3.2, we perform the baseline experiment that completes development at $T/2$ (T_f = 150), and four additional ones at different speeds: (1) A fast one finishing development at $T/4$ (T_f = 75, 2 times the normal speed), (2) an even faster one where development ends at $T/6$ (T_f = 50, 3 times the normal developmental speed) and (3) an ultra-fast one finishing at $T/10$ (T_f = 30, 5 times the normal developmental speed). Furthermore, an additional slower experiment was performed in which development ended at $2T/3$ (T_f = 200, 0.75 times the normal developmental speed). The results of the learning process for these developmental experiments are displayed in Fig. 10. Fig. 10 bottom shows the statistical analysis of the comparison among the different experiments: between the morphological development experiments and the no developmental one and the developmental ones among them. Regarding the comparison between the no development experiment and the developmental ones, the p-values obtained are less than 0.0001 for the developmental speeds of 0.75x, 1x (normal), and 2x. In the case of the 3x developmental speed experiment, the p-value is 0.00563. There is no statistical difference in the case of the 5x speed experiment with respect to the no development experiment (p-value of 3.69954). Finally, comparing the different developmental speeds between them we observe how there is only one comparison that can be considered different, the 5x developmental speed, which offers worse results than the other developmental cases.

Based on the boxplot of Fig. 10, we observe how as the developmental speed increases, the median fitness value decreases, from the most relevant one on the left of the figure (the slowest developmental speed), to the least relevant one on the right (the fastest developmental speed), reaching the extreme point at 5x developmental speed, which is irrelevant for learning. Thus, the developmental speed presents a notable influence on the ability of the learning algorithm to adapt the robot controller to each new morphology. Furthermore, analyzing Fig. 10 top, it can also be observed how in all the developmental experiments, the fitness suffers a large drop in its value in the penultimate morphological development stage. The ability to recover the previous fitness value is also linked with the developmental speed, which may indicate that slow developmental speeds may favor the adaptation of the learning algorithm to disturbances caused in the problem to a greater extent than the experiments that are developed at a higher speed. However, more experiments and results are required to validate this hypothesis.

These results are dissimilar to those obtained by Nadizar et al. [13] and Kriegman et at. [14]. However, in Nadizar et al. the authors present a single case of fast development speed, which is slower than the fast development speeds that we consider with respect to the reference experiment. We consider speeds of 2x, 3x, and 5x, while they consider 1.5x, which from our perspective, is a slow speed that allows the controller to adapt to the morphological changes. Furthermore, their morphology changes during the evaluation time, while in our case, the morphology is fixed during each individual evaluation. On the other hand, Kriegman et al's Evo-Devo experiment mentions the advantage of early morphological development, but in a phylogenetic time scale (during the lifespan of an individual, the morphology is fixed and development takes place along generations), while throughout this article we are addressing morphological development at an ontogenetic time scale, during the lifespan of an individual.

