Morphological Communication: Exploiting Coupled Dynamics in a Complex Mechanical Structure to Achieve Locomotion

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Traditional engineering approaches strive to avoid, or actively suppress, nonlinear dynamic coupling among components. Biological systems, by contrast, are often rife with these dynamics. Could there be, in some cases, a benefit to high degrees of dynamical coupling? Here we present a control scheme for a complex mechanical system which is able to exploit a high degree of dynamical coupling to its advantage. Independent struts in a tensegrity structure are able to co-ordinate their actions to achieve global locomotion by utilizing the coupling imposed by pre-stress stability as a means of ad-hoc communication. This emergence of morphology-as-information-conduit, or "morphological communication", enabled by time-sensitive spiking neural networks, presents a new paradigm for the decentralized control of large, coupled, modular systems. These results significantly bolster, both in magnitude and in form, the idea of morphological computation in robotic control. Furthermore, they lend further credence to ideas of embodied anatomical computation in biological systems, on scales ranging ranging from cellular structures up to the tendinous networks of the human hand.

Keywords: Morphological Communication, Morphological Computation, Tensegrity, Robotics

1. Introduction

Traditional engineering approaches strive to avoid, or actively suppress, nonlinear dynamic coupling among components. Especially near resonant frequencies, these couplings tend to produce undesirable vibrations and oscillations that are difficult to predict and may sometimes be catastrophic. A variety of passive and active damping techniques have been developed to diminish these effects across many fields ranging from robotics to structural engineering.

Biological systems, by contrast, are often rife with complex dynamics. Consider, for instance, the principle of tensegrity, which can be found at many scales of life, ranging from the cellular cytoskeleton (Wang *et al.* 2001) and the structure of proteins (Ingber 1998) to the tendinous network of the human hand (Valero-Cuevas *et al.* 2007). At every scale, these systems contain the type of coupled mechanical and dynamical linkages which are so assiduously avoided in engineering design. Could there be, in some cases, a benefit to this dynamical coupling?

Here we demonstrate how a highly complex mechanical system can learn to exploit its dynamical coupling as an advantage. In particular, we construct a highly connected and irregularly shaped tensegrity structure, one with a much higher degree of complexity than any previously controlled tensegrities. Independent strut modules in the structure are able to co-ordinate their actions to achieve global locomotion by utilizing the coupling imposed by pre-stress stability as a means of ad-hoc communication. This co-ordination is facilitated by spiking neural networks which are capable of tuning time-sensitive responses to match the particular dynamics of the structures.

While the relationship between robot morphology and control has been explored in less complex systems, our results arise from a significantly more complex morphology with profoundly more degrees of freedom. Within this domain, we clearly illustrate the tight coupling between our evolved controllers and the system's dynamics in two ways. First, we demonstrate how, when the timing of the gait and the dynamics of the structure are subtly changed, locomotion varies both quantitatively and qualitatively - not just in terms of robustness (Paul 2006) or stability (Iida 2006), but through drastically new gaits. Secondly, and uniquely, we clearly illustrate the emergence of dynamical interactions as a means of communication by observing the coupled behavior of independent neural network controllers within the structure.

This novel demonstration of the emergence of morphology-as-information-conduit, or "morphological communication", presents a new paradigm for the decentralized control of large, coupled, modular systems. Furthermore, these results lend credence to the idea of embodied anatomical computation in biological systems, particularly those such as the human hand, which are both highly complex and which are known to employ the principles of tensegrity (Valero-Cuevas *et al.* 2007).

2. Tensegrity Control and Locomotion

The word tensegrity, a concatenation of tensile integrity was coined by Buckminster Fuller to describe structures popularized by the sculptor Kenneth Snelson in 1948 (Fuller 1975). A tensegrity structure is a self-supporting structure consisting of a set of disjoint rigid elements (struts) whose endpoints are connected by a set of continuous tensile elements (strings), and which maintains its shape due to the self-stressed equilibrium imposed by compression of struts and tension of strings (Wang 1998). Such structures are pre-stress stable, in the sense that in equilibrium each rigid element is under pure compression and each tensile element is under pure tension. The structure therefore has a tendency to return to its stable configuration after subjected to any moderate temporary perturbation (Connely & Back 1998).

