Harnessing Growth-Based Morphological Development to Facilitate Learning ANN-Controlled Bipedal Walking

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***Abstract*—In human beings, the natural development of the body has been shown to facilitate learning. This approach has been applied in robotic learning with different results, being an advantage under some conditions and tasks. While it is still not well understood under what conditions morphological development helps to learn, several authors have proposed some high-level notions about when it could be interesting to apply it. In our previous work, we have used these notions with the objective of designing a morphological development strategy that facilitates learning in a bipedal locomotion task with an Artificial Neural Network (ANN) controlled robot. In this paper, we aim to go beyond the qualitative design principles previously used and support such considerations with an empirical quantitative study. An analysis of the learning results and how they are related to the design conditions that were established is carried out based on the evolution of the fitness landscape for each developmental stage. The long-term objective is to develop morphology-agnostic optimization strategies for morphological development, which would reduce the number of samples required and, thus, the computational cost, of learning in ANN-controlled robots.**

Keywords—Morphological Development, Bipedal Walking, Artificial Neural Network, Fitness Landscape

I. Introduction

In this paper, we provide an empirical quantitative analysis of a series of design considerations to apply a growth-based morphological development strategy in a specific experimental configuration. The objective is to provide feasible indications about how to design a long-term learning strategy for a given morphology without adding complexity to the learning algorithm. We are interested in the morphological development field because the simultaneous development of the morphology and cognitive systems in living beings has been shown to facilitate learning [1], [2]. Based on that, several authors have carried out different learning experiments over different morphological configurations and tasks, showing mixed results. Thus, in some cases, morphological development seems to improve learning [3]–[6]. In others, it does not seem to have any relevant effect [7]–[9]. Finally, there are even some cases in which its effect is negative [10], [11]. Furthermore, as important as the results are the conclusions extracted from them, and there are no clear notions about the effects of morphological development over the learning abilities of the different robot morphologies and how and why learning has been influenced by such morphological changes.

In this line, few are the studies that provide indications that help to explain these effects. Vujovic et al. [12], in an Evo-Devo experiment, mention the importance of an adequate selection of parameters of the Evo-Devo process in order to improve fitness. However, in their own words "the interplay between development and evolution during this process is complex and not yet fully understood". Ivanchenko and Jacobs [10] find the three possible outcomes of the application of morphological development (positive, irrelevant, or negative) in learning in the same experiment. They argue that adopting a "suitable" development strategy is the most important factor to improve learning, but again, what is a suitable development has not been addressed. Bongard [8] and Bongard and Buckingham [9] present problem complexity/difficulty as a relevant factor for morphological development to be relevant for learning. However, in both cases the definition of complexity is problem-related, being defined by the number of objects to grasp, or by the computational time required to achieve a certain level of performance. Finally, Bongard [13], indicates that a reduction in the learning performance is achieved when an abrupt change in the robot controller-morphology relationship occurs when development takes place. However, abrupt changes in the robot controller-morphology were also reported with successful results [14].

Thus, three are the main general hypothesis proposed to explain why morphological development could negatively influence learning: (1) Problem complexity, which is defined in a problem-related manner [8], [9]; (2) The fact that morphological development is not well aligned with the task to accomplish [10], [12]; (3) The morphological development strategy that is implemented causes disturbances in the sensory-motor relationships that affect the robot controller [13]. However, very little is said about how to select and design the developmental process to avoid the irrelevant and detrimental approximations in order to improve the chances of it facilitating learning

In this paper, with the aim to take a step forward in the study of the implications that morphological development has during learning, we have focused our attention on identifying and quantifying a series of design conditions that must be fulfilled for morphological development to be relevant to learning. In addition, we have tested different variations of the same robotic morphology and shown how the changes produced by growth can have drastic effects in learning without development.

To reduce complexity and facilitate replicability of the results presented, a very simple experimental framework based on a bipedal robot controlled by an ANN is used. Finally, to homogenize the setup, we will use the same artificial neural network based controller, neuroevolutionary learning algorithm and family of morphologies over the same tasks for the different experiments carried out, so that results can be compared and generalized.

