Evolutionary optimization of a bipedal gait in a physical robot

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***Abstract*— Evolutionary optimization of a gait for a bipedal robot has been studied, combining structural and parametric modifications of the system responsible for generating the gait. The experiment was conducted using a small 17 DOF humanoid robot, whose actuators consist of 17 servo motors. In the approach presented here, individuals representing a gait consisted of a sequence of set angles (referred to as states) for the servo motors, as well as ramping times for the transition between states. A hand-coded gait was used as starting point for the optimization procedure: A population of 30 individuals was formed, using the hand-coded gait as a seed. An evolutionary procedure was executed for 30 generations, evaluating individuals on the physical robot. New individuals were generated using mutation only. There were two different mutation operators, namely (1) parametric mutations modifying the actual values of a given state, and (2) structural mutations inserting a new state between two consecutive states in an individual. The best evolved individual showed an improvement in walking speed of approximately 65%.**

I. Introduction

This paper is concerned with evolutionary optimization of a gait for a bipedal robot. In the coming era of autonomous robots, it is generally believed that humanoid robots, i.e. walking robots with an approximately human-like shape, will play an important role, since such robots can be more naturally adapted to environments primarily designed for people and are also likely to be easier to interact with than wheeled robots with non-humanoid characteristics [1].

However, there are many difficult issues associated with humanoid robots as well, one of the most important being their complex dynamics: In general, humanoid robots require a complex coordination of limbs while walking as well as active balancing even at standstill.

During the last two decades, a large amount of work has been carried out regarding the generation of stable bipedal gaits. A variety of methods have been used, one of the most popular being the ZMP method [2], [3]. Evolutionary methods have also been applied to the problem of gait generation [4], [5], [6], [7], with the aim of generating, for example, gaits that are more responsive to sudden perturbations or other unexpected events that may cause significant trouble for more traditional gaits based on reference trajectories. However, evolutionary methods generally require that a large number of candidate soluations (individuals) should be tested, a procedure that is very time-consuming if it is carried out in physical robots. Thus, simulations have commonly been used in connection with evolutionary gait generation [4], [5], [6], [7], [8], [9], [10].

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However, simulations come with a significant drawback, namely the difficulty of accurately modeling the humanoid robot, which, in turn, leads to severe problems when transferring generated gaits to a physical robot. No matter how carefully a humanoid robot is modelled, there will always be discrepancies between the simulated robot and the physical robot. Thus, evolution directly in hardware does carry an advantage. Incidentally, the difficulty in modeling humanoid robots may be seen as another motivation *in favor* of the use of evolutionary methods (if applied directly to physical robots), since such methods normally do not require a dynamic, or even kinematic, model of the physical robot.

It is thus clear that, if only the evolutionary procedure can be made sufficiently rapid to allow for the generation of a satisfactory bipedal gait after, say, a few hundred (rather than thousands) of evaluated individuals, evolution directly in hardware would be an attractive alternative. A method for speeding up the evolutionary process is, of course, to start from a rough, hand-coded gait that can at least make the robot move, and then proceed to optimize this gait using an evolutionary algorithm (EA). Indeed, such a method was applied successfully by Wolff and Nordin [11]. However, their approach suffered from a significant drawback: The representation of individuals was such that the EA could only modify the *parameters* of the gait, not its *structure*. If no structural modifications are allowed, as in Wolff and Nordin [11], the structure of the initial hand-coded gait (i.e. the starting point for the EA) must be completely accurate in order for the EA to be able to find an optimal gait through parametric optimization. In this paper, the analysis of Wolff and Nordin [11] will be extended to the case of combined structural and parametric evolution.

II. Experiment description

A. The robot

The experiment was executed using a small, 17-DOF humanoid robot manufactured by Kondo Kagaku Co. Ltd. [12]. The robot is shown in Fig. 1. Fig. 2 shows a schematic view of the robot, with the definition of the 17 joint angles. The height of the robot is 0.33 m. The actuators of the bipedal robot consist of 17 KRS 786 ICS servo motors with integrated closed-loop control, manufactured by Kondo [12]. Each servo motor has a nominal output torque of 0.85 Nm, and a maximum rotation speed of 6.16 rad/s (0.17 s/60 degrees). The controller consists of two RCB-1 boards, also manufactured by Kondo. The RCB-1 board is based on the PIC 16F873A chip from Microchip Technology Inc. [13], and each controller board can control up to 12 servo motors.