These properties provide high strength-to-weight ratio and resilience, and make tensegrity structures highly prized in engineering and architecture. Tensegrity can be found in a variety of everyday structures, ranging from free-standing camping tents to the geodesic domes of sports stadiums. Tensegrity structures are becoming increasingly appealing as a medium for smart structures and soft robotics (Tibert 2002, Motro 2003, Sultan 1999), consequently, recent attention has been paid to their control and manipulation.

Unfortunately, these qualities which make tensegrities so attractive carry with them complex nonlinear dynamics, even for relatively small tensegrity structures (Skelton *et al.* 2001), and as a result, active control is needed to dampen the vibrational modes of relatively modest structures. In almost all cases, deformation

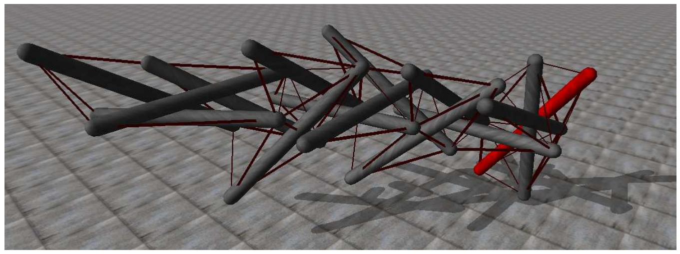

Figure 1. A complex and highly dynamically coupled fifteen-bar tensegrity structure

and control are achieved by changing the rest lengths of the tensile elements, for instance by attaching attaching strings to a reeled servo motor. In this manner, Skelton *et al.* have been able to demonstrate both active vibration damping (Chan *et al.* 2004) and open-loop control of simple structures. Efforts such as these, however, seek to minimize and control the complex dynamics of tensegrity structures, and no effective model exists for the control of the complex dynamics of relatively large tensegrity structures.

More recently, Paul *et al.* demonstrated an ability to produce static and dynamic gaits for 3- and 4-bar tensegrity robots via evolutionary optimization, and implemented these gaits on a physical robot (Paul 2006). Related work demonstrated how the overall stability of these structures results in beneficial resilience and redundancy of control mechanisms (Paul *et al.* 2005). Although these gaits did not seek to suppress the dynamical properties of the structures, and the evolved gaits contained dynamical aspects, the complexity of the structures was relatively low, and the solution relied upon a centralized and open-loop controller.

Rather than attempting to scale these control schemes to arbitrarily large and complex structures, our interest, by contrast, lies in harnessing and exploiting these same dynamics. We are particularly interested in methods of controlling large, and irregular tensegrity structures - those with much higher degrees of dynamical coupling and complexity than the regular towers of Chan *et al.* (2004) and the minimal structures of Paul (2006).

As a nominal reference structure in which to test our ideas we have chosen the tensegrity in Figure 1, which contains 15 rods and 78 strings. This structure is of particular interest because it belongs to a class of tensegrity towers generated by a single generative map L-system which can be scaled, with a degree of patterned similarity, to towers with more than 50 rods, as shown in Figure 2. Such a large and complex structure stymies conventional methods of tensegrity control, and calls for a new paradigm in the control of large, dynamically coupled systems.

(*a*) *Challenges of Tensegrity Robotics*

Constructing robots from tensegrities is a double-edged sword. On one hand the homogeneity of the rigid elements allows for a high degree of modularity: each rod can contain identical sets of sensors and actuators – the parts of a 10-bar tensegrity are identical to those of a 3-bar one. On the other hand, any solution which relies upon centralized control of the robot faces a crucial problem: that of communication between modules. As the number of modules increases, the lines of communication

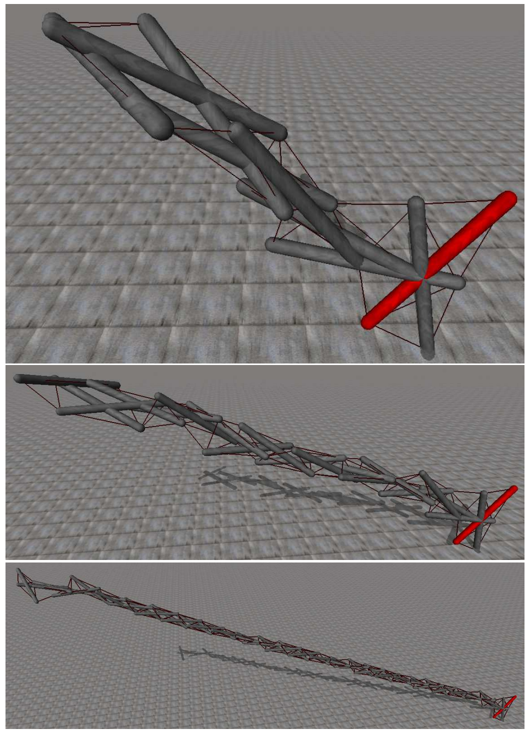

Figure 2. A family of tensegrity towers produced by the same grammar as the tower in Figure 1. As the number of iterations of the grammar increases, the tower grows from ten bars to twenty, thirty, forty and fifty, repeating the same pattern of twisting bars as it grows.

