Neuromechanical Control for Hexapedal Robot Walking on Challenging Surfaces and Surface Classification

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Abstract

The neuromechanical control principles of animal locomotion provide good insights for the development of bio-inspired legged robots for walking on challenging surfaces. Based on such principles, we developed a neuromechanical controller consisting of a modular neural network (MNN) and of virtual agonist-antagonist muscle mechanisms (VAAMs). The controller allows for variable compliant leg motions of a hexapod robot, thereby leading to energy-efficient walking on different surfaces. Without any passive mechanisms or torque and position feedback at each joint, the variable compliant leg motions are achieved by only changing the stiffness parameters of the VAAMs. In addition, six surfaces can be also classified by observing the motor signals generated by the controller. The performance of the controller is tested on a physical hexapod robot. Experimental results show that it can effectively walk on six different surfaces with the specific resistances between 9.1 and 25.0, and also classify them with high accuracy.

Keywords:
Agonist and antagonist muscle model, legged locomotion, biological inspired locomotion, hexapod robot.

1. Introduction

Neuromechanical models for animal locomotion combine neural circuits (e.g., central pattern generators, CPGs) and biomechanics (e.g., muscles). They are also used to study the interplay of muscles, CPGs, and sense organs [1], which provides good insights into developing bio-inspired locomotion systems [2]. Employing such models leads to adaptation and energy efficiency of locomotion of the bio-inspired systems [3, 4, 5].

The energy efficiency of bio-inspired walking systems is typically measured by specific resistance [6, 7]. Lower specific resistance corresponds to more efficient walking. Neuromechanical controllers exploit muscle-like mechanisms as well as neural mechanisms for effective legged robot control. In contrast, isolating them results in energy inefficient locomotion [8], thereby leading to high specific resistances [9].

For instance, the specific resistance of a hexapod robot (i.e., Gregor I) during walking over an uneven surface (i.e., obstacle course) is 70 when only a cellular neural network is used as its CPG [10]. Combining CPGs with forward models can improve the energy efficiency of a hexapod robot. For example, a CPG combined with an adaptive forward model enables a hexapod robot (i.e., AMOS) to walk over an uneven surface (i.e., fine gravel) with the specific resistance of 55.5 [11]. Adaptive leg motions generated by the neural controllers of Gregor I and AMOS depend only on the changes of neural activities of the controllers for walking over uneven surfaces. However, owing to energy efficiency [12], there are no changes detected in neural activities for controlling key muscles or performing precise limb coordination of cockroaches when walking over an uneven surface (i.e., obstacles up to three times cockroach hip height) [13]. This finding shows that cockroaches perform adaptive leg motions and compensate perturbations by relying more on their biomechanics (e.g., muscles), thereby leading to energy efficiency.

Muscles also play a vital role in legged locomotion over different terrains [14, 15, 16, 17]. In robotic applications, muscle-like mechanisms (e.g., Shape Memory Alloy (SMA) actuators) can be used for controlling lightweight legged robots. However, such SMA actuators are energy inefficient owing to their slow cycle speed. For example, the specific resistance of a small legged robot is over 12,000 when its joints are mainly actuated by SMA actuators [18]. In contrast, our virtual agonist-antagonist mechanisms (VAAMs, i.e., muscle-like mechanisms) proposed here lead to smaller specific resistances of a hexapod robot during walking on different surfaces (described below). The VAAMs can also generate variable compliant leg motions which rely only on force sensing at the end effectors of the robot legs. This technique is different from two classical methods (i.e., active and passive compliance). Typically, active compliance [19] requires the components of force/torque sensing at each joint while passive compliance [20] depends heavily on physical passive components, e.g., passive springs or artificial muscles. These components make legged robots heavier and mechanically more complex, therefore making it difficult to implement on small legged robots (weight less than 8 kg) [21].

Combining the VAAMs with a modular neural network (MNN) results in a neuromechanical controller which is able
to control, e.g., a small hexapod robot (5.4 kg). In principle, the MNN is for generating basic coordinated movements while the VAAMs are for energy efficient walking and variable compliant leg motions. Without any passive mechanisms or torque and position feedback at each joint, the variable compliant leg motions are achieved by only changing the damper or stiffness parameters of the VAAMs [22]. Proper setups of the stiffness parameters allow a physical hexapod robot to effectively walk on different surfaces, i.e., fine gravel, coarse gravel, very coarse gravel, floor, snow and sponge surfaces.

In addition, adaptive compliance motion will also help legged robots to classify surfaces. Generally, surface classification has been implemented on legged robots based on multiple sensing (e.g., current and angular positions) [23, 24], force/torque sensing [25, 26], vibration sensing [27, 28] and visual perception [29, 30]. Visual perception using conventional technique [31] cannot work well in classifying the surfaces of non-distinguishable features (e.g., snow). Owing to natural vibrations of legged robots, vibration sensing may not perform well for classifying surfaces either [32]. Compared to multiple sensing, force sensing can still provide precise surface classifications by using a simple algorithm. Force sensing embedded in the VAAMs allows a physical hexapod robot to well classify six different surfaces with high accuracy (i.e., ≥ 89%).

