Autonomous speed adaptation by a muscle-driven hind leg robot modeled on a cat without intervention from brain

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Abstract
This study aims to design a nervous system model to drive the realistic muscle-driven legs for the locomotion of a quadruped robot. We evaluate our proposed nervous system model with a hind leg simulated model and robot. We apply a two-level central pattern generator for each leg, which generates locomotion rhythms and reproduces cat-like leg trajectories by driving different sets of the muscles at any timing during one cycle of moving the leg. The central pattern generator receives sensory feedback from leg loading. A cat simulated model and a robot with two hind legs, each with three joints driven by six muscle models, are controlled by our nervous system model. Even though their hind legs are forced backward at a wide range of speeds, they can adapt to the speed variation by autonomously adjusting its stride and cyclic duration without changing any parameters or receiving any descending inputs. In addition to the autonomous speed adaptation, the cat hind leg robot switched from a trot-like gait to a gallop-like gait while speeding up. These features can be observed in existing animal locomotion tests. These results demonstrate that our nervous system is useful as a valid and practical legged locomotion controller.

Keywords
Cat-like muscle-driven hind leg robot, walking and running, autonomous speed adaptation, two-level central pattern generators

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Introduction
Neural circuits called central pattern generators (CPGs) exist in the spinal cord of animals.1,2 The CPG receives a tonic descending signal from the brain and then generates rhythmic motor activity for locomotion. Biology researchers tested animal locomotion using mesencephalic (decerebrate) cats,3,4 in which the stimulation of the mesencephalic locomotor region of the midbrain could induce locomotion on a treadmill, demonstrating the existence of the CPG. Another example is a spinal cat; when all the descending pathways from the brain were removed, the cat could not walk, but an injection of dihydroxyphenylalanine administered to the cat stimulated the descending fibers to activate spinal neurons and allowed the cat to walk on a treadmill.5 Similar experiments have been conducted on dogs and

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mice. Based on the findings, a spinal network of neurons plays a pivotal role in generating the rhythm and leg trajectory for legged locomotion.

For the mesencephalic cat, the walking speed increased when the stimulation of the descending pathway to CPG was strengthened. Interestingly, it was also reported that while the strength of the descending input was kept constant, only the variation of the speed of the treadmill allowed the hind limbs of the mesencephalic cat to walk by autonomously adapting to the treadmill speed. In the experiment, the cyclic duration of locomotion increased as the treadmill speed decreased. Similarly, spinal cats started walking when the treadmill belt was moved and continued walking according to the treadmill speed. Although the detailed mechanisms of those speed adaptations are not clear, we can assume that an animal is capable of autonomously adapting to the external speed variation without intervention from its brain by depending on the effects of sensory feedback from its legs. The change in the internal states of the CPG in those adaptive locomotions, in which the legs are forcibly moved by external force from the treadmill, should be different from that in the speed adaptation evoked by an increase in the descending signal to the CPG.

We proposed a two-level CPG model to drive a single leg with three joints in our previous simulation work. The CPG consisted of a rhythm generation (RG) part to generate basic locomotion rhythms and a pattern formation (PF) part to synergistically activate a different set of muscles in each of the four sequential phases (swing, touchdown, stance, and liftoff). There were motoneurons (Mn) under the PF part to activate the corresponding muscle according to the driving signal from the PF neurons. A measured leg load was fed back to the leg’s CPG. We applied the realistic CPG-based spinal neuron model to a simulated muscle-driven quadruped model modeled on a cat and demonstrated stable dynamic walking in the simulation. In the article, we changed its speed by adjusting the descending tonic input to the CPG, as observed in mesencephalic cats.

In our present study, we built a hind leg simulated model and robot based on the biological experiments of the mesencephalic and spinal cats. We demonstrated whether our previously proposed CPG without intervention from brains (without changing any parameter, not even the descending signal to CPG) could autonomously adapt to external speed variations by autonomously adjusting the rhythm and trajectory of the legs through sensory feedback to the CPG. Based on the results, we evaluated the validity and practicality of our neural model as a bioinspired locomotion controller. Our goal is to develop a locomotion controller for a realistic quadruped robot driven by artificial muscle actuators.

First, we built a hind leg model modeled on a cat in simulation. Each leg has three rotary joints around the pitch axis driven by six muscle models, including two two-joint muscles. The torso with the two hind legs was towed by two active wheels in front, and the cat hind leg model was forced to be pulled at an arbitrary speed. This simulation reproduced the experimental environment of a mesencephalic and spinal cat with their hind legs forcibly pulled backward on a driving treadmill. As we gradually increased the speed of the wheels by 0.85 m/s, the hind leg model was capable of continuing walking by autonomously adjusting its cyclic duration and stride in wide ranges, despite all the fixed parameters, including the descending input to the CPG. We did not observe functional breakdown in the CPG, such as divergence, convergence, or halt of the neural output because it was appropriately adjusted through leg loading feedback.