II. Designing Morphological Development

As indicated in the previous section, different authors have proposed some qualitative ideas of why morphological development may be a successful approach to learning. It is important to note here that the objective is for a final morphology to be able to carry out a task that needs to be learned. Morphological development is a way to facilitate learning the skill to accomplish that task through a series of morphological changes, starting from an initial morphology and ending in the desired one. Development occurs progressively while learning the task, and therefore the same controller leads to different fitness values when evaluated at different stages of development.

In [15], these ideas were distilled into a series of qualitative engineering considerations on how to design and implement a morphological development strategy for a given desired final morphology. These considerations were applied in the implementation of a morphological development path for a NAO robot to learn to walk. They can be summarized as:

- *Enough problem difficulty*: The difficulty of the problem should be enough to justify the need and added cost of implementing a morphological development strategy. Bipeds learning to walk is quite a difficult problem as most gaits are unstable and cause falls. To define the learning difficulty of a problem we are going to consider learning as an optimization problem, where the objective consists in finding a controller that allows the robot to optimally perform a task. Thus, as other authors have done before [16], [17], we will make use of the features of the fitness landscape to try to obtain indications on the problem difficulty.

- *Simplify learning at the beginning*: At the beginning of learning, the initial morphology should make the learning task easier. As morphological development takes place, difficulty should increase gradually so that it is adapted to the developmental state. In the case of bipedal walking, this simplification may be achieved by initially lowering the center of mass, thus increasing stability. Consequently, a growth-based morphological development strategy may be appropriate in this case.

- *Achieve a suitable synergy among morphology, controller, development, and the learning algorithm*: The synergy among the morphology, the controller, and the developmental process must be tuned to the ability of the learning algorithm to adapt to the morphological changes.

- *Availability of solutions*: The optimal solutions at the end of learning, or at least a path towards them, must be available from the beginning to avoid guiding the learning algorithm toward areas of the solution space that would not be optimal in the final morphology.

This paper seeks to quantify the mainly conceptual indications listed above. To this end, series of experiments will be carried out in order to produce data for quantitative analysis of the results in different Morphological Configurations (MC), that is, different parameters of the morphology at the beginning of learning, such as leg length. This is done with the objective of proposing alternatives to improve the learning performance of ANN based controllers without increasing the sampling cost of their training.

III. Experimental setup.

An experimental framework based on a walking task on level ground using a NAO commercial bipedal robot [18] was established. To simplify the experimental setup, the NAO robot was simulated in the CoppeliaSim simulator [19], which already has a native model of it. In order to design an engineering process that allows the NAO morphology to grow, several modifications were applied to the native model of the robot, specifically in the legs and feet (Figure 1):

- *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, and a mass of 458.7 g. The physical dimensions and weight have been chosen so as to minimize the change with respect to the original design. 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 3.5 cm.

- *Lower link*: The lower part of the legs was also changed to two different cuboids. The upper cuboid is 8x8x3 cm and has a mass of 192 g and the lower one is 9x8x3 cm and has a mass of 215.8 g. Again, the properties of the cuboids and their geometric orientation were selected to preserve the original NAO design as much as possible. 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 3.5 cm.

- *Feet*: The feet size was increased with respect to the original size of NAO’s feet to increase the robot stability. Now, they are 16x8.5x1.5 cm and weigh 204 g.

Regarding the control system, the robot controller considered is an Artificial Neural Network (ANN) with 3 inputs plus one bias and 14 outputs. 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 NN are sinusoidal functions of amplitude 2.0 rad and frequency 1.0 rad/s, with phases 0, 3.0, and 5.0 rad respectively. Initially, the ANN is fully connected. In each independent experiment, we try to optimize the neural network so that the NAO travels the