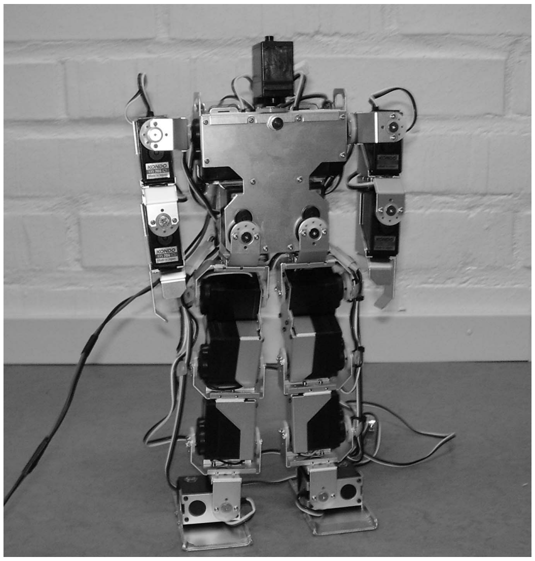

Fig. 1. The Kondo robot.

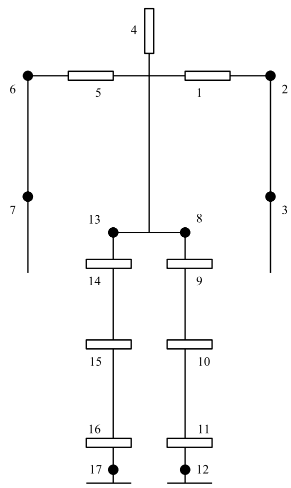

Fig. 2. A schematic view of the Kondo robot used in the experiment. The axes of rotation of the eight joints shown as filled disks in the figure are orthogonal to the frontal plane. These joints rotate in the clockwise direction for increasing set values. With the exception of the joint actuating the head, the remaining joints generate motion in the sagittal plane.

B. Experimental setup

The arena in which the robot was evaluated is shown in Fig. 3. The evaluation of an individual consisted of placing the robot at the starting point (the black line shown in the left part of the picture), uploading the gait onto the robot and then running it, starting at time T_0. A photocell was used for measuring passage of the finish line (the black line shown in the right part of the picture) at time T_1. When the finish line was reached, the time $T = T_1 - T_0$ was recorded. In case of failure, i.e. if the robot fell over or strayed too much from the intended path (such that it would not pass the finish line between the measurement points shown in the picture), the evaluation was interrupted. The distance L between the starting line and the finish line was 0.53 m, i.e. around 1.6 times the height of the robot. This value was chosen due to hardware limitations that restrict the number of executed states to 100 in any given evaluation, i.e. a maximum of 16 cycles for a gait with 6 states (see below).

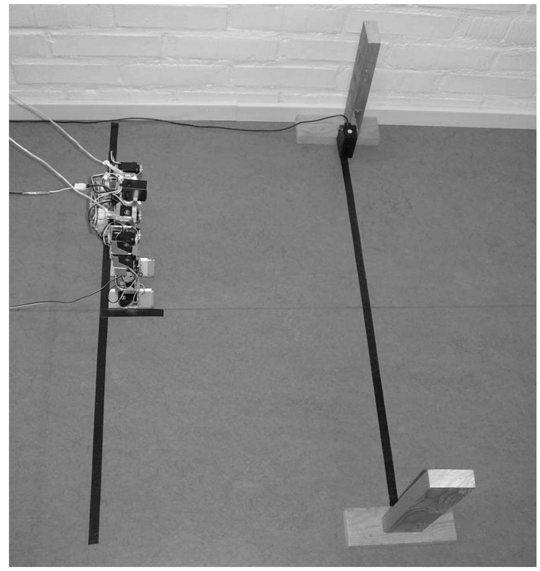

Fig. 3. The arena used in the experiment.

C. Gait architecture

In the architecture used here, a gait consists of a sequence of set angles (henceforth referred to as *states*) for the servo motors, as well as ramping times for the transition between states. An example of a gait, namely the standard, hand-coded gait, is shown in Table I. In this table, each row represents a state. The final column of each row shows the ramping parameter, i.e. the speed of the transition from the current state to the next one. The ramping parameter takes values in the range $[0, 7]$, where 0 indicates the fastest possible transition, and 7 the slowest possible transition.

