

Augmented Neuromuscular Gait Controller Enables Real-time Tracking of Bipedal Running Speed

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Abstract—Reproducing human locomotion in simulation has a variety of applications, from informing prosthetic and rehabilitation medicine to generating stable and human-like robot or animated character movement. Previously, however, heavy optimizations were required to realize gaits specific to a single speed. Novel neuromuscular controllers blending feed-forward and reflex-like control have shown state-of-the-art success in introducing speed modulation of walking gaits from a single optimization. In this work, we present a modified neuromuscular gait controller in the sagittal plane to similarly realize speed modulation for running gaits. As a result, our controller interpolates fewer than 10 parameters from a single optimization to realize a large range of running speeds on a simulated bipedal platform. We discuss the speed-evolution of these selected parameters, their significance in relation to human kinematics, and the velocity-tracking performance over the speed range between 1.3 m/s and 1.7 m/s, which scales to cover much of human running speeds.

I. INTRODUCTION

Reproducing human locomotion in simulation has a variety of applications, from aiding prosthetic and rehabilitation medicine to generating stable and human-like robot and animated character movement [1]–[3]. Biologically-inspired neuromuscular controllers are gradually expanding boundaries of biped locomotion research, and show promise for enabling state-of-the-art speed modulation for walking and running gaits [4]–[7].

Yet, human locomotion is far from being understood. Although the presence of feed-forward control through central pattern generators (CPGs) in ordinary human gaits is likely, it is still a matter open to discussion [5], [8]. CPGs are neural circuits found in some mammals that have the interesting ability to produce periodic signals capable of regulating locomotion from low-dimension control inputs [9].

Previously, biomechanical models have shown some success in generating gaits capable of a range of speeds without the introduction of feed-forward control. For instance, the work of [10], later extended in [7], achieved such locomotion on a simple human model equipped with virtual muscles controlled solely by feedback signals that mimic reflexes.

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However, prior neuromuscular approaches investigated the use of CPGs in biped control: [11] could adapt the locomotion of a biped model on uneven terrains using a CPG, and [12] developed a neuromuscular model that featured a CPG to investigate the effects of a spinal cord injury on locomotor abilities.

In [6] and [13], we developed a novel neuromuscular controller recruiting both reflexes and a CPG to generate walking gaits on a simulated model of COMAN, a 95 cm humanoid robot. This is consistent with Kuo's framework, which suggests combining feedback and feed-forward pathways in the control of a periodic locomotor task [14], leveraging the advantages of both. This blended control system enabled continuous tracking of walking speed in the sagittal plane (i.e. in 2D) on the COMAN platform (from 0.4 to 0.9 m/s) by adapting a small set of high-level parameters as linear functions of a target speed. Once scaled for height, this range is similar to that of an average adult. Indeed, similarly scaling our running speed results by height predicts a range between 2 m/s and 3 m/s.

The success of neuromuscular approaches were not limited to walking gaits. In [2], intermediate gait phases were introduced to the neuromuscular gait controller by Geyer et al. in order to produce walking and running gaits. This promising method is hindered by a costly optimization over 124 parameters to produce a single speed. In [7], running gaits were realized on a reflex-based 2D human model, which is capable of tracking speeds from 2.4 to 4 m/s using a linear policy optimized once over 64 parameters. In the present contribution, we demonstrate a marked improvement inspired by our previous work towards tracking speeds within walking locomotion [6]. By interpolating under 10 parameters as low-degree polynomial functions of desired speed, our singly optimized mixed neuromuscular controller featuring a 6-neuron CPG is capable of generating real-time speed tracking running gaits on a humanoid.

This document is divided as follows: in Section II, the COMAN platform is presented in its simulation environment; the modified neuromuscular controller is described in Section III to realize a running gait at a single speed; this controller is later augmented in Section IV to develop the velocity tracking policy, before analyzing the resulting gait features in Section V; finally, Section VI discusses our conclusions.¹

¹Code for this project is available under MIT License at <https://github.com/mharding01/augmented-neuromuscular-RT-running>. Refer to project for computational details not included in this document due to space constraints.

II. COMAN MODEL AND ENVIRONMENT

As in our previous work, [6] and [13], for our locomotion platform we employed a 3D model of the COMAN humanoid constrained to the sagittal plane, which is equipped with 23 degrees of freedom and stands at 95 cm tall ([15], [16]). Figure 1a illustrates our modified neuromuscular system overlaid onto the model.

The results presented in this contribution were obtained using the Robotran simulation software [17], [18], a symbolic environment for multi-body systems developed within the Université catholique de Louvain. The ground contact model was implemented as detailed in [10], while the actuators' dynamics were modeled as explained in [19]. Additionally, to mimic uncertainty on the real platform, uniform noise with a maximal amplitude of 0.4 Nm was added to each torque measurement. The Runge-Kutta integration scheme with a $125\text{ }\mu\text{s}$ discrete time step was employed. More information about the robot and its simulator is provided in [13], [19].