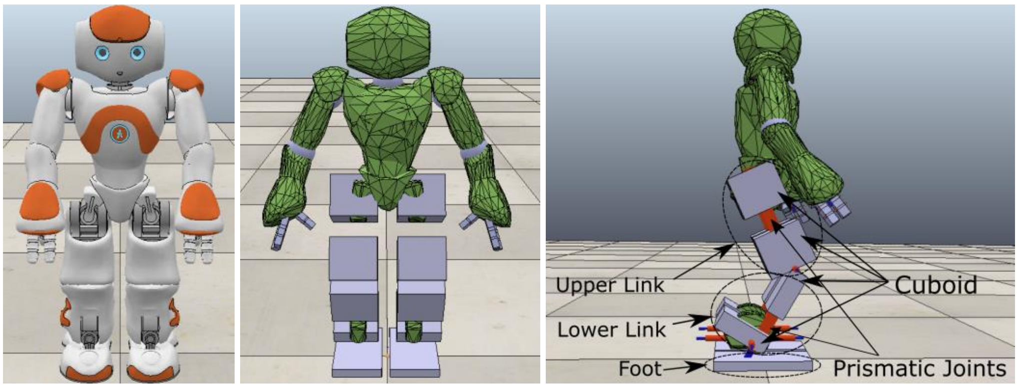

Figure 1. Left: frontal view of the original NAO robot model of CoppeliaSim. Middle: frontal view of the simulation model of the NAO robot. In green, the defaults parts of the robot. In grey, the cuboids added to the robot to create the extendible upper and lower link. Right: side view of the NAO model where its different parts are showed, including the prismatic joints.

longest possible distance. The synaptic weights of the ANN are optimized through the NEAT neuroevolutionary algorithm [20], concretely the MultiNEAT implementation [21]. A series of different experiments were performed in the already mentioned CoppeliaSim simulator, with the ODE physical engine [22]. Each NEAT execution optimizes a population of 150 individuals for 300 generations. A total of 40 independent runs were carried out for each experiment with the objective of gathering relevant statistical data, where each individual is tested 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.

As mentioned, the objective is for the NAO to travel the longest possible distance in a straight line (over axis “X”, which is the one in the direction of the NAO’s initial orientation). The distance traveled will only be taken into account when the robot walks. The distance traveled is not considered if the robot falls and keeps moving on the ground. To avoid this inconvenience, fitness is calculated taking into account the possibility of falling. In this sense, it is a fall considered when the head of the NAO is below 0.3 m above the floor. Thus, 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. The value of 16-time steps is selected because we determined empirically that, 16-time steps before falling, the NAO is still in a stable position.

To quantitatively analyze the ideas described in the design section, a series of experiments have been carried out. These experiments were performed over different morphological configurations (MC):

- *Base MC*: It is the morphological configuration and developmental strategy that has been selected by [15] as the most suitable ones based on the qualitative design considerations. It is characterized by a limited Range of Motion (ROM) of the NAO compared to the NAO’s documentation. This presumably simplifies the task of finding an optimal solution to the problem. In addition, a symmetric growth strategy has been set. That is, the upper and lower link grow the same amount (3.5 cm) at the same speed.

- *Theoretical MC*: This MC is characterized by the fact that the ROM available for each joint is the ROM given by the NAO’s documentation.

- *±10° ROM MC*: This experiment consists in having a final morphology with a ROM that exceeds by ±10° the upper limit and lower limit of the ROM of each joint with respect to the ROM established in the base MC.

- *Upper-Link extension or Lower-Link extension MC*: These are two different experiments, but they are quite similar. In these experiments, one part of the leg, either the upper-link or the lower-link, is fully extended, and the other is fully contracted in the initial configuration. In Both cases, the extended link has the same extension as the sum of the extensions of both links in the base MC. That is, in this case, each link grows 7 cm.

Based on these MCs, a series of experiments have been performed:

- *Growth-based experiment on the base MC*: The robot morphology grows during the learning process starting from the initial morphology (NAO morphology with fully contracted prismatic joints) in generation 0. Link length is grown linearly and simultaneously for the two legs during the developmental period. Thus, leg length varies according to the growth speed until it reaches the maximum length (17.1 cm for the upper link and 14.5 cm for the lower link). After that, neuroevolution continues, but without changes in the morphology. The robot does not grow during the individual evaluations, that is, each growth step is applied before the beginning of each evaluation. This is compared with an experiment where a fixed morphology, corresponding to the final morphology (NAO morphology with the maximum length of the limbs), is used for the whole neuroevolutionary process.

