

MantisBot Uses Minimal Descending Commands to Pursue Prey as Observed in *Tenodera Sinensis*

Nicholas S. Szczecinski^(✉), Andrew P. Getsy, Jacob W. Bosse,
Joshua P. Martin, Roy E. Ritzmann, and Roger D. Quinn

Case Western Reserve University, Cleveland, OH 44106, USA
nss36@case.edu
<http://biorobots.case.edu/>

Abstract. Praying mantises are excellent models for studying directed motion. They may track prey with rapid saccades of the head, prothorax, and legs, or actively pursue prey, using visual input to modulate their walking patterns. Here we present a conductance-based neural controller for MantisBot, a 28 degree-of-freedom robot, which enables it to use faux-visual information from a head sensor to either track or pursue prey with its prothorax and appropriate movements of one of its legs. The controller can switch between saccades and smooth tracking, as seen in pursuit, modulating only two neurons in its model thoracic ganglia via descending commands. Similarly, the neural leg controller redirects the direction of locomotion, and automatically produce reflex reversals seen in other insects when they change direction, via two simple descending commands.

Keywords: Real-time neural control · Praying mantis · CPG · Descending commands

1 Introduction

Praying mantises are ambush hunters who primarily use ballistic, visually-guided saccades of the head and body to track prey while standing still [7, 9, 12]. Starving them, however, will cause them to actively pursue prey, smoothly adjusting their gaze with their body joints as well as changes in their walking patterns. This behavior is of particular interest to roboticists, to understand how visual information affects the rhythms and reflexes that produce walking.

Walking is made of two phases, stance and swing (See [2] for a thorough review of how animals coordinate their walking). In stance phase, muscles must activate to support the body and move it in the intended direction. Depending on the linear and angular velocity of the animal in the ground plane, reflexes

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are modulated to excite the appropriate muscles [1,8]. The networks that control locomotion are distributed throughout the nervous system, so presumably the brain does not directly modulate these reflexes. Populations in the central complex (CX) code for intended direction [6], and stimulating these same neurons will modulate inter-joint reflexes [8]. But it is also known that descending neurons in the ventral nerve cord carry information about visual targets, presumably to the thoracic networks [16]. This suggests that the intended direction of motion is communicated as descending commands to the thoracic ganglia, which use this information to modulate reflexes locally.

In this paper we present a conductance-based neural controller for MantisBot, shown in Fig. 1 and described in [14], that can reproduce visually-guided saccades like those seen in the animal, actively “pursue” prey with appropriate movements of one leg, and adjust the direction and load-specificity of walking based on simple descending commands. The robot autonomously switches between these modes depending on the distance and location of the prey in its visual field. The walking controller requires only minimal parameter tuning based on the kinematics of the leg. The tuning is completely automated and takes less than five minutes to design the entire robot’s controller. The resulting controller is a hypothesis of how low-level locomotion control networks may be structured to readily implement the reflex reversals observed in animals via only minimal descending commands.

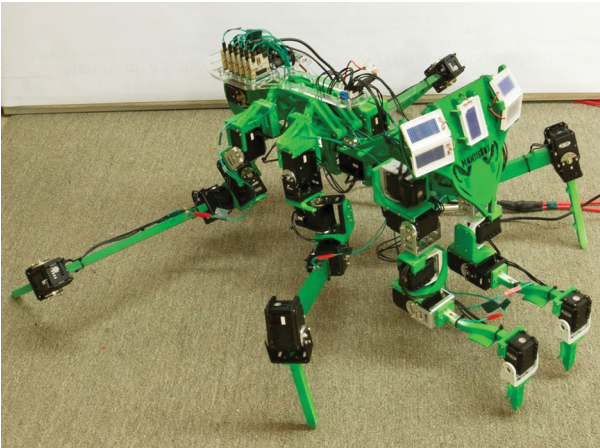


Fig. 1. MantisBot supporting its own weight on four legs, shown with its head sensor.

