

# Transforming Insect Electromyograms into Pneumatic Muscle Control

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**Abstract**— Biological inspiration has a history of advancing the field of robotics. Increasingly, robots are also being used in the modeling of biological systems. In this paper, we use recorded cockroach electromyograms (EMGs) to drive artificial muscle (braided pneumatic actuator) activation and thereby robot joint motion, in an effort to model the transformation from EMG to behavior in the animal. A muscle activation model was developed that transforms EMGs recorded from behaving cockroaches into appropriate commands for the robot. The transform is implemented by multiplying the EMG by an input gain thus generating an input pressure signal, which is used to drive a one-way closed-loop pressure controller. The actuator then can be modeled as a capacitance with input rectification. The actuator exhaust valve is given a leak rate, making the transform a leaky integrator for air pressure, which drives the output force of the actuator. We find parameters of this transform by minimizing the difference between the robot motion produced and that observed in the cockroach. Results from evaluation on reduced-amplitude cockroach angle data strongly suggest that braided pneumatic actuators can be used as part of a physical model of a biological system.

## I. INTRODUCTION

OUR laboratories have worked for over a decade on incorporating biological principles of locomotion into robotic designs. Previous research has resulted in a line of robots designed to be capable of walking and climbing behaviors observed in the cockroach *Blaberus discoidalis* [1-4]. Increasing similarity of the robotic motor systems to those in the animal has prompted us to attempt to use a leg of Robot V [4] as a physical model for investigating the behavioral relevance of EMG signals in the cockroach neuromechanical system.

The use of electromyograms for control is a matter of much investigation; particularly, the use of human EMGs to interactively control, among other things, orthoses [5, 6], prostheses [7], and exoskeletons [8, 9] is widely investigated. These projects generally use features of EMGs as an online measure of intent, with which to give commands to a feedback control system. Electromyograms are also used to estimate the state of human limbs [10]. Northrup *et al.* [11]

have used a general knowledge of the patterns of EMGs during human reaching movements to implement an activation-based controller for reaching movements in their robot actuated by braided pneumatic actuators (BPAs). They observe that this controller generates control with a lower stiffness than that generated by more traditional control methods, and humans interacting with it regard this motion as more natural. Rather than using EMGs *per se*, Reger *et al.* [12] used on-line neurograms from dissected lamprey central nervous systems to generate motion in a robot, which then feeds sensory signals back to the lamprey nervous system. Their intention has been to use this artificial behavior as a tool for investigating neural plasticity. In this paper, we are using BPAs as physical muscle models with transformed EMG signals as inputs, which is more similar to the use of EMGs in modeling by [13] in which human EMG signals are used in real time to drive corresponding simulated muscles in a computational model of the human arm.

It is broadly accepted that the compliant properties of muscles are important and useful in locomotion [14, 15]. Muscle properties are tuned by neural inputs to react effectively to physical stimuli under varying conditions [16]. Another important function is that they filter motor neuron commands [17], and it has been shown that the filtering characteristics of the muscle, referred to as the neuromuscular transform, can be highly dynamic under varying previous stimulation [18, 19]. This shows that muscles are not merely filters but can act as highly dynamic portions of the neuromechanical system. Understanding them, then, is crucial in working towards a full understanding of the behavioral relevance of motor neuron activity.

Considerable work has been done in the description of muscle properties in arthropods [20-22]. We believe our more behaviorally-oriented approach for describing neuromechanical relationships will complement their work.

In this paper, we use hardware-in-the-loop error minimization to find parameters for an EMG-to-valve-command transformation, using EMG and joint angle data gathered from the cockroach. This model consists of two components; a transform from EMG to BPA activation commands, which is necessary to model muscle activation dynamics, and the dynamics of the physical robot itself, which are used to model the associated muscle and limb dynamics in the animal. A simplified representation of the neuromuscular transform is illustrated in Figure 1a. Muscle force is related to muscle activation through the dynamics of

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the active contractile elements in the muscle fiber. In arthropod muscle systems there are relatively few motor neurons, suggesting that the activation can be approximated as a leaky integration of an EMG-derived signal. Before this integration the neural/EMG signal undergoes transformation, an important part of which occurs at the synapse between the motor neuron and the muscle.

