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A Cellular Control Architecture for Compliant Artificial Muscles

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Abstract— **Dividing an artificial muscle material into a network of small cells could provide performance benefits and eliminate unwanted behaviors such as hysteresis. This paper presents a scheme for the position control or compliance control of an artificial muscle having this kind of cellular structure. Each cell contracts or relaxes probabilistically in response to a global feedback control loop, which measures only the aggregate force and displacement of the muscle. The stochastic nature of the cells produces smooth, reliable global behavior in the artificial muscle. By choosing a control law such that the expected response of the artificial muscle is equal to the desired response, good tracking control is achieved.**

I. Introduction

Many of the basic human needs which robots can fulfill involve human-like motions, such as walking, grasping and lifting. If robots are ever to perform such tasks as effectively as humans, they will need actuators that operate at characteristic force, rate and length scales similar to human skeletal muscle. Many active materials have been produced which aim to fill this niche, including various polymer gels, shape memory alloys and phase change materials. Already, some artificial muscle materials produce strains within an order of magnitude of those in human muscle. Artificial muscle forces easily surpass their natural counterparts by several orders of magnitude [1][2]. However, none of the artificial muscle materials available today can achieve strain rates comparable to human muscle. Most of these materials rely on heat transfer or ion diffusion to move energy into the active material, effects in which rate of actuation scales inversely as the square of characteristic length of diffusion. Consequently, they perform well on a microscopic scale but sluggishly on a macroscopic scale.

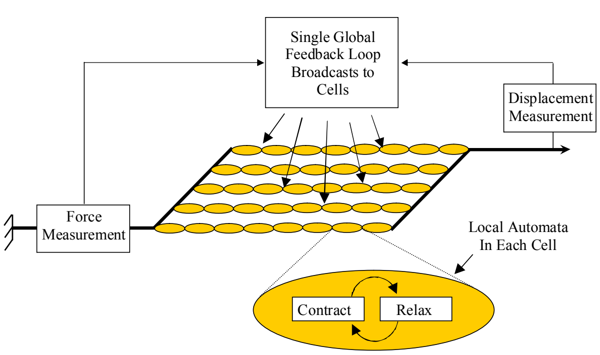

Fig. 1. A network of cells can be controlled with a single supervisory loop if the behavior of the local automata governing individual cell actions is related to the net force and the net displacement.

Several researchers, including Casalino, DeRossi et. al. [3] and Selden, Cho and Asada [4], have suggested that a cellular or segmented architecture for artificial muscles would solve many of the problems inherent in bulk control of these materials. Muscle tissue is composed of myriad small functional units, cells, which operate on small characteristic length scales, avoiding the long diffusion lengths that would cause slow actuation. In order to produce useful macroscopic motion, muscle cells are controlled via muscular recruitment mechanisms so that the displacement of the muscle appears smooth and continuous when the individual cell displacements are summed through elastic averaging effects.

In this paper, we present a recruitment scheme for artificial muscles. An active material is broken into small cells. Each cell contains a small local automaton that maintains the cell in a binary state, either relaxed or contracted, shown in fig. 1. A single global feedback loop measures the aggregate force and displacement produced by the muscle, and broadcasts a corrective signal to the cells. By designing the individual automata to respond stochastically to the broadcast input so that the relationship between local and global behavior is describable by a probabilistic distribution, a simple global control law can be used to control the artificial muscle, either using position control or compliance control.

II. Stochastic Broadcast Feedback Control

Stochastic broadcast feedback control is a method of connecting one global controller to a large network of cells with stochastic response, so that the summed output of the

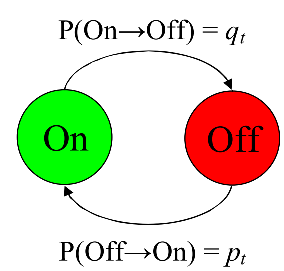

Fig. 2. Each cell contains a small stochastic decision making unit that turns the cell on if it is off with probability p_t and turns the cell off if it is on with probability q_t.

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cells appears smooth and continuous. At the heart of the notion of stochastic broadcast feedback control is the central limit theorem. A hundred fair coins flipped would sum to approximately fifty heads and fifty tails, despite the fact that each individual coin is incapable of assuming a half heads/half tails state. Similarly, a serial chain of small binary actuator cells will have a gross displacement equal to approximately 50% of the total range of motion if each cell has a fifty percent chance of contracting and a fifty percent chance of relaxing. This notion was generalized in a small two-state discrete-time Markov model, shown in fig. 2. The state transition probabilities p_t and q_t govern whether the cell is to turn on (contract), or turn off (relax). By varying p_t and q_t in response to the current state of the system, and broadcasting these quantities to all of the cells, the system can be driven to any state non-deterministically; a proof of convergence is given in [5].