2. Neuromechanical controller of a hexapod robot

Here we use the hexapod robot AMOS (5.4 kg weight, see Fig. 1) as our experimental platform. It has six three-jointed legs. Each three-jointed leg has a TC (Thoraco Coxal) joint allowing forward and backward motions, a CTr (Coxa Trochanteral) joint allowing elevation and depression motions, and a FTi (Femur Tibia) joint allowing extension and flexion motions (see Fig. 1 (b)). Each joint is physically driven by a standard servo motor (i.e., HSR-5990TG). There is a force sensor (i.e., FS Series Force Sensor) used for detecting an analog force signal at each leg (see $f_{c1-6}$ in Fig. 1 (a)). A current sensor installed inside the body of the hexapod robot is used to measure the electrical current supplied to all motors of the robot. Here, the current sensor signal is used to calculate power consumption during walking. The sensory data are transmitted via an RS232 serial connection to an external PC on which a controller is implemented. Here a neuromechanical controller (see Fig. 2) is employed to generate the adaptive and energy efficient walking behavior of the robot. The controller consists of a modular neural network (MNN) and virtual agonist-antagonist mechanisms (VAAMs). The final motor commands of the controller are sent to the robot via the serial connection.

2.1. Modular Neural Network (MNN)

The modular neural network (MNN) is a biologically-inspired hierarchical neural controller [33]. The MNN generates signals for inter- and intra-leg coordination of the hexapod robot. The MNN consists of a central pattern generator (CPG, see Fig. 3 (a)), a phase switch module (PSM, see Fig. 3 (b)) and two velocity regulating modules (VRMs, see Fig. 3 (c)). All neurons of the MNN are modeled as discrete-time, non-spiking neurons. The activation $H_i$ of each neuron develops according to:

$$H_i(t) = \sum_{j=1}^{m} W_{ij} o_j(t - 1) + B_i, \quad i = 1, \ldots, m,$$

where $m$ denotes the number of units, $B_i$ is an internal bias term (i.e., stationary input) to neuron $i$, $W_{ij}$ is the synaptic strength of the connection from neuron $j$ to neuron $i$. The output $o_i$ of all neurons of the MNN is calculated using the hyperbolic tangent (tanh) transfer function, i.e., $o_i = \tanh(H_i), \in [-1, 1]$. The weights $W_{ij}$ are manually designed, except weights $a$, $b$, and $c$ which are obtained by backpropagation learning (see Fig.3 (c)). For more details of determining the weights $W_{ij}$, we refer to our previous work [34].

The CPG consists of only two neurons with full connectivity (see Fig. 3(a)), where $B_1$ and $B_2$ are set to 0.01. The weights
$W_{12}$ and $W_{21}$ are given by:

$$W_{12}(S) = 0.18 + S, \quad W_{21}(S) = -0.18 - S,$$

where $S \in [0.01, 0.18]$ is the input of the MNN, which determines different walking patterns of the robot. The speed of its leg motion increases with increasing $S$. Here, we set $S$ to 0.04 resulting in slow walking behavior, which leads to stable and energy-efficient locomotion on uneven surfaces [11].

The PSM is a generic feed-forward network consisting of three hierarchical layers with ten hidden neurons (i.e., $H_3 - H_{12}$) (see Fig. 3 (b)). The outputs of the PSM are projected to the FTi (i.e., $F(R, L)_{123}$) and CTr (i.e., $C(R, L)_{123}$) motor neurons (see Fig. 3 (d)), as well as to the neurons $H_{13}$ and $H_{14}$ of the two VRMs (see Fig. 3 (c)). The VRMs are feed-forward networks projecting their outputs to the TC motor neurons $T(R, L)_{123}$ (see Fig. 3 (d)).

In the neuromechanical controller, the outputs $N_{1-18}$ of the motor neurons are the neural activities of the joints of the hexapod robot. $N_{1-18}$ enable the legs to perform fast swing and slow stance phases (see Fig. 4). Delays $\lambda_L$ and $\lambda$ between the motor neurons are fixed (see Fig. 3 (d)). For more details of the MNN, we refer to our previous work [11].

In our previous work [11], adaptive leg motion depends on changing of the outputs of the MNN which are controlled by additional forward models. In contrast, the proposed neuromechanical controller here only relies on changing the parameters of the muscle-like mechanisms as in cockroach locomotion [13]. Changing the mechanical parameters of the muscle-like mechanisms (i.e., virtual agonist-antagonist mechanism (VAAM)) allows the hexapod robot to not only perform adaptive locomotion, but also achieve more energy-efficient locomotion.