(quite literally) increase, bringing both the challenge of coordination and the risk of tangles.

Consider, for instance, the tensegrity shown in Figure 1. Even with a single sensor and actuator at each end of each bar, a centralized controller would need to synthesize, and co-ordinate the actions of, 30 sensors and thirty controllers.

We implement a simpler alternative to the problem of control and locomotion by doing away with the notion of explicit inter-modular communication completely. In our model we consider each rod of the tensegrity to be a simple module with a small controller only capable of sensing and affecting the tension on a single string at each end. We demonstrate how locomotion can emerge by exploiting the dynamic coupling of these otherwise autonomous tensegrity modules. In a sense, the body of the robot becomes an ad-hoc network for communication between modules.

3. A Modular Framework for Tensegrity Robotics

This work stems out of our efforts at creating innovative tensegrity-based robots. Tensegrities are a compelling, if challenging, platform for robotics. One particularly desirable feature is their collapsibility: by relaxing their strings, tensegrity robots can be quickly and easily packed into a small volume for transit, and then quickly re-deployed via string re-tightening.

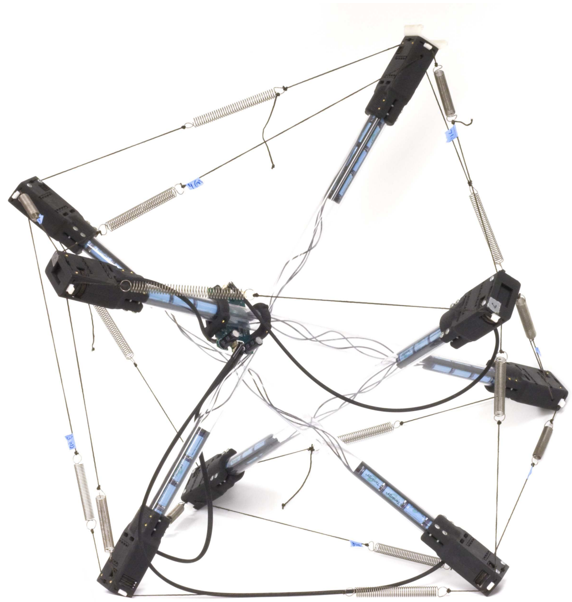

Figure 3. A tensegrity robot consisting of four strut modules and 16 strings

Of particular appeal is the highly modular nature of tensegrities, allowing for a significant amount of versatility and reuse: the struts in a four bar robot are identical to those in a sixteen bar robot. In our design each strut module consists of a rigid tube with a single servo motor mounted at each end. While, in principle, multiple strings could be actuated by multiple servos at each end, we have chosen to keep the design simple by limiting actuation on each end to a single string. Figure 3 contains a photograph of a representative tensegrity robot which contains four strut modules

(a) *Capturing Time-Sensitive Dynamics with Spiking Neural Networks*

Since our aim is to embody most of the complexity of a gait within the dynamics of the structure itself, our interest is in a relatively simple controller, such as an Artificial Neural Network (ANN). Unfortunately, conventional ANNs have a critical weakness in this application: they are unable to fine-tune their timing. Consequently, conventional neural networks within each module would require individual hand-tuning in order to find a firing rate at or near the resonant frequency of the structure, and any change in the underlying structure would require re-tuning of the network timing.

In order to add time sensitivity to our, we use a variant of ANNs called spiking neural networks. Spiking neural networks (SNNs) were developed to model more continuous processes: input and outputs are both represented as single-value spikes (as opposed the sigmoid outputs of a conventional ANN) (Maass & Bishop 1999). Instead of a sigmoid function, every SNN node contains a simple persistent counter, with adjustable offset and limit. At every time step, an SNN node sums its weighted inputs with the current counter value, and if the sum surpasses the limit the node fires a single “spike” to its output; otherwise the contents of the counter are decremented by a fixed decay rate, and persist until the next time step. This ability to fine-tune timing has proven particularly useful in time-sensitive robotics control tasks (Di Paolo 2003).