To illustrate this idea, consider a set of N cells such that the number of cells on at time t, $N_{on}(t)$, is known. It is possible to predict the expectation of $N_{on}(t+1)$, the number of cells on at time t+1 using basic probability theory:

$$E\{N_{on}(t+1)\} = (1 - p_t - q_t)N_{on}(t) + p_t N \quad (1)$$

In order to drive the future number of on cells as close as possible to the desired number, the expected value of $N_{on}(t+1)$ is set equal to the desired number of on cells N_d,

$$E\{N_{on}(t+1)\} = (1 - p_t - q_t)N_{on}(t) + p_t N = N_d \quad (2)$$

Multiple control laws will satisfy this criterion, because (2) contains two free variables, p_t and q_t. The simplest law of this form can be written in two cases, one where $N_{on}(t)$ is greater than N_d, and one where $N_{on}(t)$ is less than N_d,

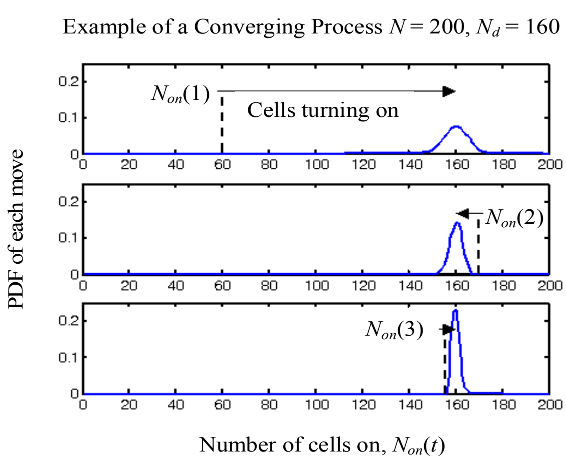

Fig. 3. By choosing appropriate values of p_t and q_t given measurements of $N_{on}(t)$, it is possible to drive N_{on} to any number of desired cells N_d.

$$\begin{aligned} N_{on}(t) < N_d: &\quad p_t = \frac{N_d - N_{on}(t)}{N - N_{on}(t)}, \quad q_t = 0 \\ N_{on}(t) > N_d: &\quad p_t = 0, \quad q_t = \frac{N_{on}(t) - N_d}{N_{on}(t)} \end{aligned} \quad (3)$$

Figure 3 shows one example of a the probability distributions of $N_{on}(t+1)$ in a controller tracking a stationary reference.

What is really desired is to control an artificial muscle displacement $y(t)$ to some position y_d, rather than the number of cells on at any given time. If N cells are all connected in series, and each cell has displacement η when on and 0 when off, then the displacement $y(t)$ of a serial chain will be

$$y(t) = N_{on}(t)\eta, \quad (4)$$

and $y(t)$ will range in value between 0 and $N\eta$. As before, the expected future value of $y(t)$ as calculated in (4) can be set equal to y_d, and the following relationship emerges:

$$E\{y(t+1)\} = (1 - p_t - q_t)N_{on}(t)\eta + p_t N\eta = y_d \quad (5)$$

Equation (4) can be substituted into (5), so that this constraint can be written entirely in terms of $y(t)$:

$$(1 - p_t - q_t)y(t) + p_t N\eta = y_d \quad (6)$$

A control law similar to (3) can be written for this case,

$$\begin{aligned} y(t) < y_d: &\quad p_t = \frac{y_d - y(t)}{N\eta - y(t)}, \quad q_t = 0 \\ y(t) > y_d: &\quad p_t = 0, \quad q_t = \frac{y(t) - y_d}{y(t)} \end{aligned} \quad (7)$$

This basic case illustrates the methodology behind these control laws: First, an expression for the expected future state of the cells must be written in terms of the current state of the cells and the transition probabilities, p_t and q_t. Then the quantity over which control is desired is calculated as a function of the cell state, and the expectation of this quantity in the future is set equal to the desired value in order to determine the broadcast control probabilities.