Finally, a new biomechanically accurate foot model was used to better allow proper push-off before the mid-gait flight phase [20]. Each foot is composed of two rigid plates (105 and 35 mm for the sole and phalanges, respectively - see Figure 1a), connected by a torsion spring. The passive compliance of this spring is modeled as $\tau_{toe} = -k_{toe} \varphi_{toe} - d_{toe} \dot{\varphi}_{toe}$, where τ_{toe} is the resulting torque, φ_{toe} the toe joint angle and $\dot{\varphi}_{toe}$ its time derivative. The torsion spring stiffness k_{toe} is set to 30 Nm/rad and its damping coefficient d_{toe} is set to 1 Nm s/rad .

III. NEUROMUSCULAR CONTROLLER

All the leg and arm sagittal joints are controlled to track torques references, while the remaining joints are maintained to their static home position. The purpose of the controller is therefore to produce torque references for these leg and arm sagittal joints. These references are obtained using virtual muscles commanded by the combined action of reflexes (feedback signals) and a CPG (feed-forward signals).

A. Musculo-skeletal model

Similarly to [10], the locomotion is achieved by recruiting virtual muscles generating torques at the joint level. In short, each group of muscles is represented by a set of equations based on the Hill muscle model [21]. When excited, these muscles react by contracting and applying forces on the body. Then, the equivalent torques applied at the joint level can be deduced from the lever arm joining the muscle virtual attachment points to the joints. These torques are sent as torque references, in turn producing voltages at the motor level using the PI controller described in [22].

In our case, eight Hill-type muscles are recruited for each leg, and four muscles actuate each arm. They are depicted in Figure 1a. Their characteristics are described in [10], [13], [23].

Each muscle is controlled by its activation A_m , capturing the neural signal provided by motoneurons. This signal is related to a neural input S_m , the muscle stimulation, using a first-order low-pass filter capturing the excitation-contraction

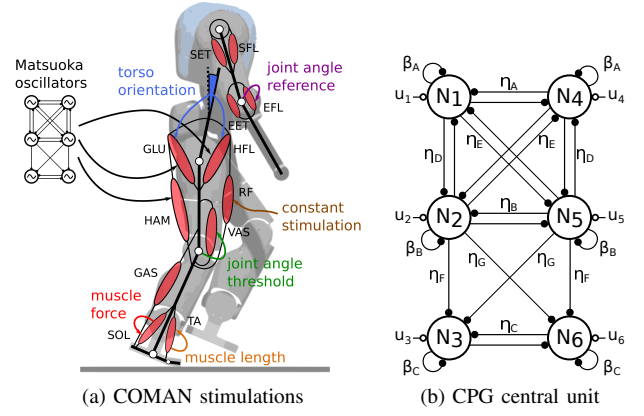


Fig. 1: (a) To actuate leg and arm sagittal joints, the controller uses 12 different Hill-type muscle models, depicted as red ellipses. These muscles are fired by a mixture of reflex and feed-forward CPG signals. (b) The CPG network of Matsuoka oscillators, as detailed in previous work, [6].

coupling [10]. Controlling each muscle thus reduces to design appropriate control rules for these neural stimulations.

B. Central pattern generator design

In this contribution, a central pattern generator (CPG) network is recruited to drive the proximal muscles, i.e. the muscles acting at the hip level. This is consistent with the proximo-distal gradient hypothesis that postulates that distal locomotor muscles are controlled mostly by reflexes as they are most impacted by external perturbations, while stronger, proximal ones are mainly driven by CPG signals [5], [24].

Here, the CPG network affects the hip flexors (HFL), gluteus (GLU) and biarticular hamstring muscle groups (HAM), i.e. the muscles having a large impact on the hip joint. The other leg muscles, i.e. the soleus (SOL), tibialis anterior (TA), gastrocnemius (GAS), vasti (VAS) and rectus femoris muscle groups (RF) are only commanded with reflexes. These virtual muscles are depicted in Figure 1a.

The CPG structure is designed as a six-neurons network of Matsuoka oscillators [25], [26]. These bio-inspired neurons structures capture the mutual inhibitions between half-centers located in the spinal chord and are widely used to model the firing rate of mutually inhibiting neurons, in both the upper and the lower extremities [27].

In this network, each neuron N_i state is represented by its firing rate x_i whose evolution with time is governed by a balance between self-inhibition and inhibition from the antagonistic half-center. Computational details are given in [6]. Figure 1b depicts the Matsuoka network developed in this contribution.

Interestingly, CPGs present attractive properties like distributed control, redundancies handling, and locomotion modulation using simple control signals [9]. In particular, they provide frequency and phasing signals, if properly synchronized with the locomotion gait. This is potentially relevant to activate reflex signals at the right moment or

to send feed-forward signals coming from the CPG to the virtual muscles.