2 Methods

2.1 Animal Experimental Procedures

Adult female praying mantises, *Tenodera sinensis*, were starved for 3 to 5 days prior to the experiment. Individual animals were placed in a clear acrylic arena,

which was then placed on top of a computer monitor. High speed video (120 fps) was taken as the mantis was presented with an artificial stimulus, a 1×2 cm black oval on a white background, which moved at 4 cm/s through a 60° arc in the center of the praying mantis's visual field. The animal was presented with this stimulus two times each at 3, 6, 9, 12, 15, and 18 cm away from the head.

2.2 Animal Data Analysis

Using the software WINanalyze (Mikromak, Berlin, Germany), the angle of the artificial stimulus and the praying mantis's head were tracked. For the artificial stimulus this angle was the angle between a line going from the center of the arc to the origin (line A), and another line from the origin to the stimulus's position. For the praying mantis's head, this angle was between line A and a line projecting perpendicularly out of the center of the animal's, representing the direction that the animal was focusing in any given frame of video. If the animal did not move significantly from its starting position, then these angles were used verbatim, but if the animal moved closer to the stimulus, they were adjusted according to a factor that varied with the distance that the praying mantis moved from its starting position to account for the fact that the visual angle to the stimulus will change if the origin moves. The animal's behaviors were also quantified by observing the video and tracking the frames in which the behavior occurred.

2.3 Robot Experimental Procedures

MantisBot's thorax was fixed in all six dimensions by bolting it to a rigid arm suspended from a wheeled frame. When the trial began, all leg joints were moved to their zero positions, and the strain gage in the leg was tared. Once the leg moved from its initial posture, an 11.4 cm block topped with a sheet of TeflonTM was placed under the foot. This low-friction surface enabled the leg to register leg strain when in stance phase, but allowed the foot to slip laterally. A 1600 lm, 23 W compact fluorescent light bulb was then presented in front of the robot as a faux-visual prey-like signal. An array of solar cells is used to detect the angular position and distance of the light source [5].

3 Animal Behavior

Mantises track prey with saccadic motions of the head, prothorax and thorax [7, 9, 12]. When starved, they may actively pursue prey, walking toward the target. Figure 2 shows the orientation of the head when presented with a prey-like stimulus. When the stimulus starts far from the mantis, it approaches, smoothly adjusting its heading over time. Once the mantis comes within reach of the prey, it strikes, and later tracks with saccades. Starting the stimulus nearer to the mantis, as in the second trial, evokes typical saccades.

Starved Mantises Pursue Prey with Smooth Motions Until Within Striking Distance

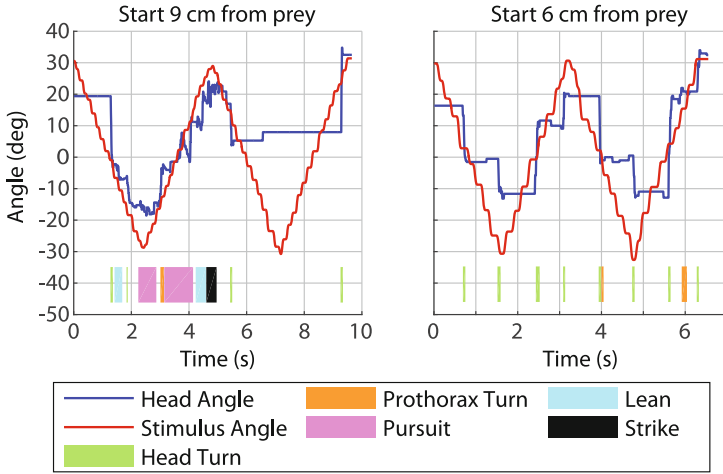


Fig. 2. Traces of mantis gaze compared to an artificial stimulus. The mantis’s state is encoded by the bars below the traces. (Color figure online)