Each strut module contains a single spiking neural network with two inputs, corresponding to the tension sensed at the single actuated string on each end, two hidden nodes, and two outputs. At every simulation time step, each module measures its inputs and feeds them through the SNN. SNN output spikes are then converted into string actuations by measuring the duty cycle of network spikes. Any spike rate above 30% over a 100 step period is considered "active", and the corresponding string was pulled by halving its rest length.

(*b*) *Simulation of Tensegrity Robots*

The representative 15-bar tensegrity shown in Figure 1 was reproduced within the Open Dynamics Engine (ODE) Simulation environment, the widely used open-source physics engine which provides high-performance simulations of 3D rigid body dynamics. Rigid elements were represented as solid capped cylinders of fixed length with a length-to-radius ratio of 24:1. Tensile elements were represented as spring-like forces acting upon the cylinder ends. A given string s_i with length L_i, rest length L_0, and spring constant K produces a force $\hat{F}_i$:

$$\hat{F}_i = \begin{cases} K * (\hat{L}_i - \hat{L}_0) & \text{if } \hat{L}_i > \hat{L}_0 \\ 0 & \text{if } \hat{L}_i \leq \hat{L}_0 \end{cases}$$

(*c*) *Evolving Controllers for Locomotion*

Using this framework, we were able to evolve the weights within the separate SNNs such that the structure as a whole was able to locomote. Each experiment consisted of a population of 150 individuals initialized with random SNN weights evolved over the course of 1000 generations.

With only 30 actuators available (one at the end of each strut module), and a choice of 78 strings to actuate, we chose to evolve both the unique weights of the SNN within each strut module, and also which particular string at each end to actuate. Genotypes of individuals within the population therefore consisted of two sub-genes. The first contained 180 floating point numbers corresponding to the collective weights of all 15 strut module controllers within the structure. The second consisted of a pairing of actuated strings with strut endpoints. A single point mutation could therefore either change a weight within the SNN or change which string was actuated at a particular endpoint.

Individuals were evaluated within our simulated environment by measuring the travel of the center of mass over the course of 20,000 simulator time steps. Members of the population were then ranked by their fitness, and the bottom scoring half of the population culled. 75 new individuals were then created as offspring of the remaining population via fitness proportional selection, in which 30% of offspring were produced with two-parent crossover, and the remainder with single-point single-parent mutation.

Figure 4 contains snapshots of the movement of one successful evolved individual over the course of its locomotion. The path of the red sphere above the structure tracks the center of mass of the structure (vertically displaced for visualization).