Next, we implemented our controller on a cat hind leg robot. Each leg of the robot was equipped with six pneumatic artificial muscles that drive three-leg rotary joints around the pitch axis, similar to the simulation. The front body was supported such that the body did not move on the treadmill, similar to the experiments of mesencephalic and spinal cats, and the hind legs were put on the treadmill. While the treadmill was speeding up, the robot walked at a speed of up to 0.8 m/s and then ran at a speed of up to 2.5 m/s, without changing any parameters. Moreover, we observed a gait transition, in which the phase difference between the left and right legs was out of phase while walking and nearly in phase while running, such as galloping.

The simulation and robotic results were similar to the autonomous adaptation to the treadmill speed observed in mesencephalic and spinal cats, suggesting that our proposed nervous system is valid.

Several other studies have also focused on a realistic neuromorphic CPG to reproduce the realistic movement of musculoskeletal legs of an animal model. Hunt et al. developed a hind leg robot modeled on a dog. Each leg joint was controlled by the corresponding single-level CPG and was driven by an antagonistic pair of artificial muscle actuators. The robot did not have two-joint muscles, which helps fast and energy-efficient locomotion. The robot succeeded in reproducing realistic walking on a treadmill. They also used the same method for a rat simulation model’s hind leg walking and extended the single-level CPG model to a two-level CPG. This enabled the rat hind leg model to walk with a more realistic leg trajectory by synergistic joint activation. Maufray et al. demonstrated the walking of cat hind legs in simulation. Each leg had three joints synaestically driven by seven muscle models. They used a two-level CPG consisting of the neural phase generator proposed by Wadden and Ekeberg and a motor output shaping stage as the RG and PF parts, respectively. However, their model was very complex with a large number of neurons, suggesting that parameter tuning for a real robot would be difficult. They also succeeded in the forelegs walking, using the same method. The most similar two-level CPG to our approach is Markin et al.’s model in which each CPG controlled three joints driven by nine muscle models for each leg, allowing simulated cat hind
legs to walk. Their two-level CPG was extended from their previous model proposed by Markin et al., which drove a single-joint limb. However, their model also seems too complex to use for a robot’s locomotion controller because their aim was to develop a testbed to study spinal control of locomotion from a physiological aspect, unlike ours. All of these realistic animal models and robots performed well, but none of the related works and other animal locomotion models and robots with simplified CPG models focused on autonomous adaptation to external speed variation.

We achieved the reproduction of the autonomous speed adaptation observed in the biological tests on our simulated model and robot with the previously proposed neural controller and the implementation of the controller on the robot. Therefore, the controller could be used for prospective bioinspired quadruped robots driven by artificial muscle actuators. In addition, since the mechanism of the speed adaptation is still not clear in biology, our achievement may help reveal the principle of the function in an animal.

**Methods**

**Simulated cat hind leg model**

We built a cat model towing its hind legs in the robot simulator called Webots, as shown in Figure 1(a). It weighs 10 kg in total. The torso is a rigid body. The two active wheels replace its forelegs and pull the hind legs, reproducing the experiment where the hind legs of the mesencephalic and spinal cats were pulled backward by the treadmill. We used this particular configuration in the simulation due to difficulties implementing treadmill motion in the simulator. The torso can tilt around the passive pitch joint on the axle shaft of the front wheels, allowing the hip position to rise and fall freely. If the hind legs then do not keep up with the speed of the wheels, the hip lowers and the hind legs are dragged, and the locomotion fails.

We briefly review the mechanism of each hind leg, which is the same as in our previous cat-simulated model. Each hind leg has the hip, knee, and ankle joints around the pitch axis, and these joints are driven by six representative muscles, including two two-joint muscles. The muscle placement in each hind leg is shown in Figure 1(b). The lengths of the leg segments and the position of the muscle attachments were modeled on a cat as in Reighard and Jennings and Krouchev et al., respectively.

We used a muscle model proposed by Brown et al.. The output force to each muscle is defined as follows

\[
F = F_{\text{max}} \cdot (\lambda \cdot f(V) \cdot F_l \cdot F_v + F_p) \quad [N]
\]

where \(F_{\text{max}}\) is the maximal isotonic force, \(\lambda\) is a gain, \(f(V)\) is the corresponding motoneuron’s activity (see equations (2)–(5)), \(F_l\) and \(F_v\) are length- and velocity-dependent forces, respectively, and \(F_p\) is a passive force. The equations of the three force components are shown in our previous article.