The full CPG network (see Figure 1b) is composed of four fully connected neurons called the *primary oscillators* (N_1 , N_2 , N_4 and N_5), and two extra neurons called the *secondary oscillators* (N_3 and N_6). The secondary oscillators are driven by the primary ones but do not impact them.

More precisely, the primary neurons fulfill two main functions: triggering the proximal muscle reflexes at the right timing and sending descending stimulations to the HFL muscles. In particular, neuron N_2 is supposed to fire just after the left strike, while N_5 is supposed to fire just after the right strike. The secondary neurons N_3 and N_6 are mainly aligned with neurons N_1 and N_4 , although their firing rates differ, due to different inhibition parameters being recruited. These secondary neurons are in charge of stimulating the HAM muscle before strike impact.

C. Muscle stimulations

The primary neurons firing rates are used to segment the running gait into four distinct phases for each leg, requiring different computation rules for the muscle stimulations. This is done by detecting when the corresponding firing rates are positive.

In the following rules, most reflexes are adapted from [10] and their equations can also be found in the code repository. The neural signal delays introduced in that contribution are also implemented here. Regarding feed-forward control through CPG signals, the stimulations' contributions are computed proportionally to the CPG outputs, defined as $y_i = [x_i]^+$. All muscle stimulations are bounded in the $[0.01; 1]$ interval, see [6] for more details.

The first phase is triggered when x_5 is positive for the right leg, or when x_2 is positive for the left leg. This corresponds to the phase directly following the corresponding leg strike impact. During that phase, the torso orientation angle θ_t is driven to a given reference θ_{ref} using PD-control as described in [2], [10].

Then, the next phase mainly includes the swing initiation and the flying phase, happening before the contralateral leg strike impact. This is detected when x_1 is positive for the right leg, or when x_4 is positive for the left leg. During that phase, the hip is propelled with the CPG control of the HFL muscle detailed in (1), where $k_{HFL,1}$ and $k_{HFL,2}$ are two gains. Its antagonist muscles GLU and HAM only receive the minimal prestimulation $S_{MIN} = 0.01$.

$$\begin{aligned} S_{HFL,R} &= k_{HFL,1} y_1 + k_{HFL,2} y_2 \\ S_{HFL,L} &= k_{HFL,1} y_4 + k_{HFL,2} y_5 \end{aligned} \quad (1)$$

After the other leg strike (being detected when x_2 is positive for the right leg, or when x_5 is positive for the left leg), swing-leg retraction is enforced by using the positive force-feedback reflex rules on the GLU and HAM muscles, as in [2], [10]. During this sub-phase, the HFL muscle still receives the CPG control detailed in (1).

In the last phase (preceding the ipsilateral leg strike, and corresponding to x_4 positive for the right leg or x_1 positive

for the left leg), the stance preparation is improved by adjusting the hip angle φ_h to a given reference $\varphi_{h,ref}$, as suggested in [28] and [2]. This is done with reflex rules that drive the HFL and GLU muscles with PD control on this desired angle. At the same time, the knee flexion is controlled by the CPG, using Equation (2).

$$S_{HAM,R} = k_{HAM} y_6 \quad S_{HAM,L} = k_{HAM} y_3 \quad (2)$$

Knee stretching is mainly achieved using the RF and VAS muscles. Similarly to [2], the swing initiation during the stance phase is detected when the signed horizontal distance between the COM and the ankle normalized by the leg length (\tilde{d}) is larger than a fixed threshold d_{si} . Similarly, the stance preparation during the swing phase is detected when $\tilde{d} < d_{sp}$, where d_{sp} is another fixed threshold.

During stance phase, the RF muscle only receives a basic prestimulation $S_{0,RF,st}$. At the same time, the VAS muscle is activated with a positive force feedback, which can be inhibited when the knee angle φ_k exceeds a given threshold $\varphi_{k,th,st}$, as in [2].

During swing initiation, the efforts are being transferred from the VAS to the RF muscles. This is done by incrementing the RF stimulation by a fixed amount s_{iRF} and by decreasing the VAS one by a fixed amount s_{iVAS} .

The early swing phase keeps the RF and VAS muscles nearly silent by sending fixed prestimulations $S_{0,RF,sw}$ to RF and $S_{0,VAS,sw}$ to VAS. However, the knee joint angle φ_k is expected to reach a given threshold $\varphi_{k,th,sw}$ before the next strike. Using PD control, this is done with the VAS muscle during the stance preparation as in [2].

Finally, the control of the ankle muscles is implemented as described in [10]. More precisely, a mixture of force and length feedback rules are applied to SOL, TA, and GAS muscles during the stance phase to create late-stance dorsiflexion for thrust. During the swing phase, plantarflexion is enabled by minimally stimulating SOL and GAS while controlling TA with length feedback rules.