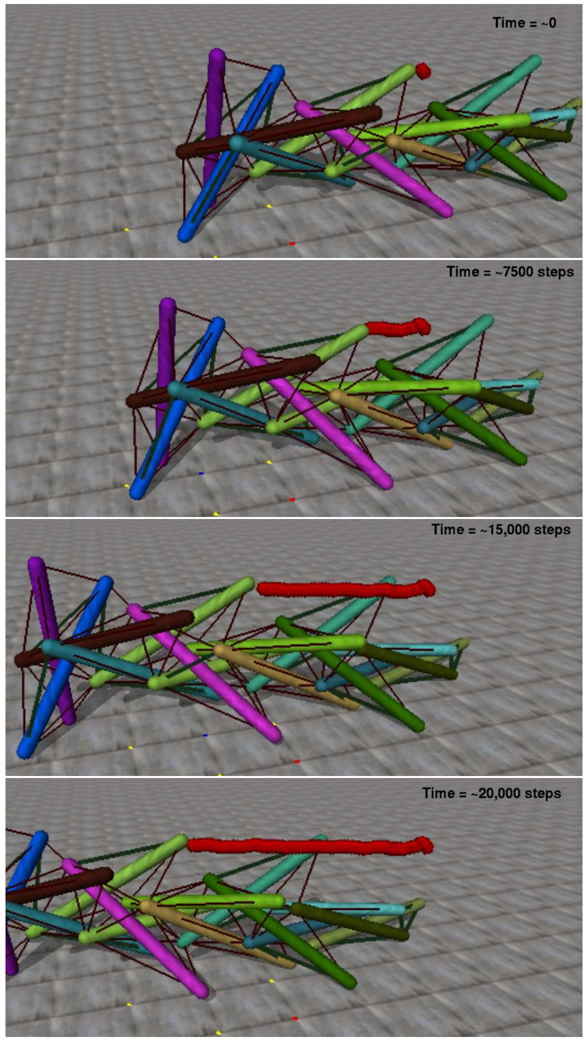

Figure 4. Snapshots of the motion of an evolved gait over 20,000 time steps

(*d*) *A Dynamically Coupled Evolved Gait*

Since our claim is that the evolved gaits are harnessing the coupled dynamics of the system, we must make efforts to differentiate the results from a quasi-static gait. In a purely quasi-static gait, the movement of the structure and its dynamics are sufficiently decoupled that it can be considered to be stable and consistent over a wide range of speeds. Consequently, neither doubling nor halving the speed of the gait should have a significant effect upon the motion. Consider, for instance a bicycle wheel which, *modulo* friction, will travel the same distance over five revolutions regardless of the specific angular velocity.

By contrast, in a more dynamic gait, such as a child on a pogo stick, the movement of the system is tightly coupled to its dynamics, and subtle changes in the timing of the gait should have considerable effects on the overall behavior.

We can therefore qualitatively measure the coupling between evolved gait and system dynamics by observing the behavior of the structure when the speed of the gait is adjusted maintaining the system dynamics. Gait “macros” were produced by recording the string actuations caused the SNNs of an evolved individual over the course of a normal 20000 time step run. These gaits were then replayed at speeds ranging from 10% of the normal speed up to 1000%. Distances covered by the center of mass over the course of the gait were then observed. Total number of simulation steps were adjusting upwards or downwards accordingly to fit the fixed number of gait cycles.

Figure 5 compares the path of the structure’s center of mass on the horizontal plane over the course of a fixed number of gait cycles for three evolved gaits. Left hand figures contain slower gait speeds and right hand figures contain faster speeds. As is evident, both the distance traveled *and the path traversed* vary significantly under varying speeds.

The degree to which the gaits vary is both significant and surprising, and reveals the deep coupling between the particular evolved gait and the system dynamics. Consider the shift when *Gait 1* varies from 1/3 to 1/4 of the normal speed: the direction of travel shifts 90 degrees. The remaining gaits also demonstrate significant shifts in trajectory under slower speeds. In general, faster gait speeds by comparison tended to exhibit more pathological changes. In several of the analyses of faster speeds, particularly for *Gait 2* and *Gait 3*, the behavior of the robot changes so much that the robot collapses onto its side, at which point motion effectively ceases. (n.b. It is worth noting that in several cases the robot appears to travel *further* under slower gait speeds than at the normal speed. This is largely due to the fact that the total amount of simulator time in which the gait is observed had to be increased in order to fit a full fixed gait cycle. At this time scale, factors such as the momentum of the structure play a larger role in the over all motion of the robot. If the graphs were normalized for a fixed number of simulation steps rather than for a fixed gait cycle, these slower gaits would of course travel much less far.)

(*e*) *Morphological Communication via Dynamic Coupling*

An equally compelling result is the emergence of *de facto* communication between independent module networks *via* the dynamical coupling of the modules. To demonstrate this phenomenon, during locomotion we disable the output of a single module network and observe changes in behavior in other module networks. Communication between networks can be measured by the degree to which the behavior of one network affects distal networks.

Figure 6 demonstrates two such examples of this phenomenon. In the first example, suppressing the output of one module network causes a distal network to also cease activity, and re-enabling the first network also re-enables the second. In the second example, suppressing the output of the first network significantly increases the firing frequency of the second network, and re-enabling the first network results in resumption of the secondary network’s original frequency.

Both of these are compelling demonstrations of how individual networks can affect the behavior of distal networks through their shared dynamical coupling. In essence, the morphology is acting as a data bus for communication between module networks.