2.2. Virtual Agonist-antagonist Mechanism (VAAM)

The virtual agonist-antagonist mechanism (VAAM) consists of a pair of agonist and antagonist mechanisms (see Fig. 5(a)). It produces active and passive forces using its contractile and parallel elements (CEs and PEs, see Fig. 5(b)). In Fig. 5(a), a physical joint is driven by a pair of the VAAM (i.e., $M_1$ and $M_2$). Virtual means that the joint, physically driven by a standard servo motor, imitates muscle-like behaviors as if it were driven by a pair of physical agonist and antagonist muscles. The joint actuation relies on the CEs, while the PEs govern joint compliance.

The parallel elements (i.e., PEs) are modeled as spring-damper systems (see Fig. 5(b)) in term of Voigt muscle model [35]. The matrix $[f_1^P, f_2^P]^T$ of passive forces created by $PE_{1,2}$ is the sum of two Hadamard products:

$$[f_1^P, f_2^P]^T = \Gamma_{2\times 1} \circ L_{2\times 1} + \Phi_{2\times 1} \circ V_{2\times 1},$$

where

- $\Gamma_{2\times 1}$ is the matrix of stiffness coefficients of $PE_{1,2}$, i.e., $\Gamma_{2\times 1} = [K, K]^T$;
- $L_{2\times 1}$ is the matrix of displacements of $PE_{1,2}$, i.e., $L_{2\times 1} = [l_1^P - l_0, l_2^P - l_0]^T$. $l_0$ is the initial length of $PE_{1,2}$;
- $\Phi_{2\times 1}$ is the matrix of damper coefficients of $PE_{1,2}$, i.e., $\Phi_{2\times 1} = [D, D]^T$. 

Figure 4: Outputs of the motor neurons $N_{1-18}$. Here the input $S$ of the modular neural network is set to 0.04. This results in slow walking behavior with a wave gait. Abbreviations are: $R(F, M, H)$ = Right (Front, Middle, Hind) leg, $L(F, M, H)$ = Left (Front, Middle, Hind) leg.
CE is the amount of L the shank with the length of the V AAM (i.e., M is the product of the neural activity i results in an external force f. The active forces produced by the CEs are approximated by \[ f = f^a + f^r = \sum_i (f_i^a + f_i^r) \]. The matrix \[ f \in \mathbb{R}^{N \times 18} \] is represented by:

\[
\begin{align*}
\tau &= f^a \sin(\theta)L + \{ rN_j - r(2K\theta r + 2D\dot{\theta}r) \}.
\end{align*}
\]

Equation (6) governs the joint angle \( \theta \) of a physical joint driven by the V AAM that is activated by the output \( N_j \) of the MNN. The joint angle \( \theta \) and joint velocity \( \dot{\theta} \) in Eq.(6) are not from sensory feedback but calculated from the fourth-order Runge-Kutta method. In principle, this bio-inspired compliant joint control approach (i.e., the V AAM) shares a connection to classical impedance control approaches in terms of spring-damper based compliance. However, it is a biological modeling where muscle-like functions (e.g., variable compliant motions) are emulated by easily changing stiffness and damper parameters (i.e., \( K \) and \( D \) in Eq.(6)) [37].

A pair of agonist and antagonist mechanisms (e.g., the V AAM) gains advantage over a single antagonist or agonist mechanism in terms of the fast achievement of stability [37, 38]. This is because the V AAM can push and pull the joint at the same time generating inverse torques to oppose each other. Furthermore, some simulations have shown that a pair of agonist and antagonist muscles acting collaboratively produces more power than the sum of each muscle working independently [39].

### 3. The implementation of neuromechanical control

The outputs \( O_{1-18} \in [-1, 1] \) of the neuromechanical controller are linearly scaled and transmitted to control the positions of the standard servo motors driving the 18 joints of the hexapod robot (see Fig. 6). For joint control, different control strategies are applied to swing and stance phases.

#### 3.1. Swing phase

When a leg is in a swing phase (i.e., \( f^a = 0 \)), the outputs \( O_{1,3,6,9,12} \) for the TC, CTr and FTi joints receive the outputs of the motor neurons \( N_{1,3,6,9,12} \) as their inputs. They satisfy:

\[
\begin{align*}
[O_{1,3,6,9,12}]^T &= [0.4N_{1,0.15N_{r6},-0.02N_{r12}}]^T - [0.05, -0.86, 0.43]^T, \quad i \in Z_{\{1,6\}}.
\end{align*}
\]

The details of Eq.(7) can be seen in Appendix A.1 (i.e., see Eqs.(A.1), (A.2), and (A.3)).
nion of actuation and compliance resulting in regular compliance), and each FTi joint (i.e., distal joint) is driven by the PEs of the VAAAM resulting in pure compliance (see Fig. 8). This control strategy also complies with the findings revealed by a biological study on three-jointed leg locomotion [41, 42]. The biological study shows that the proximal joints of animal legs mainly act as actuation while their distal joints serve as compliance and their intermediate joints show the combination.