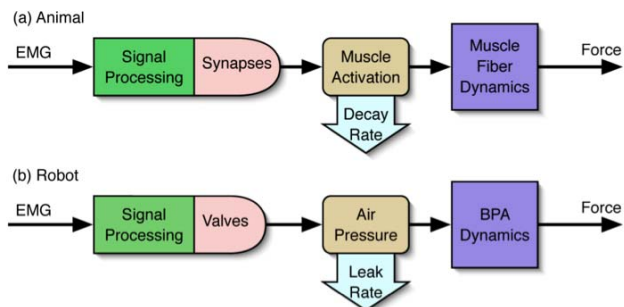


Fig. 1 Schematics of transformation between EMG and force in the animal (a) and in the robot (b).

This suggests a means of using BPAs to model these muscle dynamics by using the air pressure in an actuator as an analogue of the activation level in the corresponding muscle (Figure 1b). In this work we assume a constant leak rate for the actuator, which acts as the integrator, and we use EMG input transformation to model the first stage of signal processing which translates EMGs into behavior.

## II. METHODS

Data is gathered from the cockroach, then filtered and time-scaled for use in robot control. Cockroach EMG signals are transformed to produce on-off valve control signals for corresponding BPAs on the robot. Other moving joints on the robot leg are controlled to approximate observed corresponding cockroach joint trajectories. Because transform properties are initially unknown and are expected to vary widely between individuals, suitable transform parameters are found through hardware-in-the-loop minimization of error between the observed cockroach joint trajectory and the generated robot joint trajectory.

### A. Data from the cockroach

Data used in this paper is from restrained forward walking on an oiled plate, as described in [23]. EMG voltages were recorded at 10 kHz from levator and depressor muscles of the coxa-trochanter (CTr) joint of a *Blaberus discoidalis* cockroach. Simultaneous video was taken at 250 Hz. Prior to further processing, the time values of all cockroach data were then slowed by a factor of  $\sqrt{20}$  based on dynamic similarity scaling rules, because the robot is 20 times the size of the animal. At this new time base, the video data is available at 55.9 Hz, and the EMG data at 2.24 kHz. EMG data was then low-pass filtered with a passband of 224 Hz

and stopband of 279.5 Hz, before being resampled at 559 Hz for robot control. The video-derived angle data was low-pass filtered with a passband of 5.59 Hz and a stopband of 8.94 Hz to remove noise which was expected to introduce spurious error in the optimization process. No filtering specifically for noise removal was carried out on the EMG signal. All data was then trimmed so that the dataset represented an integral number of step cycles; this way the data could be “played” through the robot multiple times in order to reduce the effect of startup transients. The resulting data represented 7 steps, taking a period of 13.5 seconds at the robot time base, corresponding to 3 seconds of behavior in the animal.

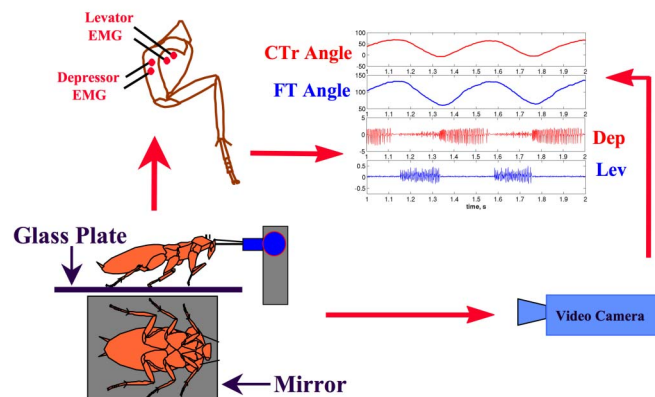


Fig. 2 Setup for gathering simultaneous EMG and joint angle data from the cockroach. Data shown are a subset of the data used in this paper, before the described filtering. (adapted from [23, 24])

### B. The robot

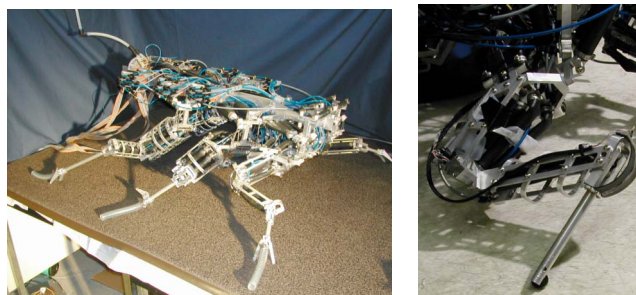


Fig. 3: Robot V, constructed with inspiration from the death-head cockroach *Blaberus discoidalis*. It is actuated by Festo® brand BPAs (artificial muscles). At right is a close-up of the right middle leg.