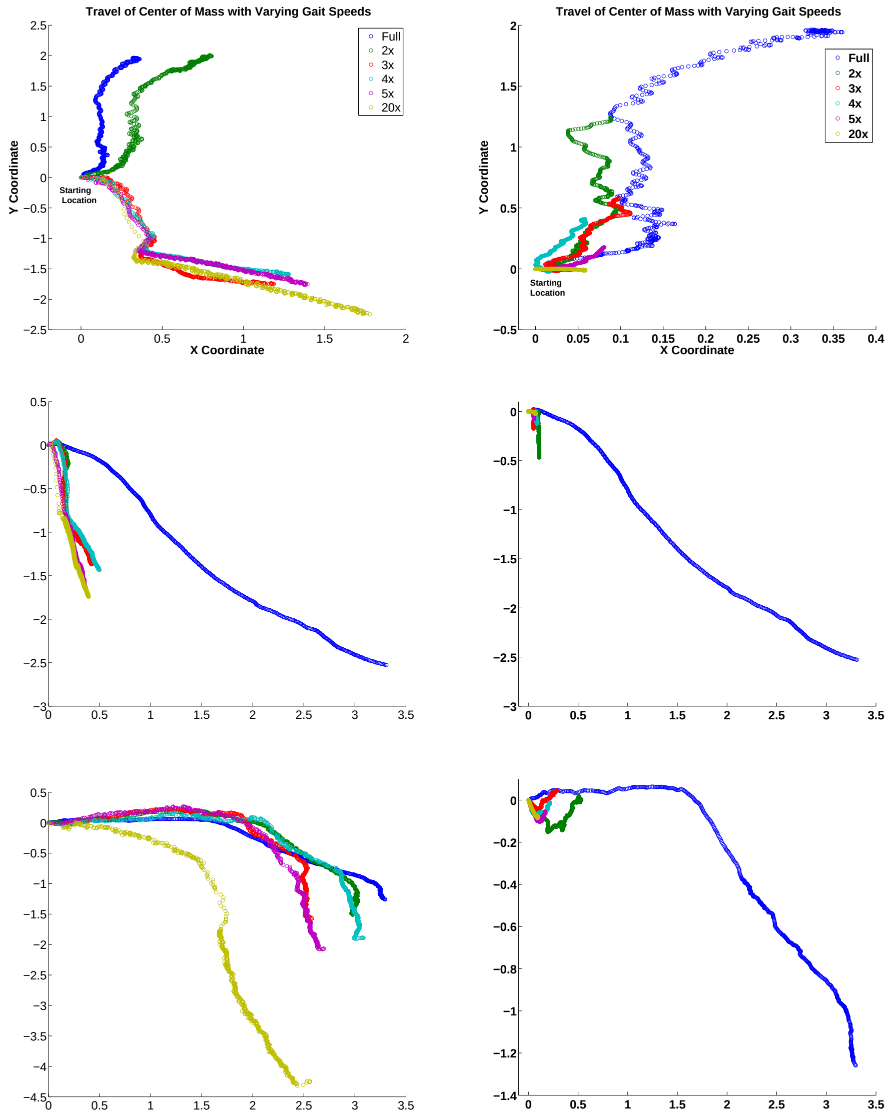

Figure 5. Gait trajectories. As the speed of the evolved gait is decreased (left hand figures) or increased (right hand figures), both the distance traveled and the path traversed vary significantly. Left and right hand figures are not on matched scales. Any increase in distance traveled (slower gaits in left hand figure) is due to the significantly longer amount of simulator time required for the structure to complete a fixed gait cycle. At this time scale, factors such as momentum play a larger role.

4. Discussion

In approaching the control of tensegrity systems, the conventional engineering approach has been to mitigate and attenuate the complex coupled dynamics and vibrational modes which the structures exhibit. Naturally, as the size and scale of

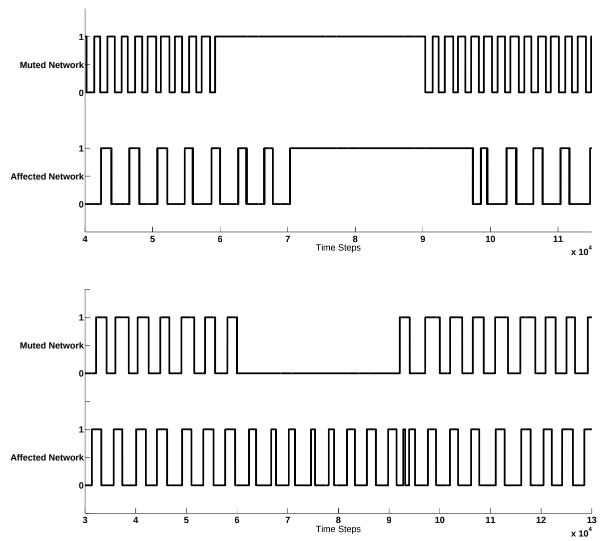

Figure 6. Demonstration of the emergence of communication between individual module networks via dynamical coupling. In the top example, suppressing the first network causes a distal network to cease activation. Enabling the first network re-enables the second. In the bottom example, suppressing the first network causes the second network to increase its firing frequency. After enabling the first network, the distal network resumes the former frequency.

these tensegrity systems increases, and as their regularity decreases, the task of control becomes exceptionally difficult.

