ABSTRACT

JENKINS, TYLER EARL. Bio-inspired Online Variable Recruitment Control of Fluidic Artificial Muscles. (Under the direction of Dr. Matthew Bryant).

This paper details the creation of a hybrid variable recruitment control scheme for fluidic artificial muscle (FAM) actuators with an emphasis on maximizing system efficiency and switching control performance. Variable recruitment is the process of altering a system's active number of actuators, allowing operation in distinct force regimes. Previously, FAM variable recruitment was only quantified with offline, manual valve switching; this study addresses the creation and characterization of novel, on-line FAM switching control algorithms. The bio-inspired algorithms are implemented in conjunction with a PID and model-based controller, and applied to a simulated plant model. Variable recruitment transition effects and chatter rejection are explored via a sensitivity analysis, allowing a system designer to weigh tradeoffs in actuator modeling, algorithm choice, and necessary hardware. Variable recruitment is further developed through simulation of a robotic arm tracking a variety of spline position inputs, requiring several levels of actuator recruitment. Switching controller performance is quantified and compared with baseline systems lacking variable recruitment. The work extends current variable recruitment knowledge by creating novel online variable recruitment control schemes, and exploring how online actuator recruitment affects system efficiency and control performance. Key topics associated with implementing a variable recruitment scheme, including the effects of modeling inaccuracies, hardware considerations, and switching transition concerns are also addressed.

© Copyright 2016 by Tyler Earl Jenkins

All Rights Reserved

Bio-inspired Online Variable Recruitment Control of Fluidic Artificial Muscles

by
Tyler Earl Jenkins

A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Master of Science

Mechanical Engineering

Raleigh, North Carolina

2016

APPROVED BY:

Dr. Matthew Bryant
Committee Chair

Dr. Gregory Buckner

Dr. Katherine Saul

BIOGRAPHY

Tyler E. Jenkins received the B.S. degree in mechanical engineering with a minor in electrical engineering from Purdue University, West Lafayette, IN, USA in 2014. His research interests are rooted in dynamics and controls applications and the integration of mechatronic systems, including novel actuator control techniques. This thesis is in pursuit of the M.S. degree in mechanical engineering at North Carolina State University in Raleigh, NC. Mr. Jenkins is the recipient of various scholarships and awards, including the Frank T. Jelinek, Grant Arrasmith, and Burl A. Dollens awards from 2010-2014.

ACKNOWLEDGMENTS

I would like to gratefully acknowledge funding support from the DARPA Maximum Mobility and Manipulation (M3) Program under the direction of Dr. Gill Pratt and our collaborators at Cornell University under Prime Agreement W31P4Q-13-1-0012. I thank my committee members for their support and feedback, and the iSSRL for providing the resources and environment necessary for completion of this research. Finally, I thank Dr. Matthew Bryant for his guidance and leadership over the past two years.

TABLE OF CONTENTS

LIST OF TABLES	v
LIST OF FIGURES	vi
1. INTRODUCTION	1
2. SYSTEM DEFINITION.....	3
2.1. <i>Efficiency modeling</i>	<i>5</i>
2.2. <i>Incompressible fluid energy</i>	<i>5</i>
2.3. <i>Mechanical work</i>	<i>7</i>
2.4. <i>Actuator force characterization</i>	<i>8</i>
3. ONLINE VARIABLE RECRUITMENT ALGORITHMS.....	10
3.1. <i>Single Equivalent Motor Unit (SEMU)</i>	<i>13</i>
3.2. <i>Batch recruitment</i>	<i>14</i>
3.3. <i>Orderly recruitment.....</i>	<i>16</i>
3.4. <i>Bundle force sensitivity to pressure</i>	<i>17</i>
4. SWITCHING CONTROLLER EFFECTS ON THE FORCE-STRAIN SPACE... 	19
4.1. <i>Force sensitivity to empirical tuning parameters</i>	<i>20</i>
4.2. <i>Controller effects on output force</i>	<i>21</i>
4.3. <i>Force-strain space analysis</i>	<i>24</i>
5. NUMERICAL SIMULATION OF ONLINE VARIABLE RECRUITMENT CONTROLLER	28
5.1. <i>Switching transition analysis</i>	<i>29</i>
5.2. <i>Performance analysis</i>	<i>31</i>
6. CONCLUSION	34
REFERENCES.....	36