4 Network Structure

All neurons in this controller are modeled as nonspiking leaky integrators. Most neurons have no additional ion channels, but those in the CPGs possess a persistent sodium channel to provide additional nonlinear dynamics [4]. A neuron’s membrane voltage V fluctuates according to

$$C_{mem} \frac{dV}{dt} = G_{mem} \cdot (E_{rest} - V) + \sum_{i=1}^n g_{syn} \cdot (E_{syn} - V) + G_{Na} m_{\infty} h \cdot (E_{Na} - V) \quad (1)$$

in which C is a constant capacitance, G is a constant conductance, g is a variable conductance, E is a constant voltage, and the subscript mem stands for membrane, syn stands for synaptic, and Na stands for persistent sodium. m and h are dynamical variables that describe the sodium channel activation and deactivation, respectively. m is fast, and thus is simulated as its steady state value m_{∞} . h changes according to

$$\dot{h} = (h_{\infty} - h) / \tau_h(V). \quad (2)$$

Both m_{∞} and h_{∞} are sigmoids, and have the same form,

$$z_{\infty}(V) = \frac{1}{1 + A_z \cdot \exp(S_z \cdot (V - E_z))}, \quad (3)$$

the primary difference being that $S_m > 0$ and $S_h < 0$. The full simulation, including all parameter values, is available for download at <http://biorobots.case.edu/projects/legconnet/mantisbot/>.

4.1 Head Networks

The robot uses the position of the light to decide whether to remain stationary and track or actively pursue it. It then uses this information to generate motion that moves the prey toward the center of its field of view. The hierarchical network in Fig. 3 enacts these behaviors.

The top section in Fig. 3 models the function of networks in the lobula and other visual processing centers, identifying the distance, angular position, and velocity of visual targets. The *Left* neuron receives a current proportional to the head sensor's left/right comparison. The *Right* neuron rests at a voltage that signifies centered prey. The comparison between the *Right* and *Left* neurons activates the *Error Right* and *Error Left* neurons. When in the *Track* state, the *Down Bias* neuron is tonically active, inhibiting the *Error Right* and *Error Left* neurons. This ensures that no error is detected as the target moves within 10° of center, mimicking the "dead zone" observed in mantises as they saccade toward prey [12]. If either *Error* neuron becomes active, it will excite both the *Error Large* and *Slow* neurons. These neurons are identical, except that the *Slow* neuron has a larger capacitance, and thus larger time constant. The *Trigger* neuron then computes the difference between these, forming a Reichardt detector [11]. Thus *Trigger* detects when the prey is leaving the "dead zone," requiring corrective action.

The visual center also computes the distance to the target by mapping the head's center panel reading to a $1/r^2$ relationship, which controls *Dist.*'s activity. When the distance to the target is small enough, *Too Close* is disinhibited, halting pursuit. The visual center also computes the velocity of the visual input via another Reichardt detector [11].

Saccades are by their nature brief bursts of motion. Therefore the *Sacc.* neuron is configured to produce brief, stereotypical pulses when *Trigger* becomes active. *Sacc.* and *No Sacc.* include persistent sodium channels, which are frequently used to model CPGs in locomotion models [4]. By biasing *No Sacc.* upward with a 1 nA tonic current, the equilibrium state of the *Sacc./No Sacc.* system is for *No Sacc.* to be tonically active, and *Sacc.* to be inactive. When *Trigger* inhibits the interneuron, it disinhibits *Sacc.*, causing it to temporarily inhibit *No Sacc.*, producing a temporary pulse which disinhibits the *Sacc. Right* and *Sacc. Left* neurons. These pulses can be observed in Fig. 6.

Flashing targets at mantises reduces the latency of subsequent saccades in the same direction [7]. This suggests that there is some memory of the previous saccade direction, which primes the system to move in that direction again. Thus the *Left Mem.* and *Right Mem.* neurons mutually inhibit one another such that exactly one is always tonically active while the other is inactive. The *Error Right* and *Error Left* neurons can change the state of this memory, which then gate the *Sacc. Right* and *Sacc. Left* neurons. These, in turn, gate the *Right Vel.* and *Left Vel.* neurons, which ultimately stimulate the motor neurons of the prothorax and leg joints.