1) The standard gait: The gait used as a starting point for the optimization procedure described below, is given in Table I. As can be seen from the table, the gait consists of six states. When executing the gait, the states are used cyclically, starting from state 1.[1] Since the standard gait (hereafter: SG) is specified using only six states, it is not very smooth. However, it allows the robot to cover the distance L in around 36.4 seconds. A sequence of images, showing the robot in each of the six states, is given in Fig. 4. Note that the SG is statically stable, so that the robot can stay balanced indefinitely in any of the six available states.

D. The evolutionary algorithm

The EA employed in this study was a fairly standard one, except for (1) the absence of a crossover operator and (2) the presence of structural mutations. No crossover operator was used, since crossover between individuals with different

[1]However, since the robot starts from the stance shown in Fig. 1, it must first take one step to reach state 1 in the gait. Thus, before the cyclical gait is executed, both the SG and all other evaluated gaits begin by a hand-coded step of the kind just mentioned.

TABLE I

THE STANDARD GAIT, CONSISTING OF SIX STATES THAT ARE EXECUTED CYCLICALLY. THE PARAMETERS SHOWN IN ITALICS ARE KEPT CONSTANT DURING THE EVOLUTIONARY OPTIMIZATION PROCEDURE, I.E. THEY ARE UNAFFECTED BY PARAMETRIC MUTATIONS, SEE ALSO SUBSECT. II-D.1.

State	φ_1	φ_2	φ_3	φ_4	φ_5	φ_6	φ_7	φ_8	φ_9	φ_{10}	φ_{11}	φ_{12}	φ_{13}	φ_{14}	φ_{15}	φ_{16}	φ_{17}	R
1	9	11	90	120	150	169	90	*97*	85	49	127	*80*	*103*	69	114	46	*78*	6
2	9	11	90	120	175	169	90	*97*	85	49	127	*79*	*103*	107	172	23	*78*	3
3	30	11	90	90	175	169	90	*97*	85	49	127	*79*	*102*	116	128	73	*76*	3
4	30	11	90	90	175	169	90	*73*	119	82	124	*104*	*79*	88	111	67	*102*	6
5	9	11	90	60	175	169	90	*73*	72	15	150	*104*	*79*	88	111	64	*102*	3
6	9	11	90	90	150	169	90	*73*	65	66	93	*107*	*75*	102	124	64	*102*	3

number of states is unlikely to produce improved results. In this subsection, the encoding scheme, the genetic operators, and the fitness measure will be described.

1) Encoding scheme: The genome of each individual was represented as 18 chromosomes. Each of the first 17 chromosomes encodes the sequence of set angles for a given servo motor j, i.e. the transitions $\varphi_j^{[i]} \rightarrow \varphi_j^{[i+1]},\ i = 1, \dots, N-1$, where N is the number of states. Due to hardware limitations, the maximum value of N was equal to 10. The final chromosome encodes the speed of transition between the different states, using an integer ramping parameter R as described in Subsect. II-C.

2) Genetic operators: In the formation of new individuals, which took place on a host computer, only mutations were used. Since the evolutionary algorithm started from a functioning gait, it was unlikely that a search involving large mutation steps would generate improved gaits. Thus, *creep mutations* were used instead. In the case of the chromosomes encoding angles (chromosomes 1-17), the mutation operator changed a given gene (set angle) $\varphi_j^{[i]}$ to a new value according to

$$\varphi_j^{[i]} \leftarrow \varphi_j^{[i]} + \Delta, \tag{1}$$

where Δ is a random number in the range $[-\Delta_{\max}, \Delta_{\max}]$. Thus, with small values of $\Delta_{\max}$ the mutation generates a new value near the old value. A $\Delta_{\max}$ value of 5 was used throughout the experiment. In case the new set angle exceeded the allowed limit of variation ($[0, 225]$) for the servo in question, the set angle was adjusted to the limiting value.

Similarly, for chromosome 18, the mutation operator changed a given ramping parameter R according to

$$R \leftarrow R \pm 1, \tag{2}$$

with equal probability for either sign, except for the limiting cases $R = 0$, where only an increase was allowed, and $R = 7$, where only a decrease was allowed.