**Cat hind leg robot**

To demonstrate that the autonomous speed adaptation observed in the simulation can be achieved even in a cat hind leg robot and that our proposed controller can be installed in a real robot in practice, we built a cat hind leg robot that locomoted on a treadmill, as shown in Figure 2. It is 480 mm long and 420 mm wide and weighs 3.0 kg. The robot’s configuration is similar to that in the simulated model. The torso can tilt around the passive pitch joint put in the front edge of the torso, allowing the legs to be dragged when the robot cannot keep up with the treadmill speed. This constraint leads to similar effects to the stepping experiments by the hind legs of the mesencephalic and spinal cats, in which their front bodies were suspended and the movement was limited to the sagittal plane.
Similar to the simulated model (Figure 1(b)), each leg has three joints and six pneumatic artificial muscles (two two-joint muscles and four single-joint muscles). Each actuator is a McKibben-type pneumatic artificial muscle manufactured by Kanda Tsushin Kogyo Co., Ltd., Tokyo, Japan, which has similar features to that of an actual muscle. All the muscles have a maximum tension of 800 N and a maximum shrinkage factor of 34%. The relaxed muscle length is 140 mm for the hip and ankle flexors, 175 mm for the hip and knee extensors, and 180 mm for each two-joint muscle. An air compressor (TFP37C-10 by ANEST IWATA, 3176 Shinyoshida-cho, Kohoku-ku, Yokohama, Japan) supplies a constant 0.4 MPa of compressed air. The artificial muscle contracts when the compressed air is supplied and relaxes when air is released. In addition, the muscle works as a tension spring while the air is trapped in it. These air circulations are controlled by electromagnetic valves. Each muscle has 3-port and 2-port air ON/OFF solenoid valves (VZ412-5MZ and VX230AA by SMC Corporation, Tokyo, Japan) for inputting compressed air (inputting time) and releasing trapped air (releasing time), respectively. We used 24 valves in total.

Air from the compressor is decompressed and supplied to the muscles by adjusting the inputting to releasing time ratio. The ratio represents the motoneuron’s activity \( f(V) \) every 50 ms, considering the response time of the solenoid valves. For example, if \( f(V) = 0.48 \) (60% of the estimated maximum activity \( f(V) = 0.8 \)), the compressed air is inputted for 30 ms (60% of 50 ms), and the trapped air is naturally released for 20 ms (40% of 50 ms). As trapped air is not fully released during this short period, rough air pressure control is achieved by controlling the valves’ motion timing. When \( f(V) = 0.8 \) (100%), each pneumatic muscle can produce approximately 350 N from 20% extension.

Although it is difficult to control air pressure as precisely as an animal controls its muscular force, we demonstrate that our robot can support its body and reproduce its leg trajectory for locomotion.

Each joint has an optical rotary encoder (HEDS-5500#A11 by Avago Technologies Japan, Ltd., Tokyo, Japan) to detect its angle. We estimate the force (leg load) applied to the knee and ankle’s two-joint muscle when it is extended in the stance phase (see the “Leg loading feedback” section for details). As this force is also exerted in the swing phase, we use two additional force sensors (FlexiForce A201-100 by NITTA Corporation, 4-4-26 Sakuragawa, Naniwa-ku, Osaka, Japan) on the bottom of each foot to determine if it is touching the ground. An inclinometer and a rate gyro are mounted on the torso to detect its body tilt for evaluation. We use a robot control board (HRP-3P-CN & MCN by General Robotics Inc., 1-1-1 Umezono, Tsukuba-shi, Ibaraki, Japan). The robot is controlled through an online system with a sampling time of 2 ms. The robot is tethered to an air compressor for the muscle actuators and a power supply, which are external to the robot.

**Neural system**

We used our previously proposed two-level CPG model for our present cat hind leg simulated model and robot with the exception of the Inab neuron to implement a stretch reflex. Since the stretch reflex had mainly worked to ensure walking stability in the lateral plane in our previous study, it was not needed for planar locomotion in this article. The equations of each neuron model used in the two-level CPG model (equations (2)–(5)) are briefly reviewed in the “Basic design of two-level CPG model” section. We describe the leg loading feedback in the “Leg loading feedback” section. The
previously applied equation (equation (6)) was used for our present simulation. The parameter values in equations (2)–(6) were heuristically determined again to ensure our simulated model and robot could adapt to a wide range of speeds in a stable manner. New equations (7) and (8) were used for our robot as leg loading feedback. We detail these in the “Leg loading feedback” section.