The robot used in this study is Robot V [3, 4] shown in Fig. 3, a robot modeled after the cockroach *Blaberus discoidalis*, but at 20 times the size of the animal. Each of its Festo® braided pneumatic actuators has separately controlled inlet and exhaust valves capable only of fully open and fully closed positions, which are fast enough to respond usefully to pulse width modulation (PWM) frequencies of up to about 100 Hz. We used the coxa-trochanter joint on the right middle leg of the robot. The range of motion of this joint is 35°-100° in the robot and is 28°-104° in the animal, both measured in a coordinate system defined such that when the coxa and femur are extended in a line the angle is 180°. To simulate the oiled-plate experimental environment, the foot

was fitted with a low-friction furniture slider. We used 55.9 Hz PWM on the control valves in order to match the rate of the angle data available from the recorded video.

During evaluations of the model performance, the body-coxa degrees of freedom on the robot were fixed as closely as possible to the near-constant orientation observed in the animal. The femur-tibia joint was controlled to track the joint angles observed in the animal, and the muscles actuating the coxa-femur joint were controlled using the transformed EMG data. Since the EMG data were available at 559 Hz, the inlet valve duty cycle commands were updated at this rate, even though the PWM frequency was only 1/10 this speed. A description of the real-time control system and control methods used for joint angle tracking can be found in [4].

C. EMG transformation

The EMG input processing method is summarized in Fig. 4. An EMG signal pre-processed as described in section A is amplified to produce a signal we refer to as “input pressure”. This signal is fed to a modified pressure controller, which produces the inlet valve duty cycles. These inlet duty cycles give rise, through valve and actuator dynamics, to air pressure in the actuator. This, along with the pressure in the opposing BPA, gives rise through actuator and robot dynamics to joint motion.

The modified pressure controller, shown in Fig. 4(bottom), converts the EMG potential (voltage/pressure) signal to a flow (current/airflow) signal, because the inlet valve controls airflow rather than pressure. The pressure error is proportional to the difference between input and actuator pressure, as the flow would be if we attached an actual pressure source to the actuator.

For each BPA, then, we must define three parameters to describe the full transformation: 1) input pressure gain, 2) pressure controller gain, and 3) actuator leak rate. Six parameters must be specified to describe the transformation for one joint; three for each muscle of the antagonistic pair.

Many assumptions and simplifications were made in the development of this model. We model only one muscle pulling in each direction, process EMG signals as if they emanate from only one excitatory motor neuron, and set the exhaust rate to be constant; evidence indicates more complex behavior in the animal in each of these cases. Also, implicit in the model is the assumption that the EMG voltage signal has a continuous, one-to-one relationship with muscle activation, and that the activation dynamics are dependent on the current activation level. The assumption of a one-to-one relationship is reasonable for the Depressor Coxa at least, since there was only one excitatory motor neuron active in these behaviors for that muscle.

D. Optimization methods

We must use optimization to systematically find the best transform parameters. Even if we did have a well-understood

transformation and analytical methods for finding the parameters, variation between individual animals and experimental setup (for example, electrode placement) would require us to either fully describe individual and experimental variation (which is not feasible) or tune the parameters for the best fit to each individual’s mapping from observed EMG voltage to observed joint motion. Therefore, we concluded that an optimization strategy would be most practical for estimating transformation parameters.

Most of our model is in hardware so any evaluation of the error must also take place in hardware. Choosing a rapidly converging optimization strategy was essential because it takes about 48 seconds to evaluate the joint angle error at one point in parameter space, the problem is six-dimensional, we initially had little knowledge of the search space, and it is undesirable to run the robot continuously for very long periods of time. There are a number of “fast” gradient descent and quadratic minimization algorithms available, but most of these suffer degradations of performance and/or stability when subjected to a noisy gradient. We chose Stochastic Meta-Descent (SMD)[25] as a method for step-size adjustment because it does not have these failings.