The parameteric mutations of servo angles and ramping parameters were carried out on gene-by-gene basis, i.e. for each gene a random number $r \in [0, 1]$ was generated, and if r was smaller than the parametric mutation probability p_{p}, the gene in question (servo angle or ramping parameter) was modified.

However, for four servos, namely 8, 12, 13 and 17, the variation in the servo angles described by the SG was kept, i.e. mutations were not allowed for these particular servos. This restriction was introduced since it was found that any mutation of these servo values led to situations in which a foot would touch the ground at an angle (rotation in the frontal plane), causing the robot to fall. Thus, in the end the EA was allowed to specify the angular variation of 13 servos and one ramp value, for each state, so that the total number of parameters was equal to $14N$.

Structual mutations were allowed as well. Such mutations may, in principle, either decrease or increase the length of the chromosomes. However, during tests preceding the experiment, it was found that removal of states generally led to disastrous results (the robot would fall), except in those rare cases where the removed state was one that had just been added. Thus, removal of states was not used, and the chromosomes were thus only allowed to increase in length.

Structural mutations were used in such a way that, with probability p_{s} a new state was inserted between states i and $i+1$, $i = 1, \dots, N-1$. In order to avoid destroying the gait, the set angles of the new state were given as

$$\varphi_j^{\mathrm{new}} = \frac{\varphi_j^{[i]} + \varphi_j^{[i+1]}}{2}. \tag{3}$$

Similarly, the gene representing the ramping parameter (inserted in the 18^{th} chromosome) was generated in the same way as the set angles.

3) Fitness measure: In this investigation, the speed of walking combined with strong punishment for instability, has been taken as the measure of quality of a gait. More specifically, the fitness of an individual was taken as

$$f = \frac{T_{\mathrm{SG}}}{T}, \tag{4}$$

where T and T_{SG} are the times taken to traverse the distance L for the individual in question and for an individual executing the SG, respectively. This fitness measure was used for individuals that actually reached the finish line, thus obtaining a value for the time taken. Individuals that fell over were given fitness 0, whereas individuals that walked in a strongly curved path (such that they would not break the light beam between the two measurement points on the finish line), were somewhat arbitrarily given fitness 0.1. Such individuals were given a non-zero fitness since an inability to walk in a straight line was considered less severe than an outright instability of the gait in question. However, it

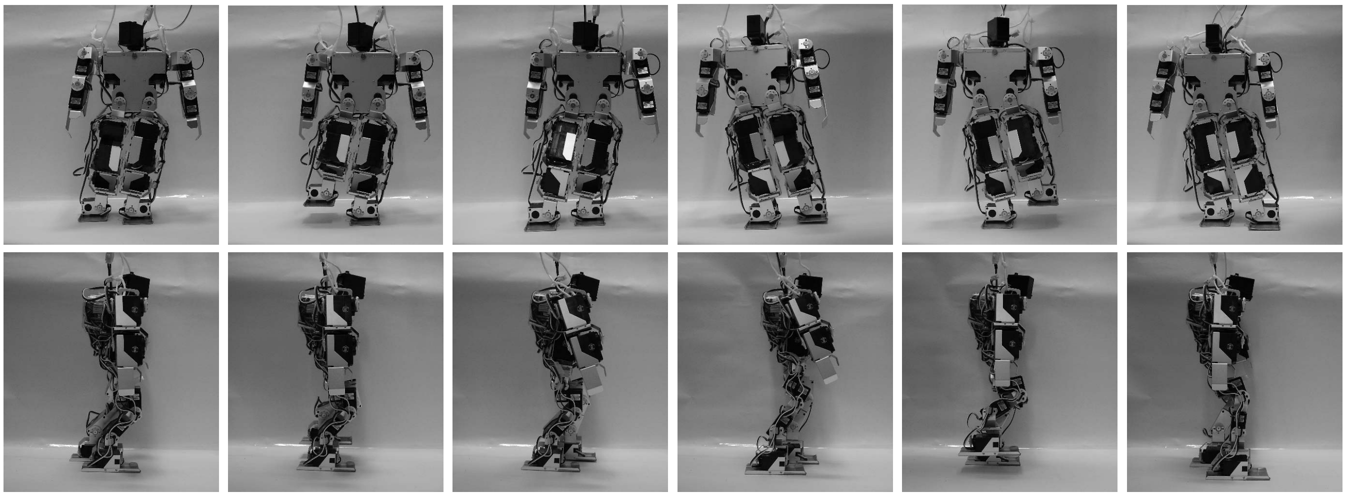

Fig. 4. The six states of the standard gait. The upper row shows the robot seen from the front, and the lower row shows a side view.