- *Fitness landscape*: To study the application of growth-based morphological development with the established design conditions, an analysis of the fitness landscape obtained for each developmental stage has been carried out. As the controller of the NAO is an ANN and the structure, weights, and dimensions of the ANN vary during the neuroevolutionary process induced by NEAT, it is complex to directly represent the fitness landscape generated by the ANN. Therefore, inspired by the 3D fitness landscape implemented in [23] a representation of the fitness landscape has been produced based on the best controller obtained by NEAT for the NAO morphology that is approximated to a series of sinusoidal functions for each joint. Each sinusoidal function is controlled by two parameters, P1 (offset) and P2 (amplitude). Thus, each joint of the robots responds to an angular value given by:

$$Angular\ Value = P1 * \left(\frac{A_0}{50}\right) + P2 * \left(\frac{A}{50}\right) * \sin(12\pi * t + \varphi)$$

Being:

$$A_0 = \frac{max.value\ for\ a\ joint + min.value\ for\ a\ joint}{2}$$

$$A = \frac{max.value\ for\ a\ joint - min.value\ for\ a\ joint}{2}$$

$\varphi =$ phase of the function. It is approximated by hand

- *1000 random controllers for different MC*: To confirm ideas extracted from the fitness landscape analysis on the apparent difficulty of each problem, a series of experiments that involve the different MCs have been performed. In a first case, each MC is evaluated only at generation 0 with 1000 random initial controllers, there is no learning in these experiments. The objective of this test is to compare the selected design decisions applied to the base MC with the other alternatives, by evaluating the performance they offer from the very beginning of the learning process, thus calibrating the initial difficulty of the problem. All experiments are carried out with a fixed morphology and there is no development in any of them.

- *500 controllers learning until generation 10*: As the number of falls in the previous experiment is so high that it is difficult to obtain any relevant data beyond concluding the difficulty of the problem of learning bipedal walking, this complementary experiment has been carried out. The number of random controllers has been reduced by half, from 1000 to 500, but they are evaluated at generation 10 instead of at generation 0. This is done with the aim of obtaining more information on the learning difficulty induced by each MC.

- *10000 random controllers at extreme developmental stages*: This test was performed with the base MC. 10000 random controllers are tested in the initial and final morphologies to evaluate the ideas related to the usefulness of simplifying the learning problem in the initial morphology versus the final one. The number of selected controllers was increased from 1000 to 10000 to obtain relevant

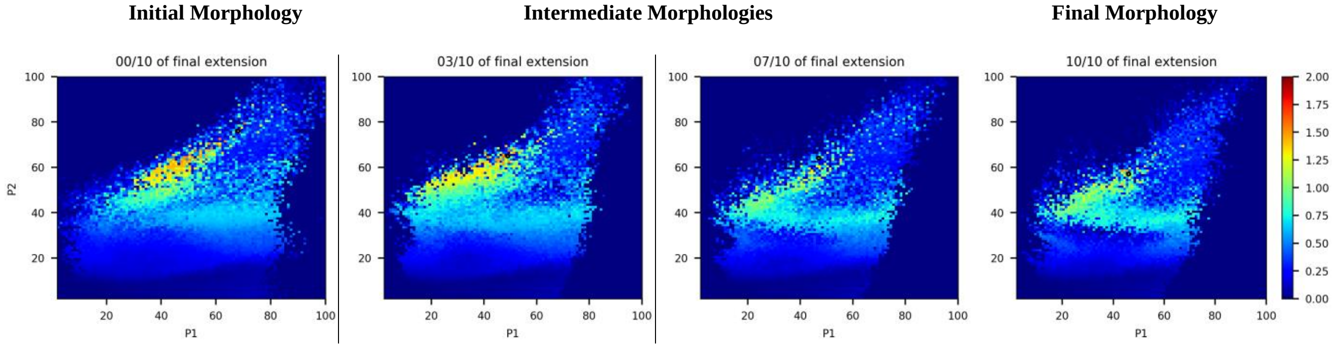

Figure 3. Fitness landscape representation for the NAO robot in the initial development stage (left), two intermediate developmental stages (middle-left and middle-right) and the final morphology (right).