Upper-body control is also active to provide rotational stability for the torso in the transverse plane: the arms swinging motion is controlled by the shoulder flexion (SFL) and extension (SET) muscles at the shoulder level and by the elbow extension (EET) and flexion (EFL) muscles for the elbow (see Figure 1a). All these muscles rely on the following feedback rules tracking desired joint positions (with $\Delta\varphi_{sh} = \varphi_{sh,ref} - \varphi_{sh}$ and $\Delta\varphi_{elb} = \varphi_{elb,ref} - \varphi_{elb}$):

$$\begin{aligned} S_{SFL} &= k_{arm} [\Delta\varphi_{sh}]^- & S_{EFL} &= k_{arm} [\Delta\varphi_{elb}]^- \\ S_{SET} &= k_{arm} [\Delta\varphi_{sh}]^+ & S_{EET} &= k_{arm} [\Delta\varphi_{elb}]^+ \end{aligned} \quad (3)$$

where φ_{sh} and φ_{elb} are respectively the shoulder and elbow joint positions, $\varphi_{sh,ref}$ and $\varphi_{elb,ref}$ are their references and k_{arm} is a constant gain arbitrarily set to 5.

Similarly to [2], the arm swing motion is obtained by relating the shoulder target angle position to the difference in the sagittal hip joint positions $\varphi_{hip,R}$ and $\varphi_{hip,L}$, respectively

for the right and left legs. This is captured by the following equations:

$$\begin{aligned}\varphi_{sh,ref,R} &= k_{sh}(\varphi_{hip,L} - \varphi_{hip,R}) - \Theta_{sh} \\ \varphi_{sh,ref,L} &= k_{sh}(\varphi_{hip,R} - \varphi_{hip,L}) - \Theta_{sh}\end{aligned}\quad (4)$$

where Θ_{sh} and k_{sh} are both arbitrarily set to 0.3. Finally, $\varphi_{elb,ref}$ is set to a constant reference of -0.25 rad to keep a constant position for the elbow.

D. Gait initialization

As a part of our optimization procedure within a simulated environment, we additionally include parameters dictating the initial dynamics of the biped. We chose to initialize the biped's initial velocity and joint parameters, which are reported in code repository, so that the biped begins in the flying phase of its running gait. The initial forward velocity of the center of mass, \dot{x}_w , is arbitrarily set to 1.5 m/s , which lies in the middle of the targetted speed range, i.e. $[1.3; 1.7] \text{ m/s}$. The initial joint angles of the elbows and shoulders are set to their respective initial position references (see Section III-C). The elbow speeds are initially zero, and the right shoulder speed is set to $\dot{\varphi}_{sh}$, which is opposite that of the left shoulder speed (see code repository for more details).

E. Gait controller optimization

Many unknown parameters were introduced in the controller development and in the simulation initial dynamics. These parameters are listed on the code repository together with their respective bounds. Here, the tuning of these parameters was performed using a particle swarm optimization (PSO) algorithm [29].

More precisely, an optimization procedure maximizes the sum of multiple weighted Gaussian functions that reward controller parameter values which attain desired gait velocity, stability, synchronization, and posture (among other characteristics). Unstable local minima represented by controller instances that repeatedly collapse during 70 s real-time trial simulations were discarded. The computation of this global fitness function is fully described in Appendix VI-A.

IV. SPEED ADAPTATION

In this section, the running controller is augmented to achieve speed tracking through the modulation of a small set of parameters. The following experiment was performed to study the impact of these parameters on the running speed. A baseline optimization was carried out as described in Section III-E, with a target speed of 1.5 m/s . The resulting running controller was called the *initial controller*. Then, all the controller's optimized parameters' values were frozen before new optimizations were performed targeting eleven key chosen parameters listed in Table I.

As in our previous work, [6], it was critical to analyze the parameterization of the CPG time-constant τ and hip muscle CPG output gains $k_{HFL,1}$, $k_{HFL,2}$, k_{HAM} to appropriately time all CPG signals and strengthen hip and knee stimulation during leg swing, respectively. To regulate torso lean during stance and perhaps better prepare the knee for impact at

TABLE I: The p-values associated with the polynomial linear least squares approximations of the speed-evolution data provided in Figure 2. Each p-value is computed using the lack of fit sum of squares analysis [30].

	order 0	order 1	order 2	selected
τ	0	0.017	0.026	2
$k_{HFL,1}$	0.036	0.102	0.093	1
$k_{HFL,2}$	0.002	0.117	0.825	2
k_{HAM}	0.146	0.146	0.356	2
θ_{ref}	0.026	0.022	0.021	0
$\varphi_{h,ref}$	0.608	0.577	0.642	0
$k_{\varphi,k}$	0.239	0.175	0.117	0
G_{VAS}	0.014	0.104	0.071	1
G_{GAS}	0.612	0.86	0.781	1
G_{SOL}	0.275	0.247	0.517	2
G_{S-T}	0.002	0.653	0.647	1

different speeds, we also selected the torso reference angle θ_{ref} and hip reference angle $\varphi_{h,ref}$.