**Basic design of two-level CPG model.** Figure 3 shows the detailed diagram of our two-level CPG for each leg. The CPG is divided into two layers: the RG part that produces basic locomotion rhythms and the PF part that synergistically activates a different set of muscles in each of the four sequential phases (swing, touchdown, stance, and liftoff). The signals from the CPG are sent to motoneurons (Mn) to drive the corresponding muscles. The RG part consists of a flexor neuron (RG-F) and an extensor neuron (RG-E). They mutually inhibit each other through an interneuron (In) and alternate activation, creating a rhythmic motion. The PF part has four PF neurons, namely PFsw, PFtd, PFst, and PFlo, to make the phase patterns of swing, touchdown, stance, and liftoff, respectively, which comprise the basic locomotion cycle of an animal. The four PF neurons are sequentially reproduced like a cat. The output from each Mn is sent to equation (1) as \( f(V) \) to activate the corresponding muscle.

The membrane potential of the main neurons in the RG and PF parts and the six motoneurons (i.e. RG-F, RG-E,
PF_{sw, td, at, lo} and Mn{1, 2, . . . , 6} in Figure 3) is expressed as follows

$$C \cdot \frac{dV}{dt} = -I_{NaP} - I_K - I_{Leak} - I_{SynE} - I_{SynI}$$

and the membrane potential of the interneurons (In in Figure 3) is expressed as follows

$$C \cdot \frac{dV}{dt} = -I_{Leak} - I_{SynE} - I_{SynI}$$

where $C$ is a neuronal capacitance, $V$ is the average membrane voltage of the neuron, $I_{NaP}$, $I_K$, and $I_{Leak}$ are persistent sodium, potassium rectifier, and leakage currents, respectively, and $I_{SynE}$ and $I_{SynI}$ are excitatory and inhibitory synaptic currents, respectively. $I_{NaP}$ and $I_K$ are eliminated from equation (3) for simplicity, similar to Rybak’s CPG model.17

The currents are expressed as follows

$I_{NaP} = \theta_{NaP} \cdot m_{NaP} \cdot h_{NaP} \cdot (V - E_{Na})$

$I_K = \theta_K \cdot m_{K}^4 \cdot (V - E_K)$

$I_{Leak} = \theta_{Leak} \cdot (V - E_{Leak})$

$I_{SynE,i} = g_{SynE} \cdot (V_i - E_{SynE}) \cdot (\sum_j a_{ji} \cdot f(V_j) + c_i \cdot d)$

$I_{SynI,i} = g_{SynI} \cdot (V_i - E_{SynI}) \cdot (\sum_j b_{ji} \cdot f(V_j) + w_i \cdot feedback + \sum k \alpha_{kj} \cdot f(V_k))$

where $g_{[NaP, K, Leak, SynE, SynI]}$ are the maximal conductances of the corresponding ionic channels, $E_{[Na, K, Leak, SynE, SynI]}$ are the corresponding reversal potentials, leg loading feedback is input to feedback, as described in the “Leg loading feedback” section. $a_{ji}$ is the gain of the excitatory synaptic input from neuron $j$ to neuron $i$, $b_{ji}$ is the gain of the inhibitory input from neuron $j$ to neuron $i$, $c_i$ is the gain of the tonic descending signal $d$ to neuron $i$, and $w_i$ is a feedback gain. As mentioned above, $I_{SynE,i}$ does not have feedback for the stretch reflex, which was included in the previous model.9 Here, $\sum a_{ji} \cdot f(V_k)$ represents the mutual inhibitory connections of the RG neurons between the legs, such as in Figure 4. This basically allows the two legs to swing out of phase, as observed in walking and trotting gaits, but there is a chance that the phase difference is adjusted through leg loading feedback according to speeds. The voltage-dependent activation variables for the potassium delayed rectifier $m_K$, persistent sodium channels $m_{NaP}$, and the voltage-dependent inactivation variables $h_{NaP}$ are described in our previous article.9 The average population activity $f(V_j)$ is an output from neuron $j$ and is expressed as follows

$$f(V) = \begin{cases} 1/(1 + \exp(-(V - V_{1/2})/k)) & \text{if } V \geq V_{th} \\ 0 & \text{otherwise} \end{cases}$$

where $V_{1/2}$ is a half-activation voltage, $k$ is a sigmoid gain, and $V_{th}$ is the threshold of each neuron.

**Leg loading feedback.** Sensory feedback is vital for the hind legs to autonomously adapt to external speed variation without changing the descending input to the CPG or the CPG parameters. Biological findings have reported sensory feedback to the CPG (e.g. the lengths of the extensor and flexor around a hip joint and that of an ankle joint flexor,39 load from the Golgi tendon organ in an ankle joint extensor,40 and load from load-sensitive cutaneous afferents in the paw pad41). We focused on leg loading feedback, which is reported to be most important to support the body and to reset the rhythm.40,42 We decided to input a leg load to the RG flexor neuron to make it inhibited, as shown in Figure 3, based on Pearson’s findings,40,43 in a realistic way. The feedback inhibits the activation of the RG flexor neuron during the stance phase, resulting in the extension of the stance duration. Further, an unloaded leg can be quickly led to the swing phase.