3.2. Stance phase

According to the three-jointed legs of the hexapod robot, the TC joint of the leg allowing only horizontal motion is not affected by the PEs of the VAAAM since there is only detection of vertical foot force at the end effector of the leg. As a consequence, the TC joint is driven by the CEs of the VAAAM. In contrast, the CTr and FTi joints of the leg allowing vertical motion can be influenced by vertical foot force. The force therefore activates the PEs to generate variable compliant joint motions. To investigate proper compliant setups for the CTr and FTi joints, we test four possible control setups in a physical simulator (i.e., Iprobots simulator [40]). A constraint for the setups is that each of them should contain at least the PEs for compliant generation. The simulation results show that setup 2 which is the combination of regular compliance at the CTr joint and sole compliance at the FTi joint is the best compared to other combinations (see Fig. 7 (a)). This combination allows the hexapod robot to achieve better coordinated movement and stable locomotion with very low body oscillation (see Fig. 7 (b)).

Therefore, the control strategy of each three-jointed leg of the hexapod robot is as follows: each TC joint (i.e., proximal joint) is purely controlled by the CEs of the VAAAM leading to pure actuation or no compliance, each CTr joint (i.e., intermediate joint) is governed by the CEs and PEs of the VAAAM (combin-
3.2.3. FTi joints

Each FTi joint is only driven by $PE_{(1,2)}$ of the VAAM (see Fig. 8 (a)). The FTi angle matrix $\theta_{16x1}$ is the sum of the Hadamard products (see Eqs.(13-15) of our previous work [9]):

$$I\theta_{16x1} = F_{ext}^{ex} \circ \sin(\theta_{16x1}) J_1 - r (2rK_{16x1} \circ \theta_{16x1} + 2 r D_1 \circ \theta_{16x1}).$$

(11)

The angles $\theta_{1m}$ ($m \in \mathbb{Z}_{[1,6]}$, see $\theta_{16x1}$ in Eq.(11)) of the FTi joints can be linearly transformed into their outputs $O_j$ (see Fig. 6). $O_j$ are given by ($j \in \mathbb{Z}_{[13,18]}$):

$$O_j = 0.92\theta_{1m+1} + 0.12, m = j - 12.$$  

(12)

The details of Eq.(12) can be seen in Appendix A.2.3 (i.e., see Eq.(A.6)).

4. Experimental Results

The proposed neuromechanical controller can produce variable compliant motions, thereby leading to adaptive and energy efficient locomotion over different surfaces. The surfaces tested here include fine gravel (diameter $\varphi = 5-8$ mm), coarse gravel ($\varphi = 16-25$ mm), very coarse gravel ($\varphi = 40-60$ mm), floor, snow and sponge surfaces. The variable compliant motions are implemented by changing the stiffness coefficients of the FTi and CTr joints (i.e., $K_{16x1}$ in Eq.(11) and $K_{26x1}$ in Eq.(9)).

4.1. Setups of $K_{16x1}$ and $K_{26x1}$

We tested 2601 setups of $K_{16x1}$ and $K_{26x1}$ for the robot in the L2pRobot simulator [40]. By using these setups of $K_{16x1}$ and $K_{26x1}$, the forward displacements $X$ of the robot are used to measure the performance of robot walking (see $X$ in Fig. 9). With each setup, the running time of robot walking is 30s. One can see that the robot performs proper walking behavior on a flat surface when $K_{1,2_{m+1}}$ are set within the range surrounded by black dash lines shown in Fig. 9. The result also certifies the bigdog-inspired control strategies [41, 42] (see Fig. 8). That is, the distal joints (e.g., FTi joints) should act more compliantly than the intermediate joints (e.g., CTr joints). Therefore, stiffness coefficients $K_{1,2_{m+1}}$ should be set as: $K_{1_{m+1}} < K_{2_{m+1}}$ (e.g., $2 \times K_{1_{m+1}} = K_{2_{m+1}}$). Four setups of $K_{1,2_{m+1}}$ are chosen for testing on our real hexapod robot ($m \in \mathbb{Z}_{[1,6]}$, see $S(1 - 4)$ in Fig. 9):

$S1$: $K_{1_{m+1}} = 2, K_{2_{m+1}} = 4$;
$S2$: $K_{1_{m+1}} = 3, K_{2_{m+1}} = 6$;
$S3$: $K_{1_{m+1}} = 4, K_{2_{m+1}} = 8$;
$S4$: $K_{1_{m+1}} = 4.5, K_{2_{m+1}} = 9$.

Note that all damper coefficients $D_{1,2_{m+1}}$ are set to 1.0.