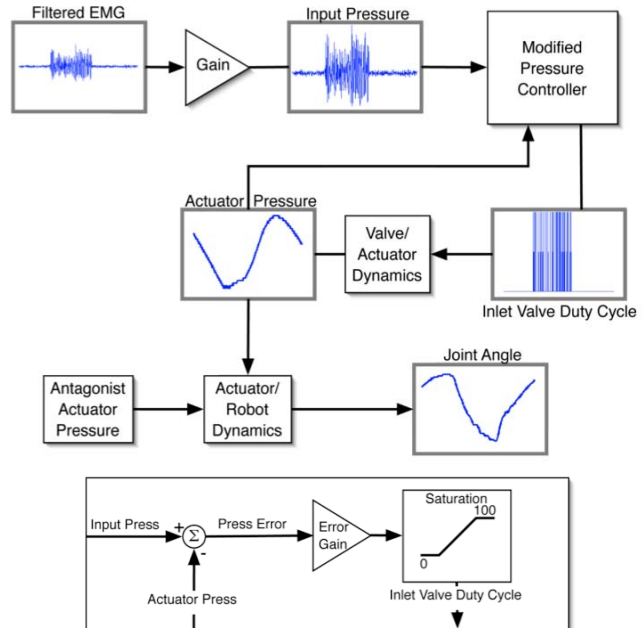


Fig. 4: EMG input transformation. Representative signals are shown at various stages in the process; the block “Antagonist Actuator Pressure” includes all the elements shown from filtered EMG through actuator pressure, for the opposing muscle. The bottom block is a detailed view of the modified pressure controller.

The Hessian of the error multiplied by a vector  $\mathbf{v}$  is necessary for SMD, and we estimated it at point  $\mathbf{p}$  in the parameter space as:

$$\mathbf{H}\mathbf{v} \approx \frac{\frac{\partial E}{\partial \mathbf{p}}(\mathbf{p} + r\mathbf{v}) - \frac{\partial E}{\partial \mathbf{p}}(\mathbf{p})}{r} + O(r) \tag{1}$$

as shown in[26] where, with the arbitrary constant  $r$  chosen sufficiently small, the  $O(r)$  term can be ignored.

We estimate the gradient by calculating the error measure at  $\mathbf{p}$ , then at six points  $\mathbf{p}+\Delta\mathbf{p}_j$  where  $\Delta\mathbf{p}_j$  is a vector containing only one nonzero element: the perturbation  $d_j$  in the  $j^{\text{th}}$  dimension. For estimation of  $\mathbf{H}\mathbf{v}$ , the same calculations are carried out for the perturbed point  $\mathbf{p}+\mathbf{r}\mathbf{v}$ .

Since the  $d_j$  required for the gradient signal to be larger than the noise inherent in the hardware-evaluated value function can be rather large with respect to the magnitude of the parameters (in some of our runs 50% or more), SMD, when configured to be stable, would often specify steps smaller than  $d_j$ . We therefore extended the algorithm to take a step of  $d_j$  in the  $j^{\text{th}}$  dimension in this case if the error value at  $\mathbf{p}+\Delta\mathbf{p}_j$  was lower than at  $\mathbf{p}$ . Otherwise, the sign of  $d_j$  was changed to look for lower values in the other direction. In this way, if SMD is not advancing the point, we are at least performing a linear parameter search. We further extended SMD so that if a convergence criterion was met, search would start again from a new point in the parameter space, looking for another local minimum rather than wasting time sitting at a local minimum doing a gradient descent on noise.

### E. Optimization run protocol

An initial set of parameters which produced a relatively large angular motion was chosen by hand. Given an initial point, the optimization program executes the following:

- 1) Run and record data from a robot diagnostic.
- 2) Run the value function 10 times to “warm up” the robot (iterations -10 to -1, gradient not computed).
- 3) Run SMD as extended above, until the specified number of iterations (typically 15) has been reached, or the run is terminated manually.
- 4) Run and record diagnostic for comparison with that recorded in (1).
- 5) Convert data gathered into a more easily useable form, and write converted data files to disk

The above sequence takes about 2.5 hours. The value function runs a shorter diagnostic, both to monitor robot status and even out differences in initial conditions, before running through the data twice and recording the coxa-femur angle output on the second run for use in calculating the error value. Error is defined as the sum of the squared difference between reference (cockroach) and robot joint angle data.

## III. RESULTS

The optimization protocol was performed using EMG and joint position recordings from one animal. Progress towards convergence is shown in Fig. 5 for two different optimization runs. The optimization illustrated in Fig. 5 converged at a point at which the corresponding joint motion is far from closely matching the motion recorded in the animal. We also used optimization to tune the model parameters to a modified reference joint trajectory with the same mean value but scaled down to  $\frac{1}{4}$  of the original range. The resulting minimum error (Fig. 6a) is greatly reduced.

This optimization converges to a local minimum and then jumps to begin searching for another local minimum.