At the knee level, we also chose to focus on the effect of the low-level gains G_{VAS} and $k_{\varphi,k}$ on speed, as these may regulate stride length through knee strength and angle at toe push-off. Lastly, in order to dictate toe push-off strength, we chose to analyze the three ankle gains during stance: G_{SOL} , G_{GAS} , and the plantar flexion-inhibiting G_{S-T} .

In these new optimizations, the initial controller is used for the first six steps, after which the values of the chosen parameters were instantaneously updated. Only the steady-state speed was measured in each trial during optimization. In order to account for the non-determinism of the optimization procedure, these reduced optimizations were performed five times each for target speeds from 1.3 to 1.7 m/s at 0.05 m/s intervals.

The results are visible in Figure 2, where the evolution of these parameters with the measured speed can be observed. Intuitively, these parameters evolution with speed can be approximated using polynomial functions. In order to select appropriate polynomial orders capturing the essence of the curve without over-fitting, a model goodness-of-fit analysis using the sum of squared values of the prediction errors was used, as described in [13], [30]. In short, for each pair of parameter and polynomial order, the corresponding p-value measures the likeliness that the selected order is appropriate to represent the parameter evolution. These p-values are gathered in Table I, for orders 0, 1 and 2. The order with the highest p-value was then selected. The only exception is the parameter $\varphi_{h,ref}$, whose p-values for orders 0 and 2 are very close. Therefore, we arbitrarily selected the order 0 for this parameter.

The polynomial approximations for the selected orders are depicted with dashed lines in Figure 2. The time constant τ decreases for faster speeds, thus favoring higher step frequencies. Interestingly, this trend amplifies for faster speeds, indicating that the robot favors step length adaptation for slow speeds, and step frequency adaptation for faster speeds.

The hip flexor is stimulated by two CPG gains during the swing phase: the swing initiation gain $k_{HFL,1}$ and the

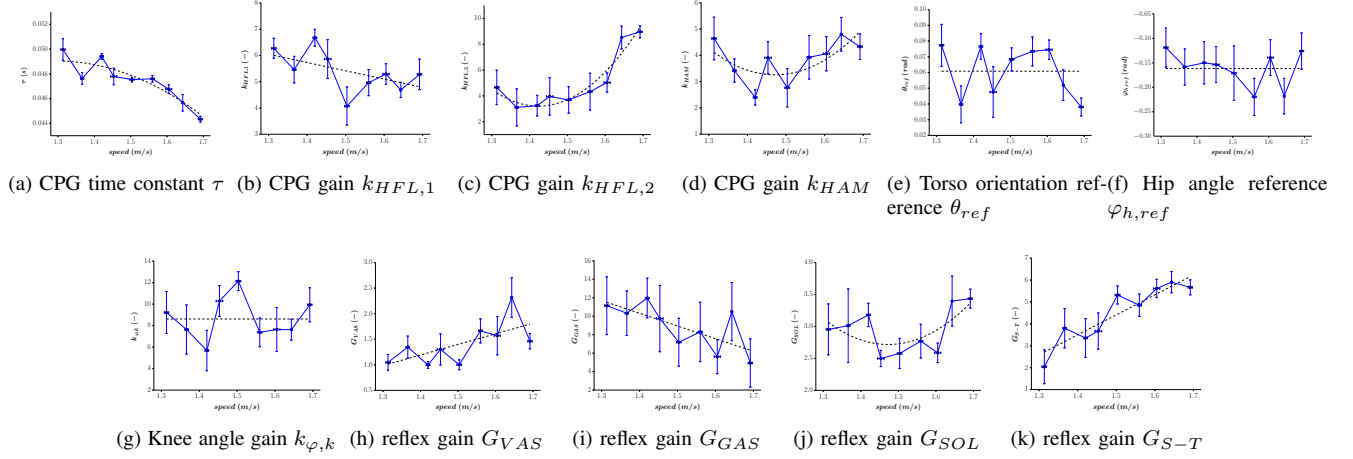


Fig. 2: Five optimizations are performed for each target speed (from 1.3 m/s to 1.7 m/s with an interval of 0.05 m/s). The actual speed of each solution is measured, along with the optimized value of the eleven open key parameters. For each target speed, we gather the five optimization final results, reporting their mean and standard deviations. For graph legibility, the error bars represent half of the standard deviations. Dashed lines correspond to the polynomial approximations whose order is computed in Table I, using the minimum mean square error method.

mid-swing gain $k_{HFL,2}$. In particular, $k_{HFL,2}$ shows an increasing trend with speed (except for the slowest speeds), resulting in larger hip flexion, and so in longer step lengths for the fastest speeds. In contrast, the negative trend of the swing-initiation stimulation gain $k_{HFL,1}$ remains unclear, but its relative variation is small (compared to the one for $k_{HFL,2}$), and should not significantly impact the gait.