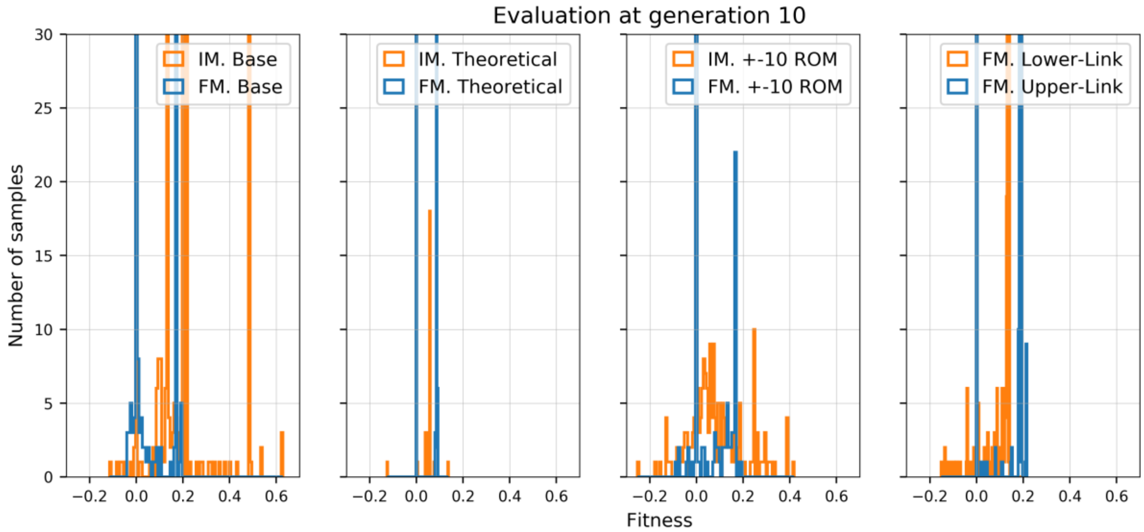

Figure 5. Results of the learning experiments testing 500 random controllers at generation 10 for different MC. To facilitate viewing the relevant information, the histogram is limited to 30 samples, otherwise, the most prevalent values distort the information shown in the histogram. Left: Fitness obtained with the IM and the FM for the base MC. Middle-Left: Results obtained with the theoretical MC for the IM and FM. Middle-Right: Fitness comparison between the IM and FM for the ±10° ROM MC. Right: Comparison between the fitness obtained with the upper-link growth and the lower-link growth MCs in the final morphology.

statistical data due to the large number of falls that occur at this early stage of learning.

IV. RESULTS

First of all, let us take a look at the whole learning process. Figure 2 displays the results of using the growth-based morphological development design strategy described in the previous sections. Figure 2 left displays the results of learning for the no-development experiment and the growth experiment in which growth occurs up to generation 120 (growth speed 0.292 cm/generation). This growth experiment was selected because it is the one that offers the best results. The figure displays the median (solid lines) of the best results obtained at each generation for each one of the 40 independent runs of each experiment. The shaded areas represent the 75 and 25 percentiles respectively. Figure 2 right displays the statistical analysis at the end of learning for the different growth ratios tested. Each boxplot represents the median and the 75 and 25 percentiles. The whiskers are extended to 1.5 of the interquartile range (IQR). All developmental samples are compared to the no-development case. The statistical analysis has been carried out using the two-tailed Mann-Whitney U Test [24]. The developmental experiments are compared with the no-development one. A p-value of 0.05 is taken as the significance value for accepting or rejecting the null hypothesis. Comparing the no-development experiment, to those of the different growth ratios, in Figure 2 it can be observed how growth has outperformed the no-development experiment in all cases except in the one with the highest developmental speed (growth up to generation 40, with a p-value of 0.07427). On the other hand, the best performance is obtained for the slowest growth ratio (growth up to generation 120, with a p-value of 0.00042).