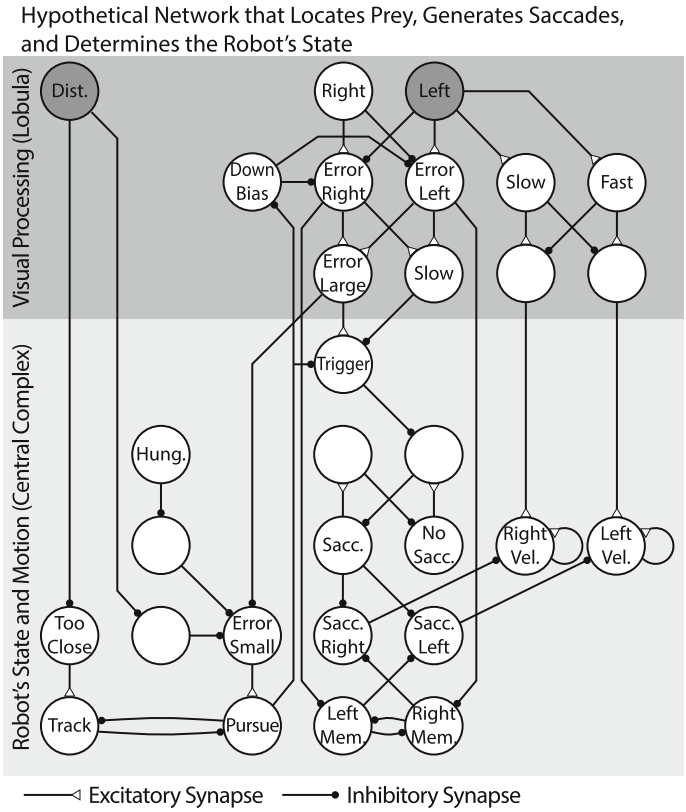


Fig. 3. Network that processes visual information for MantisBot and communicates descending commands to the thoracic ganglia model, partially shown in Fig. 4.

4.2 Thoracic Networks

Insects' nervous systems are highly distributed. How, then, are individual joints controlled to direct posture or locomotion based on descending input? Signals from load sensors signal the onset of stance phase, causing supportive and propulsive muscles to contract. Which muscles are activated depends on the direction of travel [1]. Signals from movement sensors signal the end of stance phase, causing the leg to lift from the ground and return to its position prior to stance [3]. Figure 4 shows a control network for one joint based on these observations, which underpins the leg controller in this work. Every joint's controller is identical, except for the weight of the four synapses drawn in bold, and the resting potential of the *Des. PEP* and *Des. AEP* neurons. The network's function directly informs the tuning of these values, as shown below.

Our joint network receives descending commands about the position and velocity of the prey signal, as well as the state of the robot, whether statically tracking or actively pursuing prey. The labels PEP (posterior extreme position)

Hypothetical Network that Sets a Joint's Timing and Amplitude
Based on Descending Commands and Leg Loading Information

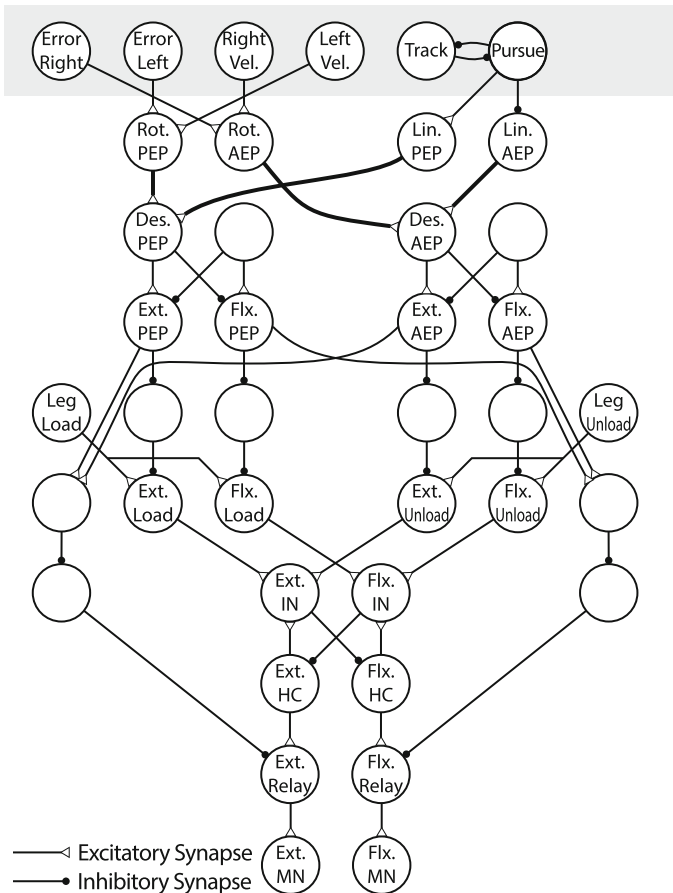


Fig. 4. Network that determines the timing and amplitude of the motion of each joint. With only minimal tuning and limited descending commands, the network produces walking motion and reflex reversals to change the travel.