LIST OF TABLES

Table 1. FAM Parameters	10
Table 2. Overview of variable recruitment transition effects.....	27
Table 3. System parameters	29

LIST OF FIGURES

- Figure 1.** A single degree of freedom rotating arm is driven by antagonistically acting FAM muscle bundles. Working fluid is supplied to the actuators by an ideal constant source pressure P_{sys} , creating mechanical output work by the robotic arm..... 4
- Figure 2.** The block diagram represents the hybrid controller, control valves, actuators, and robotic arm. Position feedback error is input to the PID controller, driving the switching logic and model computations. Bold terms represent vectors, with entries corresponding to distinct motor units within each muscle bundle. 11
- Figure 3.** The batch recruitment switching transitions are depicted for the system at (a) an initial equilibrium at t_0 , (b) in motion at t_1 , and (c) at a final equilibrium at t_f . When the increasing control pressure, P_{act} , reaches the system pressure, P_{sys} , at t_1 , a new motor unit is recruited, and the pressure is equalized to a new control pressure in the two active motor units. The 5/3 valve allows for continuous pressure control to the motor units, while the 3/2 valves control which motor units are active..... 14
- Figure 4.** The orderly recruitment switching state transitions are depicted for the system at (a) an initial equilibrium at t_0 , (b) in motion at t_1 , and (c) at a final equilibrium at t_f . When the increasing control pressure reaches the system pressure at t_1 , a new motor unit is recruited, and the pressure is increased from atmospheric pressure to a new control pressure in the newly recruited active motor unit. The initial active motor unit remains at system pressure after the recruitment state change. The 5/3 valves allow for continuous pressure control to each motor unit..... 16
- Figure 5.** Input/output relationship of the variable recruitment switching controller..... 21
- Figure 6.** Relationship of control signal and muscle bundle force output for batch recruitment at strain = 0.15, shown for (a) the entire force range, and (b) a detailed inset at first the transition event. Markers denote recruitment transitions. When discrepancies exist between the controller model and actuator output, discontinuities in the force output at variable recruitment transition events are observed. 23
- Figure 7.** Relationship of control signal and muscle bundle force output for orderly recruitment at strain = 0.15, shown for (a) the entire force range, and (b) a detailed inset at the first transition event. Markers denote recruitment transitions. When discrepancies exist between the controller model and actuator output, discontinuities in the force output at variable recruitment transition events are observed..... 24
- Figure 8.** Force-strain space for a batch recruitment bundle with model-based switching controller for (a) the corrected virtual work model, (b) the uncorrected virtual work

model, (c) 10% overestimates of empirical data, and (d) 10% underestimates of empirical data.	25
Figure 9. Force-strain space for an orderly recruitment bundle with model-based switching controller for (a) the corrected virtual work model, (b) the uncorrected virtual work model, (c) 10% overestimates of empirical data, and (d) 10% underestimates of empirical data.	26
Figure 10. Simulation results using actuators with Latex bladders and a spline input trajectory of $\Delta t = 20$ s displaying (a) angular position versus time and (b) an inset at the second transition event. The applied pressure is displayed for a counter-clockwise acting motor unit (+ MU) for (c) batch recruitment with a chatter prevention safety factor of 1.1, (d) orderly recruitment with a chatter prevention factor of 1.1, (e) batch recruitment with a 10% underestimate of ε_{fit} , and (f) orderly recruitment with a 10% underestimate of ε_{fit}	31
Figure 11. Average efficiency and Integrated Absolute Error (IAE) for (a) a batch recruitment bundle with a chatter prevention safety factor = 1.1, (b) an orderly recruitment bundle with a chatter prevention safety factor = 1.1, and (c) a SEMU. Simulations are performed over a range of trajectories and durations.	33