The HAM gain k_{HAM} obtained the largest values for the speed extrema. This increases the knee flexion before stance using the HAM muscle, therefore preventing hyper-extension and enabling greater shock-absorption to occur. At high speed, this is useful to counter the effects of the increased step length. At low speeds, this increase of the k_{HAM} gain helps to reduce the biped speed.

No trend is observed for the torso reference angle θ_{ref} , indicating that this value can be kept constant. This might be due to the optimization stage which aimed at maintaining an upright posture (see Appendix VI-A). This stage was inspired from [2], in order to achieve more robust running gaits. However, [7] argued that modulating the torso orientation is a dominant contributor for running speed acceleration and deceleration, such that, intuitively, a forward lean can help to realize faster speeds. Similarly to θ_{ref} , no clear trend is observed for the hip reference angle $\varphi_{h,ref}$.

Regarding knee control during stance, the increase of the G_{VAS} gain favors legs stretching for faster speeds. In contrast, the parameter $k_{\varphi,k}$, in charge of preventing knee overextension, is not significantly affected by the running speed.

Finally, both the SOL and GA muscles act on the ankle to create forward thrust (via plantarflexion through the G_{SOL} and G_{VAS} gains), while the antagonist TA muscle is inhibited using the G_{S-T} gain, to avoid unnecessarily fighting against the SOL and GAS actions. Intuitively, these

three parameters were expected to increase with speed, in order to favor larger push-offs for the fastest speeds. This trend is clearly visible for the G_{S-T} gain and for the major part of the G_{SOL} evolution. However, for slow speeds, the opposite trend is observed for G_{SOL} . Interestingly, the GAS muscle parameter displays a negative trend, thus favoring larger thrust for slow speeds. A possible explanation is that a significant part of the ankle propulsion efforts is transferred from the SOL to the GAS muscle for slower speeds.

Based on these results, new optimizations can be performed, in order to co-optimize all the controller parameters for the whole range of speeds. The strategy is the following. Among the eleven key parameters studied, eight presented linear or quadratic evolution trends with speed: τ , $k_{HFL,1}$, $k_{HFL,2}$, k_{HAM} , G_{VAS} , G_{SOL} , G_{GAS} , G_{S-T} (see Table I). These parameters were replaced by their corresponding linear or quadratic functions of the target speed and the remaining parameters were optimized to constant values, as presented in the code repository. Then, each set of optimized parameters was evaluated successively with different target speeds, according to the requested speed range. The fitness function was finally obtained as the sum of component fitness functions computed for each run, as detailed in Appendix VI-A.

V. RESULTS

The results presented in this section were obtained after a single optimization on the range of speeds from 1.25 to 1.7 m/s, i.e. on a range similar to the one of Figure 2, but slightly extended towards the lowest speeds.

The resulting gait is first presented during a speed tracking experiment. The gait main features and their evolution with speed are then analyzed.

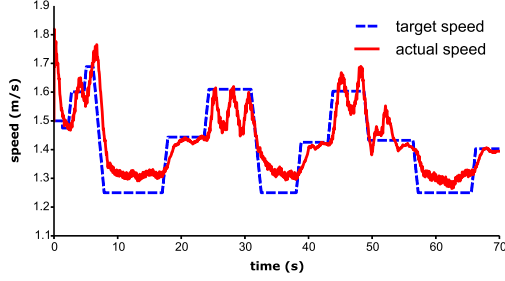


Fig. 3: In this experiment, the target speed v_{ref} is indicated with the dashed line, while the robot actual forward speed is indicated with the solid line. This actual speed is post-processed with a running average of 1 s.

A. Speed tracking

First, the robot forward speed reference v_{ref} was modulated by an operator in the $[1.25; 1.7] m/s$ range, during 70 s. Its evolution is displayed in Figure 3. The modulation of this parameter directly impacted the eight selected key parameters, according to the rules summarized the Git repository. The evolution of the robot actual speed is also displayed in Figure 3. In Figure 4, snapshots of this experiment are presented when COMAN was running at a speed close to the middle of the speed range ($1.42 m/s$).

Globally, the lowest commands (i.e. $v_{ref} = 1.25 m/s$) resulted in stable running. However, the actual (measured) speed was a bit higher and stayed close to $1.3 m/s$. For the fastest speed references (i.e. v_{ref} close to $1.7 m/s$), the gait was generally less stable, usually resulting in the biped ultimately falling in the forward direction. However, it is possible to reach these fastest speeds briefly before reducing v_{ref} to stabilize the gait. This behavior was obtained in this experiment, as can be seen in Figure 3, especially during the $[6; 7] s$ and the $[44; 48] s$ time intervals. For speed references over $1.55 m/s$, the gait speed began oscillating as can be see in Figure 3 during the $[25; 30] s$ and the $[44; 48] s$ time intervals. Finally, speed accelerations and decelerations were both around $0.145 m/s^2$ (in absolute values).