In our simulated model, the leg loading feedback was defined as follows

$$feedback = k_{load} \cdot F_{load}$$

where $F_{load}$ is the load of each leg measured by a force sensor on its paw and $k_{load}$ is a gain. This equation is input to feedback in equation (4) only for the RG-F neuron.

We estimate the force applied to the knee and ankle’s two-joint muscle actuator, which covers an ankle joint extensor, when it is extended in the stance phase. This is input into the CPG as leg loading feedback because the force applied to the ankle joint extensor is often regarded as the leg load in locomotion experiments on decerebrate cats.40 Before the foot touches the ground during
In walking at a speed of 0.45 m/s, but the model with leg loading feedback failed towing and gradually accelerated the body. Consequently, we prepared a simulated model and robot with and without leg loading feedback successfully achieved walking at speeds of up to 0.85 m/s (see Supplementary Movie 1). In the robot experiments, we gradually accelerated the treadmill. As a result, the robot without leg loading feedback failed walking at a speed of 0.46 m/s, whereas the robot with it walked at a speed ranging 0–0.8 m/s and ran at a speed ranging 0.8–2.5 m/s (see Supplementary Movie 2).

In the following sections, we evaluate these results by observing the walking cyclic duration (see the “Evaluation of autonomous adaptation to speed variation based on cyclic duration” section) and stride (see the “Evaluation of autonomous adaptation to speed variation based on stride” section), which are generally used to evaluate locomotion and compared these with results for real cats.

**Results**

We tested if the cat hind leg model and robot could autonomously adapt to a wide range of speed, similar to mesencephalic and spinal cats. We kept all the neural and muscle parameters, including the tonic descending input to the CPG, fixed in the simulations and robot experiments. We prepared a simulated model and robot with and without leg loading feedback for comparison.

In the simulation, the front active wheels (Figure 1) towed and gradually accelerated the body. Consequently, the cat hind leg model without leg loading feedback failed in walking at a speed of 0.45 m/s, but the model with leg loading feedback achieved walking at speeds up to 0.85 m/s. In contrast, the robot without leg loading feedback did not achieve walking at speeds above 0.46 m/s, whereas the robot with leg loading feedback achieved walking at speeds ranging 0–0.8 m/s and ran at speeds ranging 0.8–2.5 m/s.

**Evaluation of autonomous adaptation to speed variation based on cyclic duration**

Figure 6(a) to (c) shows the results of the simulation, the robot experiment, and a cat experiment,

**Evaluation of autonomous adaptation to speed variation based on stride**

Figure 7 shows the stride and foot position at each speed in (a) the cat hind leg simulated model, (b) the cat hind leg robot, and (c) a real cat. In each graph, the red, orange, and green

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**Figure 5.** Force against extension of the knee and ankle's two-joint muscle actuator from the shortest length of 119 mm, measured in static conditions.
dots show stride, horizontal toe position with respect to the hip at touchdown, and that at liftoff, respectively. The transparent blue areas show the same ranges.

**Figure 6.** Swing, stance, and cyclic durations with speed during autonomous speed adaptation. Swing (light blue dots), stance (red dots), and cyclic (green dots) durations at each speed in (a) the cat hind leg simulated model, (b) the cat hind leg robot, and (c) a real cat. The transparent yellow and red areas show the same ranges.

Similar to Figure 6(a) and (b), the locomotion was irregular at very low speeds (before the transparent blue areas), but during the transparent blue area, the simulated model (Figure 7(a)) and robot (Figure 7(b)) demonstrated similar aspects to the real cat (Figure 7(c)). Specifically, the strides (red dots) were extended as the speed was increased. In particular, the toe positions at liftoff (green dots) were pulled more backward than the toe positions at touchdown (orange dots).

The robot was able to adapt to higher speeds than the simulated model because the stride and foot positions in Figure 7 were reset at the end of the transparent blue area when the locomotion switched from walking to running.

**Theory of autonomous speed adaptation**

The autonomous speed adaptation, explained in the “Evaluation of autonomous adaptation to speed variation...
based on cyclic duration" section and the “Evaluation of autonomous adaptation to speed variation based on stride” section, is a result of the CPG autonomously adjusting RG-F neuron activation through leg loading feedback (“Leg loading feedback” section).

Figure 8 shows the RG-F output, hip joint angle, and left hind leg load when the robot was running at 1 m/s. In the first half of the stance phase, a large load is presented on each leg, as shown in (a) of Figure 8. This delays the swing phase by inhibiting the RG-F neurons to maintain the stance period, providing leg support for the body. Decreased leg load is presented in the stance phase’s last half (b in Figure 8) because of the leg being pulled backwards (ρ in Figure 8), leading to reduce RG-F inhibition. This results in an earlier shift to the swing phase, preventing the leg from dragging.