1. INTRODUCTION

The McKibben fluidic artificial muscle actuator has been extensively researched and characterized due to its exceptional force-to-weight ratio, low cost to construct, and natural compliance [1]. Generally consisting of an elastic tube surrounded by a braided sleeve, the relatively simple construction of McKibben muscles allows for in-house fabrication. One end of the actuator typically acts as a working fluid port, whereas the other end is plugged. Appropriate hose clamps and fittings complete the construction. Actuation is achieved by pressurizing the McKibben muscle with a working fluid, creating radial expansion and axial contraction.

McKibben muscles are often referred to as fluidic artificial muscles (FAMs) due to a variety of biological similarities. Biological musculature and FAMs exhibit force-strain dependence and geometric changes during contraction [2]. Additionally, both are single-acting tensile actuators, necessitating antagonistic pairing for bidirectional motion. FAM antagonistic grouping nomenclature draws further inspiration from biology; a single FAM is analogous to a “muscle fiber”, a group of FAMs always operating at the same level of activation make up a “motor unit”, and a group of motor units make up a “bundle” [3]. Counteracting bundles attached to a pulley system then make up an antagonistic pair.

Biological similarities naturally led to Joseph McKibben’s original FAM implementation as an orthotic in 1960 for his polio stricken daughter [4]. While applications in orthotics still exist, the 1990’s saw a renewed interest in FAM actuators for robotic motion due to the actuator’s inherent compliance and high force-to-weight ratio [5]. The force-strain

nonlinearities of the actuator have proven difficult to control, leading to a plethora of control studies. Advanced control attempts include variable structure control [5], cascaded position control with pressure feedback [6], various sliding mode model based controllers [7], [8], and neural network learning schemes [9], [10], among others.

While some researchers have been focusing on the control of FAMs, others have investigated the impact of various fabrication materials and operating fluid choices. An experimental comparison of pneumatic and hydraulic working fluid energetics lends insight into material and energy conversion effects [11]. Results show that at a pressure of 5.2 bar, an incompressible hydraulic working fluid is twice as energy efficient as the more conventional pneumatic working fluid. The authors also show that inelastic bladders offer improved energy conversion, force capabilities, and contraction ranges, whereas elastic bladders have relatively less hysteresis and greater durability. FAM force-strain model accuracy and improvement techniques were likewise assessed for effectiveness. Finally, a semi-empirical force model was developed, which is applied in this paper.

Current mobile robotics applications necessitate improving efficiency in both soft robotics [12] and traditional robotics [13]. Recent FAM studies support using multiple actuators to improve efficiency. Bryant *et al.* proposed using variable recruitment to leverage the versatility of a lightweight FAM bundle. The authors showed that it is more energy efficient to activate muscles based on the instantaneous required load, as compared to the traditional practice of sizing muscles for the maximum required load [14]. By purposely using a bundle's smallest necessary motor units, consumed fluid volume and throttling losses are minimized. Whereas Bryant's work was performed quasi-statically, Robinson *et al.* achieved similar results through

simulation and experimentation with a closed-loop PID controlled system [15]. In both studies, all distinct recruitment state switching was conducted offline by the operator using ON/OFF valves.

The purpose of this paper is to design and characterize an intelligent FAM online variable recruitment switching scheme, which has not been presented in literature to date. The variable recruitment schemes are procedurally created by first presenting a system for study throughout the paper. An actuator force-strain model from literature is also described in Section 2. In Section 0, the online variable recruitment algorithms are developed by initially crafting the PID and model based control scheme, and then creating and integrating the switching recruitment schemes. In Section 4, to characterize and compare the recruitment schemes, modeling inaccuracies within the control model are explored by performing a sensitivity analysis over the force-strain space. Finally, simulations are performed for a variety of spline position trajectories, leading to conclusions regarding the many options for variable recruitment implementation.