The snapshots of Figure 4 illustrate the running gait motion. In particular, feet strikes are visible in panels (a), (f) and (k), push-off phases in panels (c) and (h) and flying phases in panels (e) and (j).

B. Gait features

Using the same controller, the following gait features were studied: stride frequency and length, flying phase ratio and metabolic energy consumption (evaluated as presented in [31], and normalized to the biped mass and to the traveled distance). This was studied for speed references v_{ref} evolving in the $[1.25; 1.6] m/s$ range. Indeed, as mentioned in Section V-A, faster speeds could be reached during short periods, while we were interested here in measuring steady-state values.

The results are presented in Figure 5. Firstly, it can be seen that there is a gap between the measured features of most tested speed references and the last one (i.e. $v_{ref} = 1.6 m/s$). As previously mentioned, this is due to the oscillations in the measured speed observed for speed references over $1.55 m/s$.

The stride frequency and length are both shown to increase proportionally to speed (see Figures 5a and 5b). This matches the intuition that human running prefers larger steps and higher frequencies to run distances in a shorter amount of time. However, the ranges of variations of the stride frequency and length are both around 9 % of their maximal values, while it was observed that the increase of speeds in real human running was mainly related to stride length adaptation, i.e. with few variations of the stride frequency [32].

Regarding the flying phase ratio, a slight increase is observed for faster speed references (except for $v_{ref} = 1.6 m/s$). This speed evolution might suggest that the optimizer favored stronger toe push-off for faster speeds, therefore resulting in longer flying phases. However, this flying phase ratio appears to remain relatively close to its average value of 30 %, which indicates that this trend is not significant.

Finally, the gait-cycle metabolic energy cost normalized by the traveled distance decreases as the speed increases. This is perhaps mostly due to the presence of longer strides for faster speeds, which improves gait efficiency.

VI. CONCLUSION

In this contribution, we developed a neuromuscular controller mixing both reflexes and CPG signals to control the speed of a running biped. The modulation of eight key control parameters as linear or quadratic functions of the target speed resulted in the modulation of the biped forward speed. The selection of these key parameters was done by studying the evolution of these parameters with the target speed.

In steady-state, speeds could be continuously commanded in a range from 1.3 to $1.6 m/s$. During short periods, the speed could be increased up to $1.7 m/s$. In contrast, the speed adaptation of the reflex-based controller developed in [7] could reach speeds ranging from 2.4 to $4 m/s$, on an adult model. Once scaled to the size of COMAN, this lower speed bound is similar to ours. However, the model of [7] could reach faster speeds (once scaled to the biped size). In that contribution, this was done by adapting 64 parameters as linear functions of the target speed.

Therefore, it seems that this increase in the number of parameters being modulated allows for larger speed ranges. Our controller could therefore be incremented by adapting a few more parameters as functions of the forward speed. In particular, [7] pointed out that the adaptation of the torso lean angle could play a major role in speed modulation. In our contribution, this parameter appeared to remain quite constant with speed alterations. However, this might be

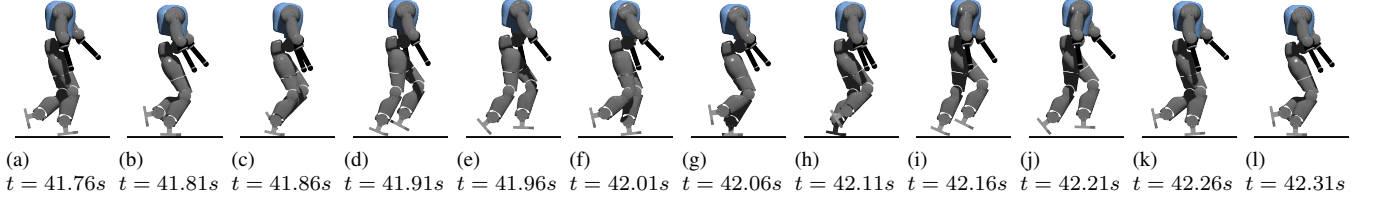


Fig. 4: Snapshots of COMAN gait during the experiment from Figure 3 demonstrating an average speed of 1.42 m/s .