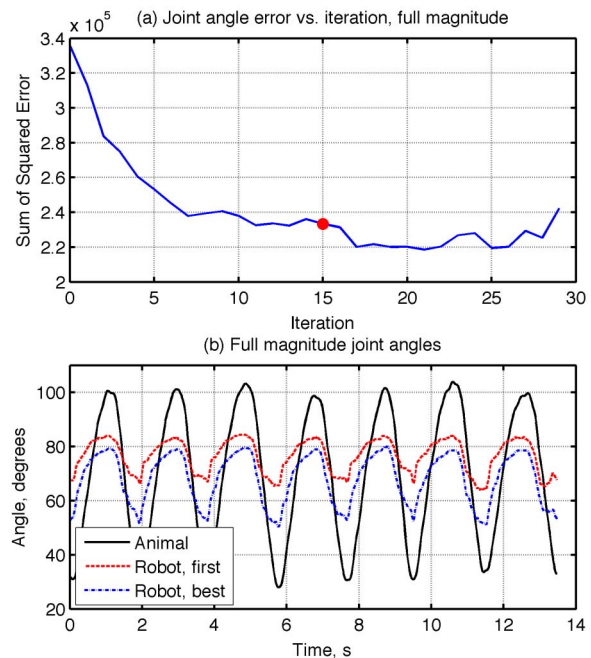


Fig. 5: Optimization runs (a) and joint angle tracking (b) executed with full-scale animal joint angle data as reference. The marker in (a) indicates where a second sub-run was initiated starting from the last point in the previous run. The robot data in (b) are from the first and best iterations in this run.

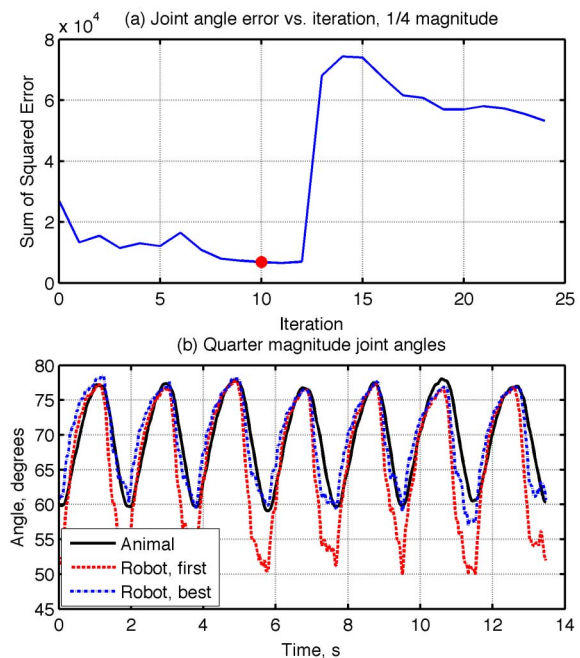


Fig. 6: Data from quarter-magnitude runs complimentary to that in Fig. 5. The sudden jump upwards in (a) is due to the algorithm jumping to a new point to search for another minimum when the software detected convergence.

Parts b of Fig. 5 and Fig. 6 show joint angle positions vs. time for the animal and the robot for full range and quarter range movements, respectively. In each case an improvement can be clearly observed, and the optimized

quarter-range results produce the best match. Fig. 7 shows that under the best set of parameters found for matching the  $\frac{1}{4}$  range signal, the transformation on the input signal produces essentially one pulse per EMG spike.

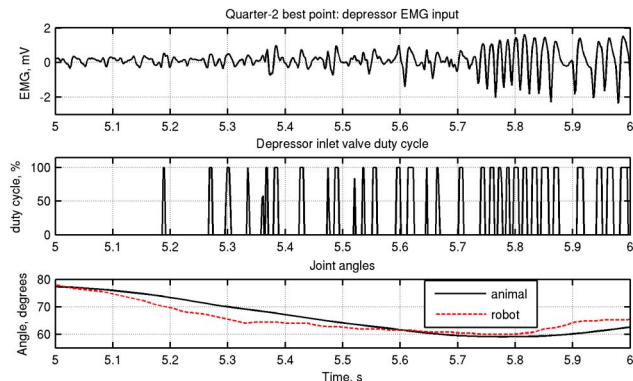


Fig. 7: Depressor inlet valve duty cycle commands in relation to EMG and joint angle output for a portion of the “Robot, best” data shown in Fig. 6b; the best match between reference and robot angles.