4.2. Real hexapedal robot walking on different surfaces

We tested the four setups (i.e., $S(1 - 4)$) of $K_{1,2_{m+1}}$ on our real hexapod robot walking on fine gravel (diameter $\varphi = 5-8$ mm), coarse gravel ($\varphi = 16-25$ mm), very coarse gravel ($\varphi = 40-60$ mm), floor, snow (thickness $8cm$), and sponge (stiffness 0.523 kN/m) surfaces. The hexapod robot had a difficulty to walk on all these uneven surfaces when the lower stiffness setup (i.e., $S1$) was used. This is because with this setup the legs of the hexapod robot shallowly penetrate into the surfaces, thereby gaining less foot contact force (see $S1$ in Fig. 10). When the higher stiffness setup (i.e., $S4$) was used, the legs penetrate into the surfaces more deeply. However, this sometimes causes unstable locomotion which can be observed from dropping of the foot contact force (see $A1$ and $A2$ of $S4$ in Fig. 10). Therefore, with the setup $S4$ the robot also had a difficulty to overcome all these surfaces. Note that “high stiffness” (i.e., high impedance [43, 44]) here means that a joint greatly resists the influence of external forces; thereby low compliance. In contrast, “low stiffness” (i.e., low impedance [44, 45]) here means that a joint allows external forces to influence its movement easily; thereby high compliance.

Quantitatively, the inverse of compliance is stiffness, typically quantified by the ratio of the greatest magnitude of a sinusoidally varying force to the greatest magnitude of a displacement [46]. According to this, the stiffness $Y_{j+6}$ and $Y_{j+12}$ ($j = 1, 2, \ldots, 5, 6$) of the CTr and FTi joints is calculated as:

$$Y_{j+6} = \frac{\text{Max}(F_{ext}^{\varphi_{1j}})}{\text{Min}(O_{j+6}) - \text{Ini}(O_{j+6})} = \frac{\text{Max}(F_{ext}^{\varphi_{1j}})}{\text{Min}(O_{j+6})},$$

$$Y_{j+12} = \frac{\text{Max}(F_{ext}^{\varphi_{1j}})}{\text{Min}(O_{j+12}) - \text{Ini}(O_{j+12})} = \frac{\text{Max}(F_{ext}^{\varphi_{1j}})}{\text{Min}(O_{j+12})},$$

(13)

where Max($F_{ext}^{\varphi_{1j}}$) is the maximum value of an analog signal of the foot force $F_{ext}^{\varphi_{1j}}$ (e.g., see $F_{ext}^{\varphi_{1j}}$ in Fig. 11 (c)). Min($O_{j+6})$ and Min($O_{j+12}$) are the minimum values of the CTr and FTi joint outputs $O_{j+6}$ and $O_{j+12}$ are their initial values, i.e., Ini($O_{j+6}) = Ini(O_{j+12}) = 0$. The examples of the joint stiffness Y7 and Y13 are shown in Figs. 11 and 12 when high and low stiffness setups were applied for walking on fine gravel and sponge.
In contrast to the setups S1 and S4, the setups S2 and S3 allow the hexapod robot to walk well on all these uneven surfaces. However, they lead to different energy efficiencies of walking on the different surfaces. Its energy-efficiency is here measured by the specific resistance \( \varepsilon \) [6, 7] as:

\[
\varepsilon = \frac{P}{mgv},
\]

where \( P \) is power consumption, \( mg \) is the weight of the hexapod robot, i.e., \( mg = 52.974 \, \text{N} \). \( v \) is its forward speed. For each stiffness setup (i.e., S2 or S3), we ran the hexapod robot at each surface ten times. For each run, the power consumption \( P \) and average speed \( v_{\text{avg}} \) were obtained. The average specific resistances \( \varepsilon_{\text{avg}} \) with their standard deviations are shown in TABLE I. Low \( \varepsilon_{\text{avg}} \) corresponds to more energy efficient walking.

One can see that the high stiffness setup S3 allows more energy efficient locomotion (see TABLE I) on loose surfaces (i.e., fine and coarse gravels, snow). This is because S3 enables the hexapod robot to obtain more foot contact force (e.g., see Fig. 11 (c)) on these surfaces owing to stiffer CTr and FTi joints (e.g., see Figs. 2 (d) and (e)). Whereas the low stiffness setup S2 results in more force (e.g., see Fig. 12 (c)) on flat (e.g., floor), very coarse (e.g., gravels), and elastic (e.g., sponge) surfaces. Therefore, S2 leads to more energy efficient locomotion on these surfaces due to softer legs (e.g., see joint stiffness in Figs. 12 (d) and (e)). Interestingly, this experimental result shows that soft legs allow the hexapod robot to achieve more energy-efficient locomotion on a soft elastic surface (e.g., sponge). The finding complies with a finding of physiological experiments on cockroach locomotion [47, 12]. Owing to energy efficiency, cockroaches also use their soft legs on soft elastic surfaces.

In addition, the neuromechanical controller leads to more energy-efficient AMOS walking over three surfaces, compared to an adaptive neural controller [11] (see TABLE II). For example, the specific resistance of walking on the fine gravel surface using the adaptive neural controller is 55.5 while the specific resistance can be reduced to 9.1 when the neuromechanical controller with the high stiffness setup (i.e., S3) was employed. This is because the neuromechanical controller stifens and enables AMOS legs to penetrate deeply into the surface; thereby gaining more foot contact force for propelling the body forwards. Whereas the adaptive neural controller cannot drive the legs to penetrate deeply into the surfaces due to the lack of stiffening them. Note that both controllers use the same modular neural network (see Fig. 3) and control input for gait generation (i.e., \( S = 0.04 \), see Fig. 4). They were also tested on the same hexapod robot (i.e., AMOS).