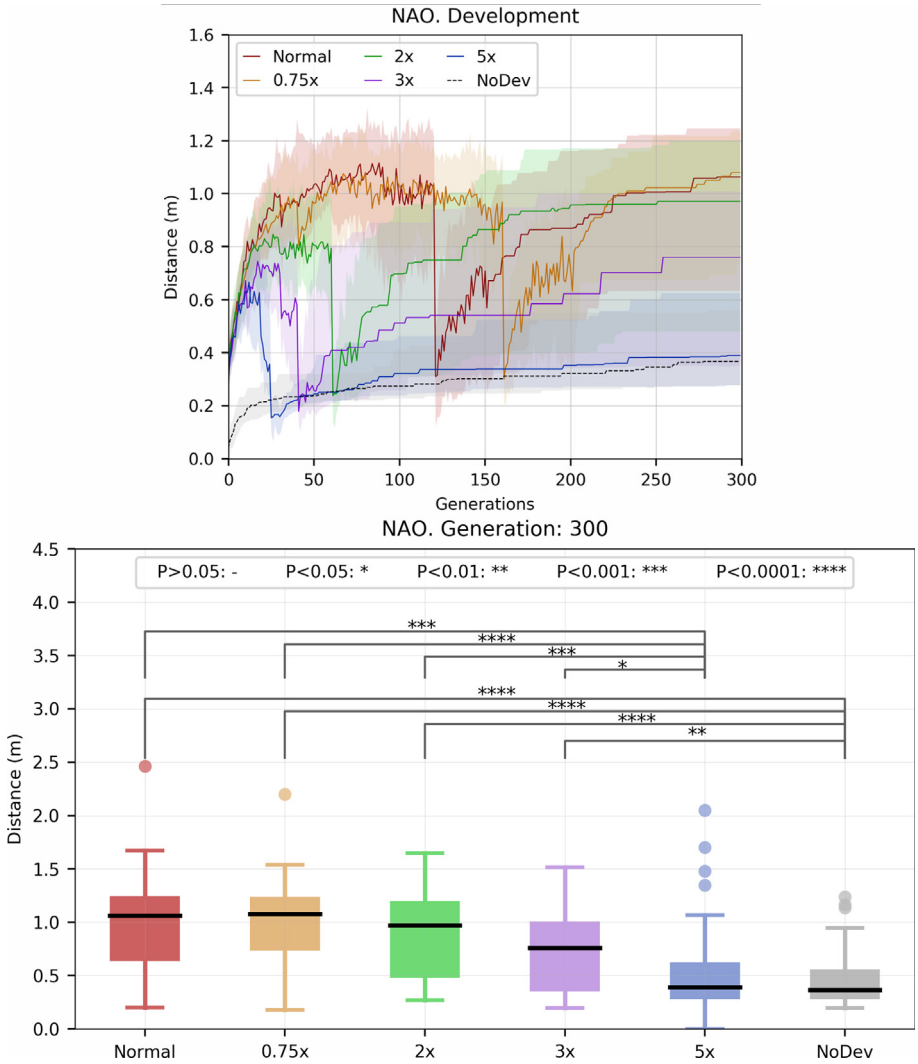

Fig. 10. Top: Learning process for the same developmental strategy but considering different morphological developmental speeds. Bottom: Statistical results at the end of learning comparing the different experiments among them. Only significant statistical values are presented.

5. Discussion

In the experiments that have been carried out, it has been observed how a remarkable improvement in the ability of a NAO robot controlled by an ANN learning to walk is achieved by establishing an adequate morphological development path from an initial morphology to the desired final morphology. To this end, an adequate synergy between the different components involved in the learning process, such as the morphological development strategy, the control system and task, and the learning algorithm is required to appropriately adapt the parameters of the controller to each morphological change. However, achieving such synergy is not straightforward. For example, in the literature there are examples of successful morphological development strategies based on abrupt changes in the morphology-controller relationship, as it is the case of freezing and freeing DOFs [41,42], but there are also others where such changes are detrimental [9,11]. In our experiments, we have found cases where abrupt changes in some of the morphological parameters (arms and feet) have been favorable for learning when combined with the linear development of other parameters Fig. 6 bottom, experiments with the linear development of the leg length, and the experiment with the linear development of the hip width), but in other cases the abrupt change of the same parameters has also been shown to be irrelevant (Fig. 6 bottom, experiment with the linear development of the mass). The difference between those results is given by the appropriate synergy or not between the factors that are part of the problem. In this sense, we have seen how the abrupt and discrete changes in the values of all the morphological parameters that define the initial morphology to the values of the final one has not given rise to an improvement in learning (Fig. 6), but also how these abrupt changes have not led to cases where the results are worse at the end of the learning process. Similar results have been shown by Benureau and Tani [15]. Nonetheless, there could be detrimental developmental paths that can worsen learning for short periods after the discrete development (as is the case of the morphological change of generation 150 in Fig. 7, or at generation 90 in Fig. 8), although in the cases we have studied, the learning algorithm was able to achieve at least the performance of the no development experiment at the end.

Thus, in the experiments carried out, we have found a series of factors or conditions that must be taken into account to achieve that synergy that allows learning to be improved over the no-development case:

Avoid unwarranted discrete developments: It seems quite clear that from section 4.2 and 4.3 that parameters that are continuous should be developed continuously during learning. Discrete transitions should only be considered when there is not an easy way to make the parameter continuous (e.g., the development of the arm). However, when applied, discrete transitions at the beginning of the developmental process do not cause large fitness drops, which is presumably attributed to the high stability of the morphology in these initial phases of development and where such precise movements are not needed for the NAO to remain upright. On the other hand, as the morphology becomes unstable and requires more precise movements, sudden changes in it end up causing unfortunate behaviors, so it is convenient to apply a smooth and progressive development when possible.