Even at high speeds, leg loading feedback prevented the robot from folding its posture by supporting the body in the stance phase’s first half and preventing the legs from dragging while striding (Figure 7(a) and (b)) by quickly shifting to the swing phase in the last half.

As leg loading feedback is inactive in the swing phase, it did not affect the swing duration of each speed, as shown in Figure 6(a) and (b).

As \( \text{load}_{\text{leg}} \) in equation (7) is an estimated force and not a direct measurement, the resulting leg loading feedback is not completely accurate. However, it was functional enough to autonomously adjust the cyclic period (Figure 6), stride (Figure 7), and leg trajectories (Figure 9) to adapt to various speeds in the limited experimental condition where the torso was constrained, similar to that of a cat’s testing. More precise leg load measurements may be required to autonomously adapt to speeds in unconstrained quadruped robots, while simultaneously maintaining balance.

Figure 9. Comparison of two CPG sensory feedbacks for the left hind leg joint angles when the robot is running at 1.0 m/s with (a) only leg loading feedback and (b) both leg loading and hip trigger feedback. CPG: central pattern generator.

Figure 10. Swing, stance, and cyclic durations during autonomous speed adaptation by the robot with (a) only leg loading feedback and (b) both leg loading and hip trigger feedback. Comparisons to hip trigger feedback for CPG

In sensory feedbacks for CPGs, as described in the “Leg loading feedback” section, the flexor length around a hip joint\(^{19}\) is likely to affect autonomous speed adaptation. When the flexor extends to a certain length, the leg is reset from the stance phase to swing to prevent dragging. We called this hip trigger feedback. We applied this feedback to our robot and compared its effectiveness to leg loading feedback.
Definition of hip trigger feedback. Hip trigger feedback is defined as follows

\[
\text{feedback} = \begin{cases} 
K_{\text{trigger}} & (\text{if } q_{\text{hip}} > Y_{\text{th}}) \\
0 & (\text{otherwise})
\end{cases}
\] (9)

where \( K_{\text{trigger}} \) is a constantly resetting positive stimulation, fed back to the RG-F neurons through feedback in equation (4), as based on Pearson’s findings. \( \theta_{\text{hip}} \) is the hip joint angle as shown in Figure 8. This phase resetting program promotes a transition to the swing phase when the hip joint is extended backwards past the threshold angle \( \Theta_{\text{th}} \), that is, when \( \theta_{\text{hip}} > \Theta_{\text{th}} = 1.66 \text{ rad} \). The values of \( K_{\text{trigger}} \) and \( \Theta_{\text{th}} \) were determined so that the robot could locomote as smoothly as possible at each speed.

Autonomous speed adaptation with only hip trigger feedback. We replaced the leg loading feedback (equation (8)) in the robot with hip trigger feedback (equation (9)) and conducted the same experiments as in the “Evaluation of autonomous adaptation to speed variation based on cyclic duration” section and the “Evaluation of autonomous adaptation to speed variation based on stride” section. We found that the robot was only capable of adapting to approximately 0.25 m/s – 1.0 m/s. This demonstrates that the adaptable speed range is limited with this feedback. Additionally, the locomotion lacked smoothness and consistency using this method, for example, the feet often left the ground during the stance phase and there was variation between experimental data.

Autonomous speed adaptation with hip trigger and leg loading feedback. We applied both hip joint and leg loading feedback to our robot. Figure 9 shows the angles of the three left hind leg joints, when the robot ran at 1.0 m/s with (a) only leg loading feedback and (b) both feedbacks. As shown in the figure, adding hip trigger feedback was effective in preventing the leg from being pulled excessively back (A in Figure 9(b)). However, since the stride was also restricted, the robot could only adapt up to 1.5 m/s.

Swing, stance, and cyclic durations of the robot with only leg loading feedback and with both feedbacks are shown in Figure 10(a) and (b), respectively (Figure 10(a) is the same as Figure 6(b)). Locomotion was disturbed during the walking to running transition in both cases but was stable afterwards in Figure 10(a) whereas data fluctuated in Figure 10(b), indicating instability. This was because the hip joint angle was always limited at the stance to swing transition by hip trigger feedback.

When we used greater values for the threshold angle \( \Theta_{\text{th}} \) in equation (9), hip trigger feedback rarely worked.
The adaptable maximum speed decreased with a smaller $\theta_\text{th}$. Therefore, it can be seen that hip trigger feedback decreased locomotion smoothness and the autonomous speed adaptation range.

Based on the comparative results, we suggest that leg loading feedback can be used to smooth locomotion and enhance autonomous speed adaptation rather than hip trigger feedback.