should be noted that the fitness values (defined in Eq. (4)) of individuals that reached the finish line was much higher than 0.1. The SG was evaluated 10 times, leading to a value of $T_{\rm SG}$ of 36.4 ± 0.3 s (95% confidence interval). During this time interval the robot executed approximately 16 steps.

III. Results

The experiment was carried out using a population size of 30 individuals. In the formation of the initial population, the genomes of all individuals were first set manually so as to encode the SG. Next, the individuals were mutated, using the procedure that normally takes place *after* the evaluation of a generation, and the resulting set of individuals formed the initial population.

The evolutionary procedure was carried out for a total of 30 generations. Thus, in all, 900 individuals were evaluated. Elitism was employed, i.e. one copy of the best individual in generation g was transferred, unchanged, to generation $g+1$. Each individual was evaluated once, and its fitness value was then stored. When all individuals in a given generation had been evaluated, the next generation was formed using the genetic operators described above. The parametric mutation rate was set to $2/K$, where $K = 14N$ is the number of parameters. The structural mutation rate was set to $1/3(N-1)$.

The results are shown in Figs. 5 and 6. Fig. 5 shows the maximum fitness as a function of generation. Note that the (average) fitness of the SG is equal to 1. From the figure, it is clear that the fitness values rise quite rapidly, from around 1.276 to 1.638 over the first 17 generations. Then there is a sudden drop, followed by oscillatory best fitness values roughly in the range 1.5 ± 0.1. In fact, the best individual appeared already in generation 15 where it obtained fitness 1.616. In generation 16 this individual obtained a fitness of 1.634, again making it the best individual in the population. Finally, in generation 17 it reached a fitness value of 1.638, the global maximum fitness value obtained during the EA

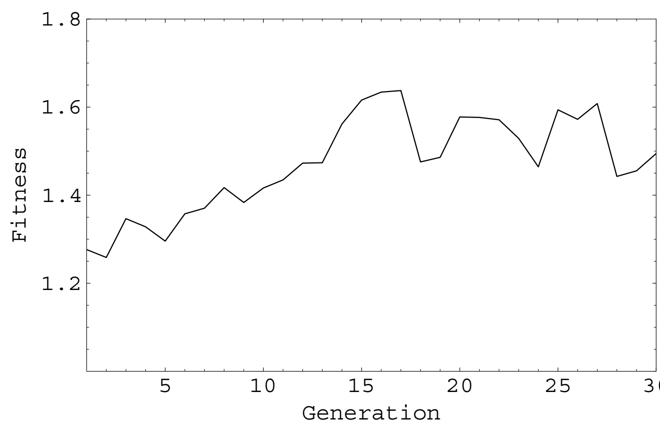

Fig. 5. Fitness of the best individual as a function of generation. Note that the maximum fitness value was obtained in generation 17.

run. However, in generation 18, the individual fell, and was therefore eliminated from the population. Note that, despite the use of elitism, the maximum fitness value may thus drop from one generation to the next, since the performance of any given individual may vary between evalutions.

The average fitness values are shown in Fig. 6. As is evident from the figure, there is no trend in the average fitness value.

Even though each individual was only evaluated once during the EA run, the genetic material of all individuals was stored so that any individual could be re-evaluated after the completion of the run. Such a re-evaluation was indeed carried out for the best individuals in each generation, and it was found that fitness values (at least for these individuals) typically remained quite stable during re-evaluations: Typical variations were around 2%. However, it should also be noted that, occasionally, even a rather good individual would fall. Of the 30 individuals that were re-evaluated, five fell during at least one re-evaluation.

In general, there was an increasing trend in the number

TABLE II

THE BEST GAIT, CONSISTING OF EIGHT STATES. NOTE THAT THE PARAMETERS SHOWN IN ITALICS ARE UNAFFECTED BY PARAMETRIC MUTATIONS.