Rather than abandon the use of these large, complex, irregular tensegrity structures for novel engineering purposes, for which there is no lack of demand, we propose harnessing, rather than mitigating, the complex dynamics. By using control schema which are able to discover and exploit the particular dynamics of the structure – in our case spiking neural networks – the structure at large becomes, at once, both data bus (distributing information between modules via their coupled dynamics) and powerful actuator (taking advantage of inherent oscillations in order to achieve locomotion). In other words, the morphology of the robot is performing both *computation* and *communication*.

(*a*) *Biomechanics and Morphological Computation*

Beyond engineering, this should be of particular relevance to biomechanics, particularly for systems which contain similar mechanical complexities. Recent research by Valero-Cuevas *et al.* (2007) on the tendinous network of the human hand indicate that the system performs in their words "anatomical computation" by distributing and switching the tension inputs of the tendon network in order to differentially affect torque at the finger tips. It is conjectured that "outsourcing" the computation into the mechanics of the structure allows related neural pathways to devote their resources to higher level tasks. Similar phenomena have been shown in the physiology of wallabies (Biewener *et al.* 2004), guinea fowl (Daley & Biewener 2006) and cockroaches (Ahn & Full 2002). Pfeifer and Paul coined the term "morphological computation" to describe this class of effect(Pfeifer 2006, Paul 2006).

The particular phenomenon we have described, in which morphology acts as a non-neural conduit of information has close ties to the mechanotransduction effects found throughout biology, such as in the ear (Mammano & Nobli 1993) and in heart tissue (Parker & Ingber 2007).

Consider also the biomechanics of soft-bodied invertebrates, such as the *Manduca sexta* caterpillar. Although considered a well studied model species, the particular mechanics of *Manduca* locomotion and control remain poorly understood. The caterpillar achieves remarkable control and flexibility despite the fact that each of its segments contains relatively few motoneurons (one, or maximally two per muscle, with approximately 70 muscles per segment), and no inhibitory motor units (Taylor & Truman 1974, Levine & Truman 1985). Studies of the properties of the organisms muscles indicate a high degree nonlinearity, pseudo-elasticity, and strain-rate dependency (Dorfmann *et al* 2007, Woods *et al.* 2008). It is conjectured therefore that, much like the tendon in the human hand, the complex biomechanics caused by the interaction of hydrostatics, the body wall, and the muscles, all contribute to a degree of morphological computation (Trimmer 2007).

The results described in this paper, in which the dynamical coupling between independent strut modules plays a large role in their ability to co-ordinate action to achieve locomotion, therefore lends credence to the existence of "mechanism as mind" in biological systems, and provides a compelling new paradigm for robotic locomotion.

5. Conclusion

One remaining challenge in leveraging these results lies in the "reality gap" between simulated and physical tensegrity structures. Dynamical effects such as those our solutions exploit are notoriously difficult to model with high fidelity. There are two possible and promising approaches to resolving this challenge in order to create physically embodidied robots capable of similar feats of mechanism-as-mind. The first lies in dispensing with the simulator entirely and evolving dynamic gaits *in situ* using embodied evolutionary techniques - such approaches can be slow, but have shown considerable promise (Hornby *et al.* 2000, Zykov *et al.* 2004). The second possibility lies in continuous self-modeling approaches which seek to co-evolve robotic gaits alongside an emerging self-model (Bongard *et al.* 2006).

These results demonstrate how the coupled dynamical properties of a complex mechanical system can be exploited for benefit rather than "engineered down". Simultaneously, they lend insight into why biological systems often contain the kind of complex coupled dynamics that are so often assiduously avoided in engineering. It has been conjectured that biological systems which appear under-actuated or under-controlled - such as the tendinous network of the human hand and the body of the *Manduca sexta* are able to achieve complex behavior through *"mechanism as mind"*, that is, through the outsourcing of complex control tasks away from the neural directly into the structural mechanics. Here we have demonstrated how such morphological computation can occur in complex mechanical systems, and lend credence to similar phenomena in biological systems.

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