**Conclusions**

We applied our CPG-based neural controller to our hind leg simulated model and robot modeled on a cat and forced them to change their speed by the active wheels and the treadmill. We found that the cat model and robot could adapt to a wide range of speed by autonomously adjusting the cycle and stride, similar to locomotion tests by mesencephalic and spinal cats, despite all the parameters (including the tonic descending input) being fixed. In their trials, they shortened their stance periods more than their swing periods as their speed increased. In addition, their back- ward stride was larger than their forward stride. Similar resulting features can be seen in autonomous speed adaptation of mesencephalic and spinal cats.

In addition, the gait of our cat hind leg robot autonomously switched from a trot-like gait to a gallop-like gait, similar to an animal.

Our simulated hind leg model and robot achieved similar results to those in an animal, and we did not see any collapse of the CPG, such as the divergence, convergence, or halt of the CPG outputs. Although our CPG model is simpler than the comparable Markin et al.’s CPG model (as described in the “Introduction” section), we consider ours practical enough for use as a biomimetic locomotion controller for a robot, due to its autonomous speed adaptation ability as demonstrated in this article, as well as stable quadrupedal walking shown in a previous simulation.

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**Supplemental material**

Supplemental material for this article is available online.

**References**

1. Brown TG. The intrinsic factors in the act of progression in the mammal. Proc R Soc Lond B 1911; 84(572): 308–319.
2. Grillner S. Control of locomotion in bipeds, tetrapods, and fish. Compr Physiol 2011; 46: 1179–1236.
3. Shik ML, Orlovskii GN, and Severin FV. Organization of locomotor synergism. Biofizika 1966; 11(5): 879–886.
4. Orlovsky GN, Severin FV, and Shik ML. Locomotion induced by stimulation of the mesencephalon. In: Dokl. Akad. Nauk, SSSR, 1966, Vol. 169, pp. 1223–1226.
5. Forssberg H and Grillner S. The locomotion of the acute spinal cat injected with clonidine iv. Brain Res 1973; 50: 184–186.
6. Schurrager P and Dykman R. Walking spinal carnivores. J Comp Physiol Psychol 1951; 44(3): 252–262.
7. Stelzner D, Ershler W, and Weber ED. Effects of spinal transection in neonatal and weanling rats: survival of function. Exp Neurol 1975; 46(1): 156–177.
8. Weber ED and Stelzner DJ. Behavioral effects of spinal cord transection in the developing rat. Brain Res 1977; 125(2): 241–255.
9. Habu Y, Uta K, and Fukuoka Y. Three-dimensional walking of a simulated muscle-driven quadruped robot with neuro-morphic two-level central pattern generators. Int J Adv Robot Syst 2019; 16(6): 1729881419858288.
10. Hunt A, Szczecinski N, and Quinn R. Development and training of a neural controller for hind leg walking in a dog robot. Front Neurorobot 2017; 11: 18.
11. Hunt AJ, Szczecinski NS, Andrada E, et al. Using animal data and neural dynamics to reverse engineer a neuromechanical rat model. In: Conference on biomechanics and biobehavioral systems, Barcelona, Spain, 28–31 July 2015, Springer, pp. 211–222.

12. Deng K, Szczecinski NS, Arnold D, et al. Neuromechanical model of rat hindlimb walking with two-layer CPGs. Biomech Biomater 2019; 4(1): 21.

13. Maufroy C, Kimura H, and Takase K. Towards a general neural controller for quadrupedal locomotion. Neural Netw 2008; 21(4): 667–681.

14. Wadden T and Ekeberg Ö. A neuro-mechanical model of legged locomotion: single leg control. Biol Cybern 1998; 79(2): 161–173.

15. Maufroy C, Kimura H, and Takase K. Towards a general neural controller for 3D quadrupedal locomotion. In: 2008 SICE annual conference, Chofu, Japan, 20–22 August 2008, pp. 2495–2500.

16. Markin SN, Klishko AN, Shevtsova NA, et al. A neuromechanical model of spinal control of locomotion. In: Neuromechanical modeling of posture and locomotion, New York, NY: Springer, 2016, pp. 21–65.

17. Markin SN, Klishko AN, Shevtsova NA et al. Afferent control of locomotor CPG: insights from a simple neuromechanical model. Ann NY Acad Sci 2010; 1198(1): 21–34.

18. Tsujiita K, Tsuchiya K, and Onat A. Adaptive gait pattern control of a quadruped locomotion robot. In: Intelligent robots and systems, 2001. Proceedings 2001 IEEE/RSJ international conference on, Maui, HI, USA, 29 October–3 November 2001, Vol. 4, pp. 2318–2325.