In order to try to elucidate what is happening during learning, Figure 3 displays the representation of the fitness landscape for the initial morphology, two intermediate developmental stages, and the final one. The fitness landscape shows a similar configuration and structure for the 4 different developmental stages: (1) It is characterized by a notable blue color, which indicates low fitness values. Concretely, the dark-blue color indicates areas with 0 fitness value. (2) It presents a rough and deceptive landscape for all the developmental stages, although it becomes more so as the morphology progresses towards the final one. (3) It can be noticed that, as the morphology grows, the fitness landscape changes. The areas with the highest fitness values (red and orange ones) are smaller and those of lower fitness become larger, including the dark-blue ones, the ones with 0 fitness value.

Thus, it seems that the learning difficulty in the case of the initial morphology is less than in the case of the final morphology. To complement this first impression and provide a more detailed statistical look at these results, Figure 4 left displays the fitness at generation 0 for the initial and final morphologies using the base morphological condition. In addition, Figure 4 also compares the effects of the changes in the morphology under different MCs. In this figure, out of the different morphological configurations considered, only in the base MC has it been possible to maintain the equilibrium of the body and walk forward on more than 10 occasions, which represents a successful learning rate of 1%. For the initial morphology, there are 13 individuals with positive fitness values and 5 with negative values. For the final morphology, there are 11 individuals with positive fitness values and 10 negative ones. In the rest of the MCs considered, this value is lower, highlighting the low learning level obtained when using the angular values given by the NAO documentation. In this case, there are 2 positive fitness values and 5 negative ones with the final morphology, 1 positive fitness value, and 2 negative ones with the initial morphology. That is, grouping the experiments performed with the initial and the final morphology (2000 experiments), forward walking was only achieved on 3 occasions.

Due to the difficulty of extracting any kind of statistically valided conclusion from the previous results, beyond the fact that learning to walk is a difficult task for the different MCs selected due to the high number of falls that occur, we have analyzed how difficult it can be to learn with these MCs, for which we have studied 500 random initial controllers in generation 10 for each MC. These results are displayed in Figure 5. In it, a large amount of data spread is obtained comparing this figure with the previous one. In addition, the data tend to cluster mostly towards positive fitness values, reflecting the fact that learning is improving along with the generations. The graph on the left shows that, for the base MC, out of the 500 random controllers, in generation 10, there are 327 positive fitness values and 19 negative ones for the final morphology, while there are 370 positive fitness values and 8 negative ones in the case of the initial morphology. Although these results may seem similar, there is a big difference between them. In the case of final morphology, there are 154 individuals whose value is 0, and only 46 different individuals, whereas for the case of initial morphology, there are 122 individuals whose value is 0, but there are a total of 89 different individuals, indicating a bigger disparity of the neuroevolutionary population. The middle-left graph displays the results of the theoretical MC. It displays a total of 297 positive fitness values and no negative ones for the final morphology, whilst it shows 27 positive fitness values and 1 negative one for the initial morphology. The middle-right graph displays a total of 61 positive values and 9 negative ones in the initial morphology of the ±10° ROM MC. The final morphology with this configuration shows a total of 145 positive values and 36 negative ones. Finally, the right graph shows 263 positive values and no negative ones for the upper-link MC, and 368 positive values and 23 negative ones for the lower-link MC. That is, of the different IM-MCs considered, there are two that have offered better results than the others, which are the initial base morphology and the initial±10° ROM morphology, since in both of them, already in generation 10, some individuals can walk up to 0.4 m. However, the initial base morphology has provided better results, with higher and more distributed fitness values. Regarding the final morphologies of the MCs considered, the final base morphology and the final lower-link morphology offer the best results (both with more than 300 positive fitness values) but the final base morphology has produced higher fitness values.