III. Position Control With Compliant Cells

We are interested in networks of compliant cells for two reasons: First, because most active materials are compliant enough that these effects cannot be ignored. The second, more interesting reason is that skeletal muscles are compliant, and this compliance seems to be a useful energy storage mechanism for tasks such as manipulation [6].

Consequently, a control system for active material actuators in which the inherent material compliance could be exploited could have useful robotic applications.

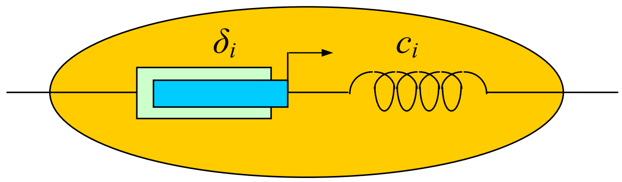

Fig. 4. Each cell is modeled as having some rigid displacement δ_i in series with a compliance c_i. These quantities have different values when the cell is on and when it is off.

The basic model for a compliant cell, shown in fig. 4, is a rigid displacement δ_i placed in series with a spring having compliance c_i. When cell i is off, $\delta_i = 0$ and $c_i = c_o$. When cell i is on, $\delta_i = \eta$ and $c_i = c_o + c'$. The displacement of a single cell in the presence of a force $F(t)$ is the sum of the rigid and compliant displacements,

$$y_i(t) = \delta_i(t) + F(t)c_i(t) \tag{8}$$

Because the same force $F(t)$ is experienced at every cell in a serial chain of N cells, the net displacement will look like one large rigid displacement in series with one large spring,

$$\begin{aligned} y(t) &= \sum_i \delta_i(t) + F(t)\sum_i c_i(t) \\ &= N_{on}(t)(\eta + F(t)c') + F(t)Nc_o \end{aligned} \tag{9}$$

As before, a control law for this compliant actuator can be derived by setting the expectation of $y(t+1)$ equal to some desired y_d. Because compliance is now considered, this expectation can be conditioned on force:

$$\begin{aligned} &E\{y(t+1)\} \\ &\quad = N_{on}(t+1)(\eta + F(t+1)c') + F(t+1)Nc_o = y_d \end{aligned} \tag{10}$$

If the assumption is made that $F(t)$ is a reasonably good prediction of $F(t+1)$, that is, that the force the actuator exerts is changing slowly, then the state evolution model from (1) can be substituted into (10),

$$\begin{aligned} &\big((1-p_t-q_t)N_{on}(t) + p_t N\big)(\eta + F(t)c') + F(t)Nc_o \\ &\quad = y_d \end{aligned} \tag{11}$$

Through back-substitution from (9), (11) can be expressed in terms of $y(t)$ and $F(t)$:

$$\begin{aligned} &(1-p_t-q_t)\left[N_{on}(t)(\eta + c'F(t)) + F(t)Nc_o\right] \\ &\quad + p_t N(\eta + F(t)c') + (p_t + q_t)F(t)Nc_o = y_d \end{aligned} \tag{12}$$

$$\begin{aligned} &(1-p_t-q_t)y(t) + p_t(N\eta + F(t)N(c_o + c')) \\ &\quad + q_t F(t)Nc_o = y_d \end{aligned}$$

The control law for this system can then be written in a fashion similar to (7), (13)

$$y(t) < y_d: \quad p_t = \frac{y_d - y(t)}{N(\eta + F(t)(c_o + c')) - y(t)}, q_t = 0$$

$$y(t) > y_d: \quad p_t = 0, \quad q_t = \frac{y(t) - y_d}{y(t) - N\eta - F(t)Nc_o}$$

The compliance-aware control law is more robust to constant or slowly-varying loads than the control law from (7), which does not account for force. A simulation of the two laws was performed on an actuator undergoing a constant disturbance force. In both cases, the control laws were simulated for a network of 200 cells in series tracking a sinusoidal reference. the accuracy of the controller in tracking a sinusoidal input was noticeably decreased when force was not used to compensate for compliance. The trajectory tracking results are shown in fig. 6.

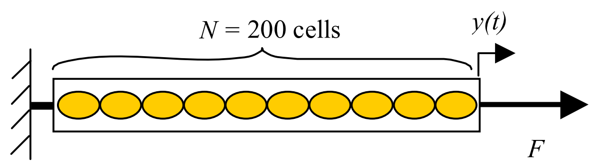

Fig. 5. The simulation results presented here are computed using a network of 200 cells in series. A constant force F is applied and the closed-loop position response of the actuator is then computed while tracking a sinusoidal reference.