and AEP (anterior extreme position) refer only to the intended position of the joint at the end of stance and swing, respectively. When *Track* is active, the transition to swing is inhibited, and the PEP is simply the desired position of that joint. If *Pursue* is active, then the AEP and PEP are different, establishing the beginning of stance and swing, respectively. This is manifested by the excitation of *Lin. PEP* and the inhibition of *Lin. AEP*. Visual information affects the rotation of the PEP (*Rot. PEP*) and AEP (*Rot. AEP*). Even though this paper only presents results from one leg of MantisBot, our design method is general, and is intended to control all the legs simultaneously. Here we describe how to tune the network in Fig. 4 for a single joint. If we were to translate and rotate

some point on the robot distance p and angle θ , as shown in Fig. 5, then a particular foot would have to move distance d at angle ϕ from straight ahead to stay in the original position. For each ϕ , the Moore-Penrose generalized inverse of the leg’s Jacobian matrix can be used to find the joint velocities required to move the foot in the \hat{d} direction, which minimize the norm of the joint velocity vector [10]. The ratio between joint velocities in the leg specify the relative proportion of motor neuron activation required to move the foot in a straight line in the direction specified. If negative position feedback is present at each joint, then scaling this proportion will specify an equilibrium position.

Each joint has a map of its deflection from rest as a function of the body’s rotation and translation (for example, Fig 5C). We can draw a line showing the body motions that would require no change in the joint’s position. Points above that line represent body motions that would require the joint to flex, and those below correspond to motions that require extension. Because this map is specifying the

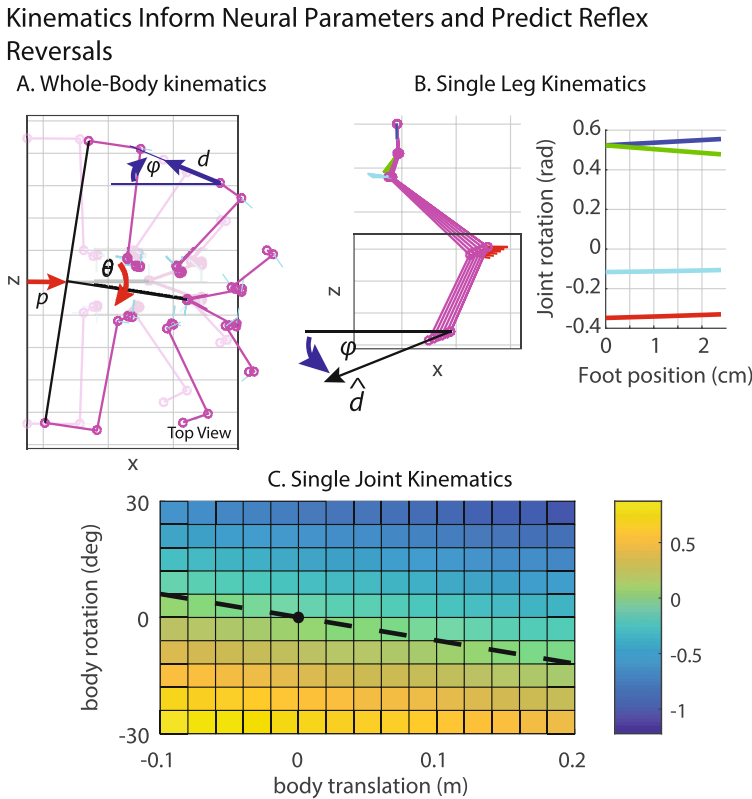


Fig. 5. Inverse kinematics used to design the joint network. To move the robot’s body in a particular direction (A), each leg must move in a different direction (B). The inverse kinematics reveal at which body rotations and translations the joint must change its direction of travel (C). (Color figure online)

PEP of the leg, the line predicts at what locomotion speeds and turning radii a reflex reversal should take place, a consideration of prior studies [8, 13].