Additionally, Figure 6 shows a comparison of the results of 10000 random controllers evaluated in generation 0 for the base MC, both in the case of the initial and final morphology. Only those results that obtained a fitness value other than 0 are represented. This graph shows the results of 139 individuals with a positive fitness value, and 126 with a negative fitness for the initial morphology, while for the final morphology, there are 61 individuals with positive fitness and 62 negative fitness and a similar disparity of results, which indicates that it is easier to learn with the initial morphology than with the final one.

V. DISCUSSION

Figure 2 shows how the design and implementation of morphological development using the base MC has improved learning compared with the no developmental case. Concretely, the growth-based strategy outperformed the no-development learning in 4 of the 5 growth ratios selected. On the other hand, the different hypotheses established for in the morphological development design section have been supported by the results obtained in the previous section.

The design condition that indicates that for morphological development to make sense, a problem must be sufficiently difficult to learn, is supported by the results shown in Figure 3. First, the fitness landscape of the final NAO morphology, Figure 3 right, shows an uninformative fitness landscape, being mostly dominated by the dark blue color, indicating that, in most of the cases considered, the robot is not able to walk and falls down. And second, the area that we could call informative, which is not dark blue, presents as its main characteristics a high level of (1) roughness and (2) deceptiveness. That is, we have large color changes between points that are very close in the fitness landscape, which indicates a large variation of fitness from one point to another (roughness) while at the same time there are areas with turquoise or green colors, but far from the areas of higher fitness value (yellow and orange) that indicate suboptimal solutions of the fitness landscape. Both are features that make it difficult for the learning algorithm to find the optimum. Furthermore, looking at the evolution of the fitness landscape in Figure 3, as the morphology grows, the areas of the fitness landscape with the highest values are reduced. Indicating that more precise movements are required to really achieve an optimum behavior, and controllers capable of such precise movements are quite difficult to find, that is, it progressively becomes “a needle in a haystack” type of fitness landscape, making learning using only the adult morphology very difficult.

This difficulty in learning is supported by the results shown in Figure 4, Figure 5, and Figure 6. These results indicate that for the MC, controller type, and learning algorithm selected, it is difficult to find a controller that allows the robot to walk in a natural way, given the high number of falls observed in Figure 4 and Figure 5. For example, in Figure 4 we find that the best learning results are obtained by the base MC, but it only produces 13 individuals with positive fitness values and 5 with negative ones. This implies that only 1.8% of the individuals avoid falling in the first generation, which gives a more reliable measure of the difficulty of the problem. Furthermore, the problem is so complicated that little information can be obtained about the different morphological configurations selected because there are less than 1.8% of individuals that contribute with values other than 0. Of course, the fact that a function produces low values in random exploration does not mean that the function is difficult to optimize in all cases (e.g. gaussian function with very low sigma). However, in our experiments, the fitness of most controllers is still showing falls (below 0.2) after 10 generations, which again signals the difficulty of the problem.

The design condition indicating the need for learning with the initial morphology to be easier than with the final morphology is also supported by Figure 3, Figure 5, and Figure 6. In the fitness landscape of the initial morphology of the base MC (Figure 3 left) it is observed that, although the fitness landscape is rough and deceptive, there is a larger area with higher fitness values than those observed in the adult morphology (yellow-orange area) as well as a decrease in the number of falls that occur with respect to the adult morphology, since the dark blue area of the fitness landscape in the initial morphology is smaller than in the final morphology. These characteristics of the fitness landscape are in consonance with Figure 5 and Figure 6. The experiment carried out with the base MC, displays better results than the ones obtained using the final