State	φ_1	φ_2	φ_3	φ_4	φ_5	φ_6	φ_7	φ_8	φ_9	φ_{10}	φ_{11}	φ_{12}	φ_{13}	φ_{14}	φ_{15}	φ_{16}	φ_{17}	R
1	10	11	90	120	150	169	90	*97*	85	49	127	*80*	*103*	69	114	46	*78*	5
2	9	11	90	120	175	169	90	*97*	85	49	127	*79*	*103*	113	172	23	*78*	0
3	31	11	90	90	175	169	90	*97*	82	49	127	*79*	*102*	121	128	73	*76*	0
4	30	11	90	89	175	169	90	*85*	99	65	125	*91*	*90*	104	122	71	*89*	3
5	30	11	90	90	175	169	90	*79*	108	73	124	*97*	*84*	96	119	68	*95*	4
6	30	11	90	90	175	169	90	*73*	117	82	124	*104*	*79*	88	116	67	*102*	3
7	9	12	90	60	178	172	87	*73*	72	15	154	*104*	*79*	88	111	64	*102*	3
8	9	11	95	90	147	174	90	*73*	65	71	94	*107*	*75*	102	124	64	*102*	0

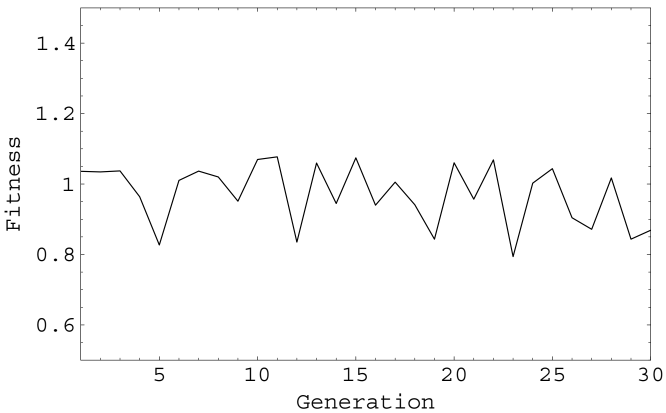

Fig. 6. Average fitness as a function of generation.

of states. This is not surprising *per se*, since, as described above, states could not be removed. The number of states increased from an average of 6.5 in the first 10 generation to an average of 8.9 in the last 10 generations.

The best gait, generated in generation 15 (but obtaining maximum fitness in generation 17, as mentioned above), is described in Table II. As is indicated in the table, this gait consisted of eight states, i.e. two states were added in addition to the six states present in the SG. The added states were inserted at positions 4 and 5. When the EA run had been completed, the best individual was re-evaluated 10 times, leading to a fitness value of 1.643 ± 0.112 (95% confidence interval). Note that, in order to carry out 10 successful re-evaluations for this individual, 12 attempts were needed. In other words, even the best individual would sometimes fail.

The sideways deviation over the distance L was also measured and was found to be, on average, 0.09 m (always in the same direction), compared to 0.08 m for the SG.

IV. DISCUSSION AND CONCLUSION

The most important conclusion that can be drawn from the experiment described above is that it is indeed possible to obtain significant improvements of a functioning but non-optimized bipedal gait using an EA running directly on a physical robot. It is interesting to note that, already after 17 generations, i.e. after the evaluation of around 500 individuals, an improvement in walking speed of around 65% could be obtained.

From Table II, it is clear that the values of the ramping parameter have been somewhat reduced (on average), compared to the values used in the SG, so that the transition between states becomes faster than for the SG. A reasonable hypothesis, in the light of this result, may be that the SG could perhaps be improved simply by reducing the values of the ramping parameter. However, this approach was tested and was shown to lead to a highly unstable gait. Thus, in order for the gait to be improved, an increase in transition speed must be accompanied by modifications of the set angles and, possibly, the number of states, and is thus very difficult to obtain by manual tuning.

The dip in fitness values after generation 17 was caused by an unfortunate failure (in generation 18) of the best individual in generation 17: The robot fell, and the corresponding individual was thus eliminated. If multiple evaluations had been used to form a reliable average performance of each individual, this particular individual may have survived and even higher fitness values might then have been obtained. However, the choice of using a single evaluation was motivated by the fact that, even with this limitation, the evaluation of 900 individuals took quite a long time (around 3-4 full working days). It is doubtful whether the use of, say, 3 re-evaluations per individual would have led to a *better* final result, since then only 300 individuals could have been evaluated unless, of course, the experiment was extended in time. Nevertheless, it is important to note that a strong improvement of the original gait (the SG) was obtained even though a single evaluation was carried out for each individual.