### 4.3. Surface classifications

Among the four stiffness setups, S3 is better for the hexapod robot to achieve energy efficient locomotion over fine and coarse gravels. With S3, we ran the hexapod robot from fine gravel to coarse gravel. The CTr and FTi joint signals (i.e., \( O_{\text{CTr}} \), \( O_{\text{FTi}} \)) at various positions are shown in Fig. 11. Note that both controllers use the same modular neural network (see Fig. 3) and control input for gait generation (i.e., \( S = 0.04 \), see Fig. 4). They were also tested on the same hexapod robot (i.e., AMOS).

<table>
<thead>
<tr>
<th>Surface</th>
<th>Average Specific Resistance</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fine gravel</td>
<td>9.1 ± 0.4</td>
<td>18.1 ± 0.7</td>
</tr>
<tr>
<td>Coarse gravel</td>
<td>25.0 ± 0.6</td>
<td>16.9 ± 0.7</td>
</tr>
<tr>
<td>Very coarse gravel</td>
<td>23.6 ± 0.5</td>
<td>14.0 ± 0.4</td>
</tr>
<tr>
<td>Floor</td>
<td>22.7 ± 0.5</td>
<td>20.7 ± 1.1</td>
</tr>
<tr>
<td>Snow</td>
<td>18.8 ± 0.5</td>
<td>21.8 ± 0.9</td>
</tr>
<tr>
<td>Sponge</td>
<td>18.8 ± 0.5</td>
<td>21.8 ± 0.9</td>
</tr>
</tbody>
</table>

Figure 10: Analog signals of foot force with stiffness setups S1 and S4. The signals were sensed when the hexapod robot walked on final gravel and sponge surfaces.

Figure 11: Joint outputs, foot force signals, and joint stiffness that resulted from two stiffness setups S2, S3 during walking on fine gravel. (a) CTr joint outputs \( O_{\text{CTr}} \). (b) FTi joint outputs \( O_{\text{FTi}} \). (c) Analog signals of forces \( F_{\text{CT}} \). The setup S3 enables the hexapod robot to obtain more foot contact force during stance phases than the setup S2. (d) CTr joint stiffness \( Y_{\text{CTr}} \). (e) FTi joint stiffness \( Y_{\text{FTi}} \). The joint stiffness \( Y_{\text{CTr}} \) and \( Y_{\text{FTi}} \) are calculated by Eq. (13). The setup S3 makes the legs stiffer than the setup S2.
and $O_{13}$ of its right front leg are shown in Fig. 13. One can see that the hexapod robot can autonomously adapt its CTr and FTi joint motions during walking on the surfaces. Other different FTi joint signals can be seen in Fig. 14 when the hexapod robot walked on sponge and snow. Therefore, the FTi joint signals can be seen in Fig. 14 when the hexapod robot walked from fine gravel ($\varphi = 5$-$8$ mm) to coarse gravel ($\varphi = 16$-$25$ mm).

We ran the hexapod robot on six different surfaces, respectively. Six FTi outputs (i.e., $O_{13}$) of the right front leg were obtained as order datum streams $FT_i(t)$ and used as the inputs of the cumulative moving averages (CMA). The CMA outputs are calculated by Eq. (15). The deviations $DEV_j$ between $CA(t)$ and $CA_j(t)$ are given by:

$$DEV_j = \sum_{i=0}^{14} |CA(t) - CA_j(t)|, \quad j = 1, 2, \ldots, 6,$$

$$SC = \min(DEV_j), \quad \text{when } h = j. \quad (16)$$
of the classification for the run \((h \in \mathbb{Z}_{[1,6]})\). \(h\) is set to 1 – 6 denoting fine gravel, coarse gravel, very coarse gravel, floor, snow, and sponge surfaces, respectively. For example, if \(SC\) is \(DEV_2\) (i.e., \(h = 2\)), the result of the surface classification is coarse gravel.

The experimental statistics (i.e., the numbers of correct and wrong classifications) of the surface classifications is shown in TABLE III. One can see that eight of nine runs are classified correctly for fine gravel and coarse gravel surfaces. Thus, the success rates of classifying fine gravel and coarse gravel surfaces are 89%. The success rate (SR) is used to evaluate the performance of surface classifications, which is the ratio of the number of correctly classifying a given surface and the total number of classifications on this surface. SR = 100% is found for the classifications of very coarse gravel, floor, snow and sponge surfaces (see TABLE III). We emphasize that the ability of well terrain classification presented here is due to the exploitation of compliance signals generated by the VAAMs. Here, the signals are determined by the motions of the FTi joints. From this point of view, the VAAMs are one of key components enabling the hexapod robot to well classify some types of surfaces where the robot moves. Note that the key components include force sensing, the VAAMs, and the cumulative moving average algorithm.