Using this method, the four synapses in bold in Fig. 4 are designed such that the descending commands, which encode intended *body* translation and rotation, can be used to command the *joint's* rotation. This network is duplicated, once to command the PEP and once to command the AEP. If the desired PEP, encoded by *Des. PEP* is greater than the resting posture, then the joint needs to extend in stance phase, and the *Ext. PEP* neuron will be active. When active, it disinhibits the pathway from the leg's strain gage, exciting *Ext. IN* and inhibiting *Flx. HC* during stance, causing the joint to extend. Changing the descending commands may instead cause *Flx. PEP* to be active, which will route load information to the opposite half-center of the CPG. The AEP network works the same way, but with a signal that the leg is unloaded. In this way the kinematics of the robot are used to not only cause desired foot trajectories, but also enforce known reflex reversals with minimal descending commands.

5 Results

Figure 6 shows that the network in Fig. 3 can accurately orient the robot toward prey using the same strategy as the animal. The target is tracked smoothly when in active pursuit, and with saccades when tracking. Locomotion also halts when this change takes place, and produces saccadic motions afterward. When the target strays from the center of view, the *Error Left* or *Error Right* neuron's

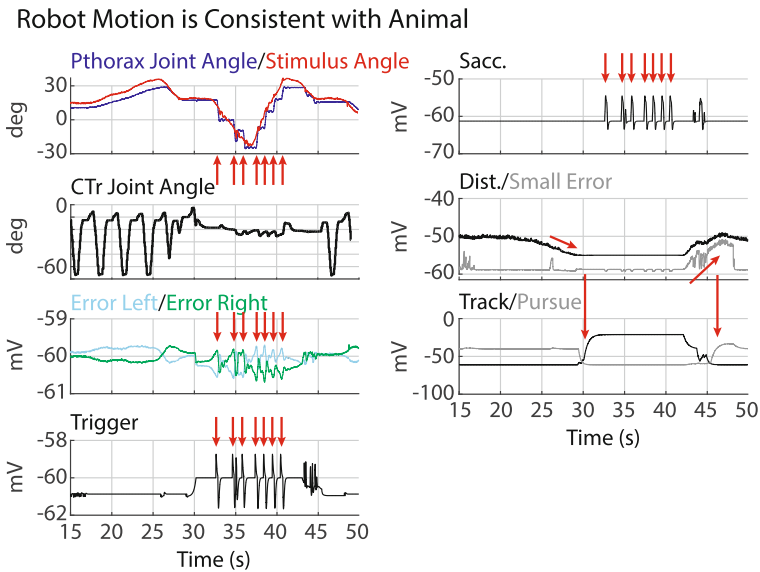


Fig. 6. Traces from MantisBot tracking a stimulus and autonomously changing between tracking and pursuit. (Color figure online)

Foot Motion Changes Significantly when Pursuing Target at Different Visual Angles