Correct selection of developmental features: Some morphological parameters are more relevant than others. This is a premise also pointed out by Vujovic et al. [6] and Savastano and Nolfi [7]. In our case, it seems clear that the only parameter that can generate improvements over the no development case, when applied by itself, is the leg length (Fig. 8), being also the one of the 5 morphological parameters considered that most influences learning. We relate such relevance with the modification of the position of the center of gravity while the morphology develops thus, changing its stability. Hip development has not been shown to be enough to improve learning by itself (Fig. 8 right, p-value of 0.2745), although it was the one with the highest median and 75 percentile. This seems to indicate that widening the hip width at the beginning of learning also has an influence on the stability of the NAO, but to a lesser extent than the variation in the length of the legs. This influence in the robot stability does not happen in development of the other parameters, with the exception of the 4th arm development step characterized by adding the wrists and hands of both arms. We presume that the addition of these elements abruptly distorts the position of the center of gravity of the robot (displacing it forward with respect to the vertical) and they disturb the morphology of the NAO in advanced stages of morphological development, being one of the possible causes of the high drop in fitness that occurs in most of the experiments carried out.

Developmental speed: The developmental speed needs to be appropriately selected. This speed is related to the learning capacity of the algorithm. In our work (Fig. 10), a wide range of developmental speeds were found that help the learning algorithm to surpass the performance of the no development experiment (from 0.75x to 3x). However, the fastest one selected (5x) does not. With this speed the learning algorithm is not able to adapt the robot controller to the morphological changes and the samples obtained in the solution search space are too far from each other, hindering a smooth transition between solutions of developmental stages, and thus, making the task of the learning algorithm harder. These results are in consonance with our previous published work [32]. So, we see how an adequate developmental speed, linked to a specific type of problem and morphology has improved learning. However, it is difficult to give a specific definition of what "a suitable developmental speed" means other than a speed for which the changes in the morphology do not induce extreme changes in the controllability of the robot. Finally, as Nadizar et al. [13] also mention, morphological development needs some generations after the development process finishes to adapt to the final morphology. In fact, the fitness rises quickly after development ends. Thus, slow developmental speeds that do not leave enough time to adapt to the final morphology will underperform.

Sequential development of features or all at once: There are infinite ways of applying morphological development to several parameters, but one important decision is whether all of them should be developed at the same time or should be developed sequentially. And if they are developed sequentially, which is the best order for the development. In our experiments, it seems that there are no big differences in developing all the features at the same time or sequentially. It is true that developing parameters sequentially is a Manhattan like approach to morphological development and thus, the optimality of this approach will depend on whether in the particular problem that is being addressed this Manhattan like walk over the parameter space leads to suboptimal areas of the search space that are hard to get out of. This is quite problem and initial morphology dependent (search space dependent). Nevertheless, even though this topic still needs much more research and experiments to achieve reliable conclusions, our results seem to hint that development should be applied to all features more or less at the same time removing the problem of having to select an order for the development.

6. Conclusions

This work has addressed the study of one of the four design conditions established by Naya-Varela et al. in [21] that help to improve learning in a given morphology and scenario. To meet this objective, a series of morphological development strategies have been established, based on 5 morphological parameters of experiments where a NAO robot had to learn to walk. These developmental strategies have been specified based on a previous formal definition of morphological development and have served to give a more general and defined vision of what it means to achieve an adequate synergy between the components involved in morphological development.

We have initially proposed a series of intermediate morphologies as a path towards the final one with abrupt transitions among them. This did not turn out to be a good solution and we saw that it is necessary to meet a series of conditions which define a synergy between the different parameters of morphological development, and that have been shown to lead to the best learning results. These conditions are: (1) Identify the most relevant feature that conditions learning, given a morphology, controller and task. In our case, this parameter was the robot stability (section 4.2). (2) Identify the morphological development parameters that have the greatest influence on it and implement development strategies based on those parameters. In our case, the best results have been obtained in those development strategies that involve the leg development (section 4.5). (3) Avoid abrupt changes in the morphology, implementing smooth and progressive developmental strategies, to maintain the morphology-control relationship stable (section 4.2 and section 4.3). (4) Set a morphological development order that best matches the characteristics of the problem. Although our first approximation to the morphological development order displays no statistical difference between one developmental sequence or the other (section 4.4), nature development clearly specifies a cephalocaudal and proximodistal development. Thus, a properly designed morphological development strategy should take this developmental order into consideration. Finally, (5) the developmental speed must be in line with the ability of the learning algorithm to adapt the robot controller to changes in morphology. In our case, there is a whole range of developmental speeds that result in learning improvements compared to the no-development one (section 4.6).

The general conditions that we have grouped under the name of synergy have been obtained from performing a series of experiments that address the task of learning to walk in a bipedal robot. To continue the work and provide more information on the design conditions that can be included under the synergy umbrella, it would be interesting to validate and compare these conditions considering other morphologies and scenarios and varying the learning algorithm and its parameters. For example, the experi-

ments presented here are clearly influenced by the stability of the morphology, while it would be interesting to see how synergy is applied to learning in a task such as reaching with a static robot, where stability has no bearing on learning, but other parameters, such as range of motion (ROM) do.