An interesting possibility for future work would be to base the fitness value on the heritage of a given individual, i.e. to form its final fitness value as a sum of the current fitness value and that of its ancestors, perhaps using a discounting factor for individuals from earlier generations. In this way, the elimination of a good individual based on a single failure could be avoided, *without* having to carry out time-consuming re-evaluations of each individual.

At a first glance, the absence of a trend in the average fitness values may seem surprising, particularly since the best fitness values *do* improve. However, one must keep in mind that the initial population consists of individuals executing a

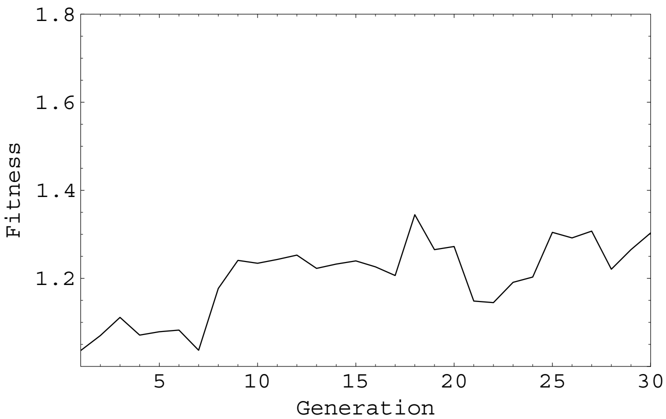

Fig. 7. Average fitness as a function of generation, taken over those individuals that successfully (without falling) traversed the whole distance L, without excessive sideways deviation. See the main text for a further discussion of this figure.

slightly modified version of the rather stable standard gait (with an average fitness of 1), whereas later generations will contain individuals whose gaits are more significantly modified compared to the SG. Some of these individuals will have gaits that outperform the SG whereas other individuals will fail altogether, thus obtaining a fitness value of 0 or 0.1, depending on the mode of failure, as described above. Thus, the numerical average value may be misleading, since it depends on the somewhat arbitrary fitness values (0 and 0.1) assigned to failed individuals. A better measure of the actual average performance can be obtained by measuring the average fitness value of those individuals that do not fail. A plot of these values is shown in Fig. 7. As can be seen from this figure, there is indeed an increase in the average, from 1.036 in the first generation to 1.303 in the last, with a maximum of 1.345 in generation 18. Admittedly, this is an overestimate of the average performance, since the number of failed individuals also rises, from an average of 3.0 in the first 10 generations to 7.2 in the last 10 generations, but it does indicate that the EA is able to improve the performance of those individuals that do not fail completely.

As for the walking speed, the best individual walked a distance of 0.53m in approximately 22.2s, i.e. with a speed of only 0.024 m/s. Scaling from the height of the robot (0.33 m) to the height of a typical human (1.75 m), this would correspond to a speed of roughly 0.12 m/s which, of course, is quite slow. However, what matters is the improvement compared to the SG, with an average speed of only 0.015 m/s. The low *absolute* speed can be attributed to hardware limitations. In fact, even though the robot has a humanoid shape, the placements of joints differs quite significantly from those of a human. Furthermore, the body of the robot is, of course, much more rigid.

As for the robustness of the generated gaits, it was found (as mentioned in Sect. III) that even the best individuals would sometimes fall. Thus, the evolved gaits displayed somewhat lower robustness than the SG. An interesting topic for future work would be to optimize the SG while placing even higher emphasis on the robustness of the generated gaits. In order to be successful, such a study would probably require the use of several re-evaluations of each individual for the formation of the fitness value.

The initial motivation for carrying out the gait generation in physical robots rather than in simulations can be strengthened further by noting that the sideways deviation of the best individual always occurred in the same direction, as a result of the peculiarities of the particular components (and their placement) used in that robot. Had simulations been used, it is unlikely that such an effect would have been correctly modelled, at least without extensive and time-consuming detailed system identification. Thus, even though evolution in physical robots is a complex procedure, in view of the direct applicability of the results obtained, it appears to be well motivated in the case of gait optimization in bipedal robots.

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