### 5. Discussion

Here, we briefly discuss some aspects of neuromechanical control for legged locomotion, since most of the relevant discussions have been provided in above sections. The motivations and benefits of neuromechanical control are in detailed described in [48, 1, 8, 2] compared to pure neural control or mechanical control (e.g., compliance control). Many neuromechanical controllers have been developed for different types of locomotion, e.g., salamander-like trotting [3, 49], lamprey-like swimming [4, 50] and insect-like walking [5, 51]. However, rather than physical robot implementations, most of them are only presented by computer simulations owing to their complexities. For instance, a neuromechanical model of insect locomotion uses 264 ordinary differential equations (ODEs) for describing its central pattern generator, muscles actuating jointed legs, and joint torque feedback to motoneurons [52]. By using phase reduction and average theory, the model is reduced to 24 one-dimensional phase oscillators activating agonist-antagonist muscle pairs shown in later works [5, 53]. However for the muscles, there are up to 26 parameters to be tuned in the model, which is impractical for applying it to physical legged robots. Different from this, agonist-antagonist muscles can be physically implemented by artificial muscles (e.g., fluidic muscles) [54, 55]. For instance, some insect-like robots use McKibben fluidic muscles as their actuators, e.g., AirBug (weight 27.2 kg) [56] and Robot V (Ajax) (weight 15.1 kg) [57]. But these artificial muscles make the mechanical structures of legged robots more complex and bulky, therefore rarely presenting their use in small legged robots (weight less than 8 kg) [21]. Whereas the virtual agonist-antagonist mechanism introduced here is a muscle model with only two tunable parameters. It can be easily applied to generate variable compliant leg motions of small legged robots. These applications do not require force/torque sensing at each joint or physical compliant components (e.g., springs or artificial muscles). The proposed neuromechanical controller is based on biological findings [13, 47, 12] and can improve the energy efficiency of a hexapod robot. The specific resistances of the robot during walking on different surfaces are between 9.1 and 25.0 (i.e., \(\varepsilon = 9.1-25.0\)) (see TABLE I). On surfaces, like fine gravel, coarse gravel, and floor, the specific resistances are less than the ones obtained from walking driven by the adaptive neural controller (see TABLE II). As a comparison, the specific resistance of the RHex robot (i.e., a hexapod robot) is between 2 and 14 [7] when it ran
on different surfaces (i.e., gravels). Considering that the RHHex robot has only one degree of freedom (DOF) for each leg (totally six motors), our robot consisting of three DOFs for each leg (totally 18 motors) consumes more energy. However thanks to the three DOFs for each leg, our robot can reproduce insect-like leg movements, and its legs can be extended for climbing [58] as well as allow for omnidirectional walking including sideways walking [34].

Taken together our main contributions here which is an extension of our previous work [9] include: 1) the experimental part dealing with in more details of parameter setups (stiffness coefficients $K(1, 2)$, see section 4.1) which can be applied to other legged robots, 2) the new walking experiments on six challenging surfaces (see section 4.2), and 3) the exploitation of compliance signals generated by the VAAMs for surface classifications (see section 4.3).

6. CONCLUSIONS

We developed a neuromechanical controller that allows for variable compliant leg motions of a hexapod robot, thereby leading to its adaptable and energy-efficient walking on six challenging surfaces. The controller consists of a modular neural network (MNN) and virtual agonist-antagonist mechanisms (VAAMs, i.e., a muscle model). The main features of the neuromechanical controller are as follows: (I) It allows the hexapod robot to easily achieve variable leg compliance by only changing the stiffness parameters of the VAAMs. The implementation does not require any passive mechanisms or torque and position feedback; (II) The VAAMs also enable the hexapod robot to classify six different surfaces with high success rates; (III) It presents a control strategy on the three-jointed leg of the hexapod robot which also agrees to the principles found in the biological study on three-jointed leg locomotion [41, 42]. In future work, the surface classification will be used for the hexapod robot to autonomously change its leg compliance with respect to a surface. Moreover, we will also apply a learning mechanism for the adaptation of muscle parameters on different surfaces.