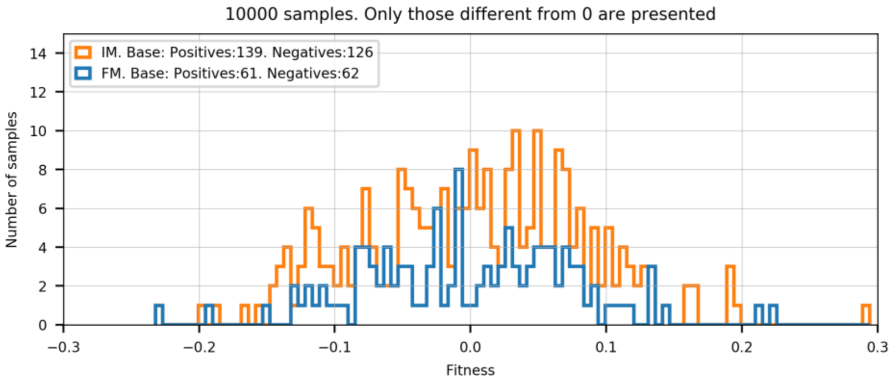

Figure 6. Results of the learning experiments testing 10000 random controllers at the beginning of learning for the IM and FM in the case of the base MC.

morphology. Comparing the initial morphology with the final one in Figure 6, there are double the number of individuals with a fitness value different from 0, (139 vs 61 and 126 vs 62) indicating that it is easier to find an informative solution for the initial morphology than for the final one. From Figure 5, it is possible to observe a higher disparity in the results of the MC initial morphology than in the MC final morphology for all the cases. The final morphologies are prone to converge prematurely as shown by the spikes of non-cero fitness (e.g. in the theoretical MC), while the initial morphologies are more dispersed. This disparity may also help to support the design condition that learning with the initial morphology is easier than with the final one: if learning with the initial morphology were not easier, there would not be more individuals with positive fitness values with greater disparity. Furthermore, such disparity in the fitness results is associated with a disparity in the population, indicating: (1) a better exploration of the solution space, increasing the possibilities of finding the area of optimal solutions, and (2) helping to prevent the stagnation of the learning algorithm in local optimum.

Regarding the availability of solutions, we can observe that the solutions are located in the same area of the fitness landscape, as shown in Figure 3. We hypothesize that the extension of the legs does not produce completely new optimal behaviors that are not accessible in the initial morphology. However, this could be different in different tasks. For example, if there were obstacles on the floor, it could be necessary to be able to lift the feet over the obstacles. In that case, the initial morphology, which has shorter legs, could not use the same solutions that are available after development.

Finally, the design condition that indicates the need for an adequate synergy among the given morphology, the selected initial morphology, the controller, the development strategy, and the learning algorithm so that it can adequately adapt to changes in morphology is supported by the results from Figure 2. It can be observed how morphological development favors learning in 4 of the 5 cases considered. This means that, although part of the design conditions have been met, these are necessary conditions, not sufficient, to ensure that morphological development can improve learning, and it is still necessary to find a factor as difficult to define and/or specify as "an adequate synergy" to ensure that morphological development implies an improvement in learning. In this case, the optimal synergy was obtained in terms of the relation of the morphological growth rate and the stable learning capability of the algorithm. Here this occurred for a growth rate ending at generation 120 (120 generations to complete the growth process), whereas in a similar morphological development strategy applied to a quadruped robot learning to walk [25], the optimal synergy was obtained for growth up to generation 60. That is, in the case of the quadruped, the morphology could grow at double the speed of the biped. This makes sense, as biped walking is less stable than quadruped walking, and large changes in morphology may lead to destabilization of the controller.

VI. Conclusions

In this paper, we have shown how the design considerations established in the literature as indications to design appropriate morphological development strategies can be supported quantitatively. They have allowed us to notably improve the learning speed and its quality in an ANN-based controlled NAO robot while trying to learn how to walk in a straight line using a neuroevolutionary algorithm.

As it has been hypothesized before, morphological development needs some specific conditions to improve learning in robots. In this paper, we have shown that (1) enough complexity of the task, (2) simpler learning in the initial stages of development and (3) synergy between development and learning seem to be valid for a successful application of morphological development. The selection of the design conditions is supported, both by the analytical results of comparing the performance of various morphological configurations and by the analysis of the fitness landscape and its characteristics. However, there is still much work to be carried out in order to determine sufficient conditions and, more importantly from a design point of view, an appropriate methodology to allow choosing the correct strategies and parameter values for each particular problem.

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