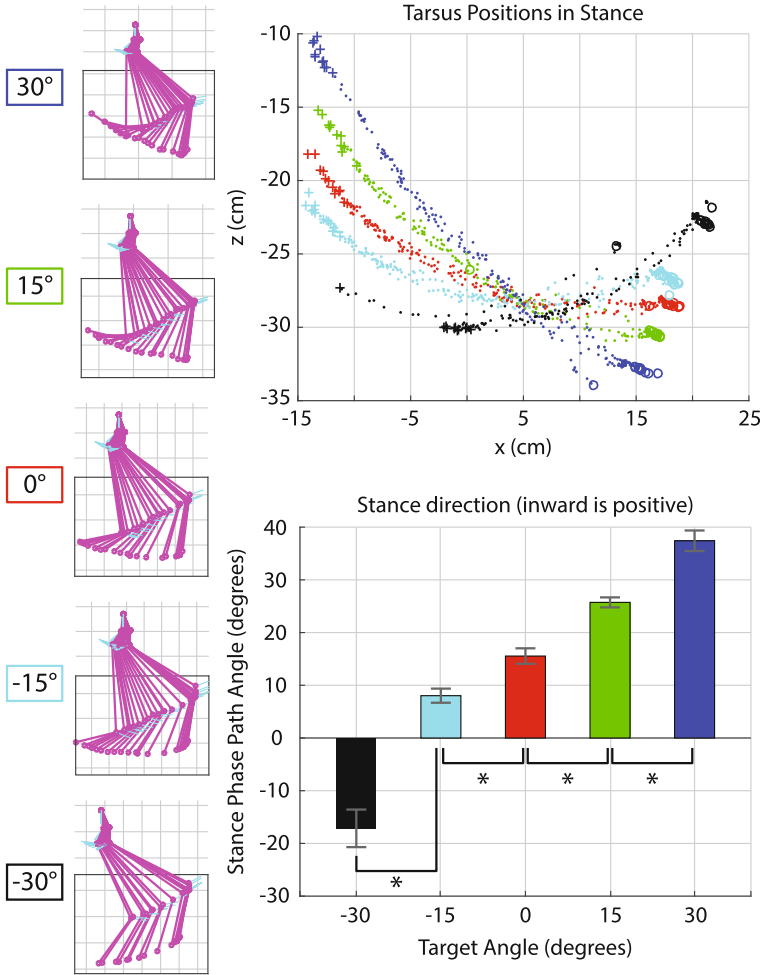


Fig. 7. Foot positions as MantisBot walks when presented with stimuli at different angles. (Color figure online)

activity increases over the permissible threshold, causing the *Trigger* neuron’s activity to fluctuate rapidly (red arrows). These in turn cause the *Sacc.* neuron to pulse and generate the saccades seen in the top plot. The transition between tracking and pursuit is mediated by the *Dist.* and *Small Error* neurons. When the distance to the target is decreased, the pursuit has been “successful,” and the robot begins to track the prey with saccades. When the distance again decreases and the prey is located within the field of view, the robot again pursues.

Reflex Reversals Naturally Occur from the Hypothetical Leg Controller

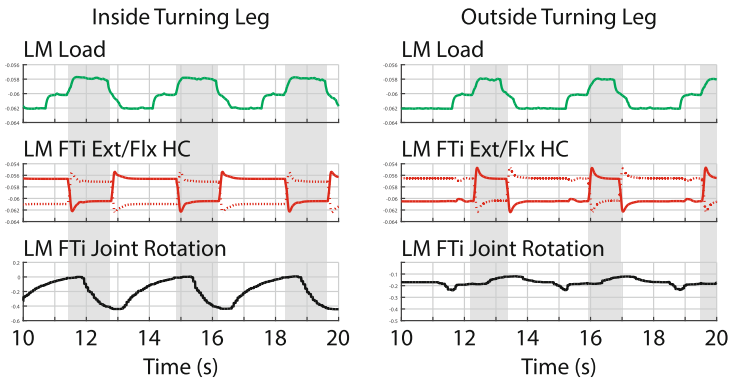


Fig. 8. The network in Fig. 4 automatically produces the reflex reversals observed in other insects.

Figure 7 shows that the network in Fig. 4 can control the direction of the foot in stance. Leg kinematics were recorded as the robot took 12 steps toward the light in five different positions. The joint angles read from the servomotors were fed through the kinematic model to create 3D plots of the leg motion over time, as well as the foot placement on the ground. Calculating the angle of the line that passes through the AEP and PEP with respect to straight ahead for each step shows that the stance direction is statistically significantly different for each target presented ($p < 0.001$, 1 sided ANOVA). This includes both inward and outward stance directions, suggesting that reflex reversals must take place to change the stepping so drastically. Figure 8 shows that this is the case; the sign of the load information fed to the femur-tibia joint is reversed by the network in Fig. 4. Rather than guessing when this transition should occur, our network automatically changes the sign of this reflex with minimal descending commands.

6 Conclusion

The data shows that this joint controller is capable of producing basic stance and swing motions, and modifying them with minimal descending commands. Insects use a host of reflexes to counteract external forces and transition from stance to swing, and vice versa (for a review, see [2]). Reflexes in response to decreasing or excessive load, as well as searching for missing footholds, will be added in the future [15]. In the future, this controller will be expanded to use all of the legs of MantisBot to orient towards and pursue faux-visual targets.

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