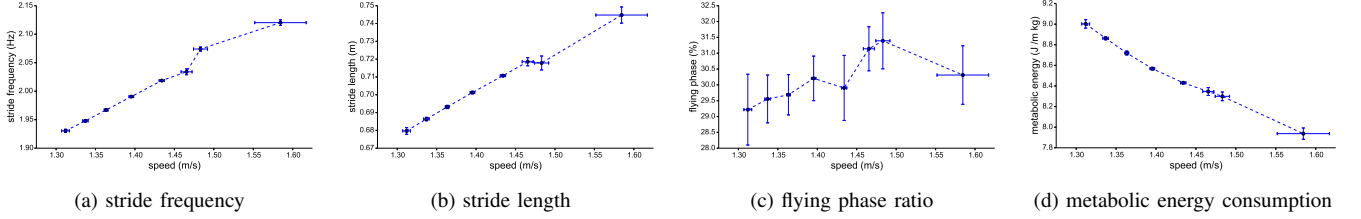


Fig. 5: Panel (a) presents the stride (i.e. two steps) frequency, while panel (b) shows the stride length. Panel (c) displays the flying phase ratio. In panel (d), the muscles metabolic energy consumption per unit distance is computed (only for the lower-limb muscles acting in the sagittal plane, the arm muscles energy being negligible in comparison). For each speed reference v_{ref} (from 1.25 m/s to 1.6 m/s , discretized at an interval of 0.05 m/s), five simulation runs are performed. For each speed, the means and the standard deviations (from the five corresponding runs) of the different actual speeds and measures are pictured.

related to our fitness function, which aims to enforce an upright posture to increase stability as suggested in [2].

A natural extension of this work would be to add lateral control in order to reach full 3D running. To begin with, we have already managed to obtain 3D walking gaits in [13].

Another interesting avenue to explore is to use the CPG to trigger transitional knee reflexes between stance and swing phases. In the present contribution, these intermediate reflexes are prompted by position of the center of mass (COM). This strategy was adapted from [2], where no CPG control was implemented. Further studies could analyze the gait stability of a controller that coordinates not only hip muscle stimulation but also critical inter-phase reflexes from CPG firing rates.

Finally, the robustness of the controller could be improved in particular for the fastest speeds. For instance, in [20], we showed that the use of prosthetic-like compliant feet during walking could improve the biped robustness on uneven grounds. Therefore, the same controller could be tested using these prosthetic feet. Another avenue to explore is presented in [33] where a method is developed to learn muscle stimulations that resist unpredicted external perturbations. As this previous approach also relies on muscular control, a similar strategy could be investigated for running gaits to improve biped robustness, perhaps based on the desired COM position.

APPENDICES

A. Optimizer fitness function

A global fitness function is computed by aggregating the scores of 7 component functions that reward certain gait

characteristics after each simulation run. Each run ends after 70 s or sooner due to robot collapse.

Two types of component functions are used: 1) a clamped linear function that constrains reward within a non-negative range using Equation (5) or 2) a bell-shaped function centered at x^* that distributes reward according to a defined Gaussian shown in Equation (6). The Gaussian is parameterized by $(x^*; \alpha; \beta)$, and the linear function by $(c; \gamma)$.

$$g(x) = \max(0, \min(cx, \gamma)) \quad (5)$$

$$f(x) = \beta e^{-\alpha(x-x^*)^2} \quad (6)$$

The foremost component function rewards the average speed of gait controllers x_{avg} using a Gaussian f_{vel} centered at a target speed v_{ref} defined by $(v_{ref}; 85 \text{ s}^2/\text{m}^2; 700)$. The next strongest contributing component function encourages the synchronization of the neuron firing rates with foot strikes, which is necessary for the CPG to stably align hip stimulation with distal reflexes. The average prediction error x_{cpg} of neurons N_2 and N_5 (predicting left and right leg foot strikes, respectively) is minimized using a Gaussian f_{cpg} defined by $(0 \text{ s}; 1100 \text{ s}^{-2}; 500)$. Similarly to [2], the optimizer also aims to maintain an upright posture by minimizing mean torso angle in the sagittal plane $x_{\theta_{torso}}$ using the third largest component Gaussian $f_{posture}$ defined by $(0^\circ; 20^\circ{}^{-2}; 350)$.

Next in order of contribution to the global fitness, two component linear functions improve gait robustness by rewarding the running time and distance traveled before falling. A linear function g_{fall} , which is defined by $(30/7 \text{ s}^{-1}; 300)$, rewards gaits proportional to the time it took to collapse

before the simulation completes x_{ttf} . Another linear function g_{dist} with parameters $(6\text{ m}^{-1}; 300)$ takes as input the total distance traveled x_{dist} and rewards maximally beyond 50 m .

A running gait is favored by constraining the proportion of the gait period spent in flight phase to be above 10%. More precisely, a modified Gaussian f_{flight} given the average flight phase proportion $x_{pflight}$ is specified by $(.10; 450; 250)$; however, for input exceeding 0.1, the maximal reward is granted.

A final component Gaussian f_{energy} , which is parameterized by $(0\frac{J}{m\cdot kg}; 0.01\frac{(m\cdot kg)^2}{J^2}; 200)$, aims to minimize the equivalent metabolic energy consumption (as computed by [31]) in virtual leg muscle contraction per unit distance traveled. The motivation for this is to further encourage the generation of a human-like running gait. Further implementation details can be found in the source repository.

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