Data availability

Due to size limitations, data will be available on request. Complementary information can be found in: https://github.com/GII/morphological_development/tree/main/publications

Declaration of Competing Interest

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Appendix

This appendix presents the specific formalization of the developmental function for the two discrete variables of the morphology: the foot size, $\Delta FS(\mathrm{t})$, and the arm development, $\Delta\mathrm{AD}(\mathrm{t})$ for two different morphological development strategies, the linear change of the morphology and the sequential one.

Linear change of the morphology ($MD_{linear}(t)$):

For the development of the foot, we can define the $\Delta FS(\mathrm{t})$ function as a step function by obtaining the constant values from equation A(1). Thus,

$$\Delta FS(\mathrm{t}) = \begin{cases} 0, ift < \frac{T_f}{5} \\ \frac{\max(\Delta foot)}{T_f} * \left(\frac{T_f}{5}\right), if \frac{T_f}{5} \geq t < \frac{2T_f}{5} \\ \frac{\max(\Delta foot)}{T_f} * \left(\frac{2T_f}{5}\right), if \frac{2T_f}{5} \geq t < \frac{3T_f}{5} \\ \frac{\max(\Delta foot)}{T_f} * \left(\frac{3T_f}{5}\right), if \frac{3T_f}{5} \geq t < \frac{4T_f}{5} \\ \frac{\max(\Delta foot)}{T_f} * \left(\frac{4T_f}{5}\right), if \frac{4T_f}{5} \geq t < T_f \\ \max(\Delta foot), ift \geq T_f \end{cases} \# \tag{A1}$$

The development of the arm is a discrete variable, defined as:

$$\Delta AD(\mathrm{t}) = \begin{cases} 0, ift < \frac{T_f}{5} \\ addUA, if \frac{T_f}{5} \geq t < \frac{2T_f}{5} \\ addUA + E, if \frac{2T_f}{5} \geq t < \frac{3T_f}{5} \\ addUA + E + F, if \frac{3T_f}{5} \geq t < \frac{4T_f}{5} \\ addUA + E + F + WH, if \frac{4T_f}{5} \geq t < T_f \\ addUA + E + F + WH + Fi, ift \geq T_f \end{cases} \# \tag{A2}$$

where the initial morphology contains the shoulder of the arm and each developmental transitions adds the Upper Arm (UA), Elbow (E), Forearm (F), Wrist and Hand (WH) and Fingers (Fi) respectively.

Sequential development ($MD_{sequence_x}(t)$):

The specification of the sequential development both for the foot size ($\Delta FS(\mathrm{t})$) and arm development ($\Delta\mathrm{AD}(\mathrm{t})$) are displayed in equations A(3) and A(4) respectively.

$$\Delta FS(\mathrm{x}) = \begin{cases} 0, ifx < \frac{T_f}{25} \\ \frac{\max(\Delta foot)}{\left(\frac{T_f}{5}\right)} * \left(\frac{T_f}{50}\right), if \frac{T_f}{25} \geq x < \frac{2T_f}{25} \\ \frac{\max(\Delta foot)}{\left(\frac{T_f}{5}\right)} * \left(\frac{2T_f}{25}\right), if \frac{2T_f}{25} \geq x < \frac{3T_f}{25} \\ \frac{\max(\Delta foot)}{\left(\frac{T_f}{5}\right)} * \left(\frac{3T_f}{25}\right), if \frac{3T_f}{25} \geq x < \frac{4T_f}{25} \\ \frac{\max(\Delta foot)}{\left(\frac{T_f}{5}\right)} * \left(\frac{4T_f}{25}\right), if \frac{4T_f}{25} \geq x < \frac{T_f}{5} \\ \max(\Delta foot), ifx \geq \frac{T_f}{5} \end{cases} \# \tag{A3}$$

$$\Delta AD(\mathrm{x}) = \begin{cases} 0, ifx < \frac{T_f}{25} \\ addUA, if \frac{T_f}{25} \geq x < \frac{2T_f}{25} \\ addUA + E, if \frac{2T_f}{25} \geq x < \frac{3T_f}{25} \\ addUA + E + F, if \frac{3T_f}{25} \geq x < \frac{4T_f}{25} \\ addUA + E + F + WH, if \frac{4T_f}{25} \geq x < \frac{T_f}{5} \\ addUA + E + F + WH + Fi, ifx \geq \frac{T_f}{5} \end{cases} \# \tag{A4}$$

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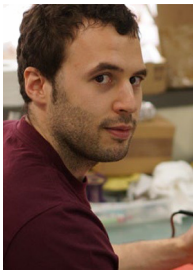

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