19. Fukuoka Y, Kimura H, and Cohen AH. Adaptive dynamic walking of a quadruped robot on irregular terrain based on biological concepts. Int J Robot Res 2003; 22(3–4): 187–202.

20. Kimura H, Fukuoka Y, and Cohen AH. Adaptive dynamic walking of a quadruped robot on natural ground based on biological concepts. Int J Robot Res 2007; 26(5): 475–490.

21. Harischandra N, Knuesel J, Kozlov A, et al. Sensory feedback plays a significant role in generating walking gait and in gait transition in salamanders: a simulation study. Front Neurorobot 2011; 5: 3.

22. Fukuoka Y, Habu Y, and Fukui T. Analysis of the gait generation principle by a simulated quadruped model with a CPG incorporating vestibular modulation. Biol Cybern 2013; 107(6): 695–710.

23. Spröwitz A, Tuleu A, Vespignani M, et al. Towards dynamic trot gait locomotion: design, control, and experiments with Cheetah-cub, a compliant quadruped robot. Int J Robot Res 2013; 32(8): 932–950.

24. Wu X, Teng L, Chen W, et al. CPGs with continuous adjustment of phase difference for locomotion control. Int J Adv Robot Syst 2013; 10(6): 269.

25. Tran DT, Koo IM, Lee YH, et al. Central pattern generator based reflexive control of quadruped walking robots using a recurrent neural network. Robot Auton Syst 2014; 62(10): 1497–1516.

26. Ferreira C and Santos CP. Combining central pattern generators and reflexes. Neurocomputing 2015; 170: 79–91.

27. Fukuoka Y, Habu Y, and Fukui T. A simple rule for quadrupedal gait generation determined by leg loading feedback: a modeling study. Sci Rep 2015; 5: 8169.

28. Li J, Wang J, Yang SX, et al. Gait planning and stability control of a quadruped robot. Comput Intell Neurosci 2016; 2016: 1–13.

29. Owaki D and Ishiguro A. A quadruped robot exhibiting spontaneous gait transitions from walking to trotting to galloping. Sci Rep 2017; 7(1): 277.

30. Zeng Y, Li J, Yang SX, et al. A bio-inspired control strategy for locomotion of a quadruped robot. Appl Sci 2018; 8(1): 56.

31. Fukui T, Fujisawa H, Otaka K, et al. Autonomous gait transition and galloping over unperceived obstacles of a quadruped robot with CPG modulated by vestibular feedback. Robot Auton Syst 2019; 111: 1–19.

32. Zhu Y, Zhou S, Gao D, et al. Synchronization of nonlinear oscillators for neurobiologically inspired control on a bionic parallel waist of legged robot. Front Neurorobot 2019; 13: 59.

33. Sun T, Xiong X, Dai Z, et al. Small-Sized reconfigurable quadruped robot with multiple sensory feedback for studying adaptive and versatile behaviors. Front Neurorobot 2020; 14: 14.

34. Michel OCyberbotics Ltd. Webots TM: professional mobile robot simulation. Int J Adv Robot Syst 2004; 1(1): 5.

35. Reighard JE and Jennings HS. Anatomy of the cat, New York, NY: H. Holt, 1901.

36. Krouchev N, Kalaska JF, and Drew T. Sequential activation of muscle synergies during locomotion in the intact cat as revealed by cluster analysis and direct decomposition. J Neurophysiol 2006; 96(4): 1991–2010.

37. Brown IE, Scott SH, and Loeb GE. Mechanics of feline soleus: II design and validation of a mathematical model. J Muscle Res Cell Motil 1996; 17(2): 221–233.

38. Klute GK, Czerniecki JM, and Hannaford B. McKibben artificial muscles: pneumatic actuators with biomechanical intelligence. In: IEEE/ASME international conference on advanced intelligent mechatronics, Atlanta, GA, USA, 19–23 September 1999.

39. Rossignol S, Dubuc R, and Gossard JP. Dynamic sensorimotor interactions in locomotion. Physiol Rev 2006; 86(1): 89–154.

40. Pearson K. Role of sensory feedback in the control of stance duration in walking cats. Brain Res Rev 2008; 57(1): 222–227.

41. McCreanora DA. Spinal circuitry of sensorimotor control of locomotion. J Physiol 2001; 533: 41–50.

42. Duysens J, Clarac F, and Cruse H. Load regulating mechanisms in gait and posture: comparative aspects. Physiol Rev 2000; 80(1): 83–133.

43. Pearson K, Ekeberg Ö, and Büschges A. Assessing sensory function in locomotor systems using neuro-mechanical simulations. Trends Neurosci 2006; 29(11): 625–631.

44. Halbertsma JM. The stride cycle of the cat: the modelling of locomotion by computerized analysis of automatic recordings. Acta Physiol Scand Suppl 1983; 521: 1–75.