#### IV. DISCUSSION

Optimization was successful in finding model parameters giving local minima of error, both for full-scale and  $\frac{1}{4}$  magnitude reference angle signals. Regarding the performance of the optimization, we have not found search parameters which make SMD useful with an error signal this noisy—perhaps a better method of estimating  $\mathbf{H}_v$  would be helpful. With our current implementation, the strategy is essentially a linear parameter search with ad-hoc step size. This is probably slower than a working SMD, but it is stable, and it appears to work for this problem. Incidentally, with evaluation times as long as they are, choosing step size updates by hand every 15 iterations involves a little more human input, but not necessarily much more time overall, than automating the process. Explicit modeling of noise in the error measurement may make more elegant methods of optimization useful for this problem.

The duty cycle output to the robot shown in Fig. 7 indicates that most of the transformation is effectively being ignored, at least at this time scale. The best sets of model parameters effectively turn it into something resembling one pulse per EMG spike. It is possible that with higher flow valves or a much higher PWM frequency duty cycles lower than 100% would be chosen regularly. The forcing of this transformation into one pulse per EMG spike is quite interesting, however, since it points strongly to another input transformation we have been considering: one pulse of air per spike, the duration of which is determined by the area under the corresponding EMG spike. This is in effect an even more “direct” transformation— one could argue it’s hardly a transformation at all; just a discretization. This method would also lose less information than the current one, since it is possible to time the opening of valves quite precisely even though the valves do not open and close fast

enough to do PWM much faster than in the current set up.

The EMG activity in Fig. 7 before the high-frequency burst starting between 5.7 and 5.8 seconds is noise in the signal either from crosstalk with the levator EMG or some other neuronal activity. The kink in the robot angle trace at about 5.35 seconds, following the onset of inlet valve pulses related to this noise, is a good indication that this signal does not have the meaning being ascribed to it by our transformation, because the animal trace has no corresponding change in slope. Explicit removal of this crosstalk could significantly improve performance of the transformation. A thresholding function for the spike detection necessary for the pulse-per-spike transform mentioned above can accomplish much, if not all, of this crosstalk removal.

As shown in Figure 6b, it appears that although this robot is capable of reaching within  $7^\circ$  of the minimum and maximum angles observed in the animal’s behavior, it is not capable of approaching this range while under control of this transformation. One of the most likely contributing factors for this problem is that we have chosen constant exhaust rates in the actuators, corresponding to a constant decay rate in the activation dynamics of the muscle. Including a dynamic exhaust rate would enable a considerably larger motion, since muscles could retain more air during contraction and release more during relaxation. Indeed it is apparent that relaxation dynamics are not constant in real muscle[27], sometimes to an extreme extent, with apparent sudden switching from “hold” to “relax”[19, 28]. Adding this further complexity to the system may enable a better fitting of the shape of the joint motion as well.

Another probable contributing factor for the limited motion produced by the robot is dissimilarity between the robot and the cockroach, particularly in range of motion. The robot can generate almost the full range of motion desired here, but the cockroach EMGs are controlling muscles in the animal which can generate a much larger range of motion, and are therefore less affected by saturation of the muscle length-tension relationship. Higher maximum inlet flow rates, introduced by using higher-capacity valves and hosing, may mitigate this effect but are unlikely to solve it completely. When the amplitude of the joint motion to be modeled is reduced, the robot is also farther from saturation, and is able to match the gross shape of the trajectory quite well (Fig. 6b).

Despite these concerns, the model performance as shown in Fig. 6b strongly suggests that our approach holds promise. Five out of seven angle maxima are matched well, amplitudes of the minima are matched, although the shape is different, and the speed of motion also generally matches quite well. There is no angle feedback in the model system, as there is not in the corresponding transformation of EMG to motion in the animal. The similarity in motion produced by both systems when given the same EMG input is therefore indicative of some input-output equivalence between the systems, though we have not shown any direct

evidence the analogue between BPA air pressure and muscle activation is valid.

The simplicity of the input transformations used here also suggest that in cases where a system is to be controlled using EMG as a command input, the use of BPAs as the actuators may substantially simplify the control system.

In conclusion, we have developed and tested a method for transforming EMG recordings from the cockroach *Blaberus discoidalis* into control signals for pneumatic artificial muscles in a robotic joint. We used optimization methods on the physical robot to find parameters that minimize the error between animal and robot motion. While it is possible that further and/or improved optimization will find parameters with somewhat better performance, results from evaluation on reduced-amplitude cockroach angle data strongly suggest that braided pneumatic actuators could be effectively used as part of a physical model of insect EMG response.

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