7. Acknowledgment

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Appendix A. Neuromechanical control of the legs

Appendix A.1. Swing phase

When a leg is in a swing phase (i.e., $f_{lu}^\text{sw} = 0$, $i \in \mathbb{Z}[1, 6]$, see Fig. 6 (a)), outputs $O_{i(j+6)}$ for its TC, CTr and FTi joints receive the outputs of the motor neurons $N_{i(j+6)}$ as their inputs.

$$O_{1-6} = \frac{N_{1-6} - (-0.81)}{0.91 - (-0.81)}(0.32 - (-0.37)) - 0.37$$

$$\approx 0.4N_{1-6} - 0.05. \quad (A.1)$$

Appendix A.1.2. CTr joints

The CTr neuron outputs $N_{7-12} \in [-1, 0, 1, 0]$ are scaled into the CTr outputs $O_{7-12} \in [0.71, 1.0]$:

$$O_{7-12} = \frac{N_{7-12} - (-1.0)}{1.0 - (-1.0)}(0.71) + 0.71$$

$$\approx 0.15N_{7-12} + 0.86. \quad (A.2)$$

Appendix A.1.3. FTi joints

The FTi neuron outputs $N_{13-18} \in [-0.9, 1.0]$ are scaled into the FTi outputs $O_{13-18} \in [-0.41, -0.45]$:

$$O_{13-18} = \frac{N_{13-18} - (-0.9)}{1.0 - (-0.9)}((-0.45) - (-0.41)) - 0.41$$

$$\approx -0.02N_{13-18} - 0.43. \quad (A.3)$$

Appendix A.2. Stance phase

Appendix A.2.1. TC joints

All TC joints are purely controlled by $CE_{(1,2)}$ of the VAAM. $CE_{(1,2)}$ are activated by the outputs $N_{1-6}$ of the modular neural network. The TC neuron outputs $T_{j,l}$ are scaled into the TC outputs $O_{j} \in [-0.37, 0.32]$ (see Fig. 8 (a), $j \in \mathbb{Z}[1, 6]$):

$$O_{j} = \frac{T_{j,l} - (-0.81)}{0.91 - (-0.81)}(0.32 - (-0.37)) - 0.37$$

$$\approx 0.4T_{j,l} - 0.05. \quad (A.4)$$

Appendix A.2.2. CTr joints

Each CTr joint is driven by $PE_{(1,2)}$ and $CE_{(1,2)}$ of the VAAM. $CE_{(1,2)}$ are activated by one of the outputs $N_{7-12}$ of the modular neural network (see Fig. 8 (a)). The angles $\theta_{2m,1}$ ($m \in \mathbb{Z}[1, 6]$) of the CTr joints are linearly transformed into their outputs $O_{j}$ (see Fig. 6). $O_{j}$ are given by ($j \in \mathbb{Z}[7,12]$):

$$O_{j} = \begin{cases} \theta_{j,6} - 0.785 & -1.745 - 0.785(1 - (-1)) - 1 \\ \approx -0.8\theta_{j,6} - 0.38 \end{cases} \quad (A.5)$$
Appendix A.2.3. FTi joints

Each FTi joint is only driven by $PE_{(1,2)}$ of the VAAAM (see Fig. 8 (a)). The angles $\theta_{1,m,1}$ ($m \in \mathbb{Z}_{(1,6)}$) of the FTi joints can be linearly transformed into their outputs $O_j$ (see Fig. 6). $O_j$ are given by ($j \in \mathbb{Z}_{(13,18)}$):

$$O_j = \theta_{j,-1,2} - \left(\left(-1.22\right) \times \left(1 - (-1)\right) - 1\right) \approx 0.920 \theta_{j,-1,2} + 0.12. \quad (A.6)$$

Appendix B. Notations

- $F_{6 \times 1}^f$ is the matrix of the forces, i.e., $F_{6 \times 1}^f = [f_1^f, f_2^f, \ldots, f_6^f]^T$;
- $F_{6 \times 1}^i$ is the Hadamard product of $F_{6 \times 1}^f$ and $\sin(\theta_{6 \times 1})$;
- $L_1$ is the length of the link between the FTi joint and the end effector of the leg, e.g., $L_1 = 0.115$ m;
- $I$ is the inertia of the FTi and CTr joints, i.e., $I = 0.5 \times 10^{-3}$ kg m$^2$;
- $\dot{\theta}_{6 \times 1}$ and $\theta_{6 \times 1}$ are the acceleration and velocity matrices of $\theta_{6 \times 1}$, $r$ is set to 0.1;
- $K(1.2)_{6 \times 1}$ and $D(1.2)_{6 \times 1}$ are matrices of the stiffness and damper coefficients of $PE_{(1,2)}$, which control the compliance of the FTi and CTr joints;
- $L_2$ is the length of links between the CTr and FTi joints, i.e., $L_2 = 0.075$ m;
- $\dot{V}_{6 \times 1}$ and $V_{6 \times 1}$ are matrices of the displacement vectors of the CTr and FTi joints relating to the forces $f_{1 \times 6}^f$;
- $\dot{\theta}_{6 \times 1}$ and $\theta_{6 \times 1}$ are the acceleration and velocity matrices of $\theta_{6 \times 1}$;
- $C_{6 \times 1}$ is the matrix of the CTr neuron outputs of the MNN, i.e., $C_{6 \times 1} = [N_7, N_8, \ldots, N_{12}]^T$.

[27] F. Bermeudez, R. Julian, D. Haldane, P. Abbeel, R. Fearing, Performance analysis and terrain classification for a legged robot over rough terrain,