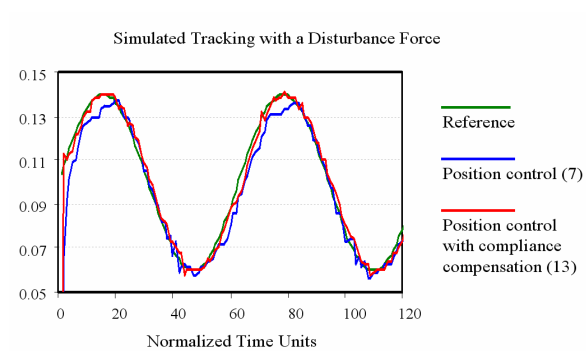

Fig. 6. Two controllers using the same simulated stochastic actuator try to track a sinusoidal reference in the presence of a constant disturbance force. The control law which compensates for compliance by measuring force converges more quickly on the desired trajectory than the control law which does not.

IV. COMPLIANCE CONTROL

The control law in (13) demonstrates that compliant artificial muscles using this architecture can be made robust to series compliance, and yet many robotic tasks require that some virtual series compliance be added into the actuator's behavior. One easy modification can be made to this control law to exploit the natural compliance of the active material. Instead of driving the expected value of $y(t+1)$ to be equal to some reference y_d, the actuator can be controlled as a spring with approximate compliance equal to the compliance of the active material when off, Nc_o, and virtual neutral position x_d. The future neutral position, assuming this desired compliance, can be predicted by the expression

$$E\{y(t+1)-F(t+1)Nc_o\}=x_d \tag{14}$$

The derivation of the expressions for p_t and q_t are quite similar to that of (13), so it will not be repeated. The resulting control law differs only by one term,

$$\begin{aligned} & y(t)-F(t)Nc_o<x_d: \\ & \quad p_t=\frac{x_d+F(t)Nc_o-y(t)}{N(\eta+F(t)(c'+c_o))-y(t)}, q_t=0 \\ & y(t)-F(t)Nc_o>x_d: \\ & \quad p_t=0, \quad q_t=\frac{y(t)-x_d-F(t)Nc_o}{y(t)-N(\eta+F(t)c_o)} \end{aligned} \tag{15}$$

This control law was tested in simulation by applying a constant load and tracking a neutral position as a reference. Because some compliance about the neutral position was allowed, a constant offset proportional to the externally applied force was observed in the response, shown in fig. 7.

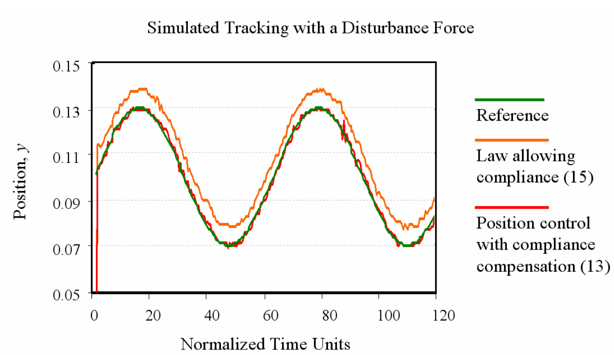

Fig. 7. The performance of the compliant control is demonstrated by tracking a reference position at constant load with compliance and without. The compliant control law response is offset from the desired neutral position by a constant amount due to the constant external force. The position control law of (13) is shown for comparison.

It may be desirable to vary the degree of effective series compliance; this may be accomplished by augmenting (14) to use a compliance substantially different than the passive compliance of the material. However, it is worth noting that the actuator will behave at high frequencies according to its passive compliance, so the closed-loop virtual compliance will only be guaranteed within the bandwidth of the actuator. It would be better to alter number of actuator cells or the serial and parallel configuration of the cells to match the passive artificial muscle compliance to the tasks which it must perform.

V. CONCLUSION AND FUTURE WORK

This paper has demonstrated the ability of a serial chain of active material cells to provide position and compliance control, using many distributed stochastic cell controllers and one central supervisory loop. Interestingly, simulations of several serial chains in parallel indicate that the control laws obtained in (13) and (15) can be applied, despite some difficulty involved in coming up with probabilistic models for these parallel chains. These cases are being explored and will be expanded upon in the future. Also, prototype actuators utilizing these control schemes are being constructed, and the experimentally determined active material dynamics will also be included in future analyses of stochastic broadcast feedback control systems.

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