2. SYSTEM DEFINITION

In order to quantify variable recruitment performance, a representative system is first developed. The plant under consideration in Figure 1 is a one degree-of-freedom rotating robotic limb of length L_{arm} and mass m_{arm} with a tip mass M_{ext} , driven by an antagonistic pair of artificial muscle bundles. This system was chosen because the nonlinear gravitational terms combine with the decreasing force output of a contracting FAM to provide a simple, yet

Figure 1. A single degree of freedom rotating arm is driven by antagonistically acting FAM muscle bundles. Working fluid is supplied to the actuators by an ideal constant source pressure P_{sys} , creating mechanical output work by the robotic arm.

illustrative test case for variable recruitment implementation. For comparison purposes, each actuator bundle is made up of a variable number of motor units. The bundles provide counteracting torques on a pulley of mass m_{pulley} and radius r_{pulley} , creating rotation of the robotic arm. Damping is introduced as a mechanical loss, approximating bearing losses and actuator braid friction. The equation of motion for the system is given in equation (1), where $\tau_{actuators}$ is the net actuator torque, τ_{ext} is the external torque, I is the rotational mass moment of inertia of the system, and c is the system damping coefficient.

$$\Sigma \tau = \tau_{actuators} + \tau_{ext} = I\ddot{\theta} + c\dot{\theta} \quad (1)$$

Net actuator torque, $\tau_{actuators}$, is defined in equation (2) as the difference of the antagonistically acting muscle bundle forces multiplied by the pulley radius of the robotic arm, where F_+ and F_- are the net forces produced by the positively and negatively acting muscle bundles, respectively. Individual motor unit forces are assumed to directly sum without any interaction effects to reduce the net actuator force. When considering the summation of actuator forces in a muscle bundle, experimental data in [14] shows a 16% muscle bundle force

overestimation at low pressures, and a 2% muscle bundle force overestimation at high pressures. Although not treated here, consideration needs to be given to FAM bundle arrangement to minimize asymmetrical loading torques and interaction effects.

$$\tau_{actuators} = F_+ r_{pulley} - F_- r_{pulley} \quad (2)$$

External torque acting on the system, shown in equation (3), is from gravity, g , acting on the arm and the tip mass. Rotational position θ and FAM length l are related by equation (4), with the assumption of inextensible transmission mediums and negligible pulley slipping.

$$\tau_{ext} = -m_{arm} g \frac{L_{arm}}{2} \cos(\theta) - M_{ext} g L_{arm} \cos(\theta) \quad (3)$$

$$l = l_0 - r_{pulley} \theta \quad (4)$$

2.1. Efficiency modeling

To isolate the energy conversion of the actuators, the working fluid is assumed to be incompressible. This realistically translates to using hydraulic fluid or water as the working fluid, as the high bulk moduli of the fluids leads to relatively trivial compression relative to the total fluid volume. System efficiency is defined as the average efficiency of the actuators for a given lifting task. The average efficiency η is calculated in equation (5) as the ratio of the total mechanical work output $W_{out,mech}$ to the fluid energy input $E_{in,fluid}$ to the system.

$$\eta = \frac{W_{out,mech}}{E_{in,fluid}} \quad (5)$$

2.2. Incompressible fluid energy

The fluid energy input to the system is defined in equation (6) as the volumetric integral of system pressure P_{sys} multiplied by differential FAM volume dV , which can then be represented

as a time integral using chain rule properties. The resulting equation is a function of system pressure and volumetric flow rate into the system, $\dot{V}$. The fluid volume needed to initially fill a completely vacated FAM is intentionally excluded in order to only analyze working fluid consumed during the operation tasks.

$$E_{in,fluid} = \int_{V_i}^{V_f} P_{sys} dV = \int_{t_i}^{t_f} P_{sys} \dot{V} dt \quad (6)$$

It is important to note that only volumetric flow into the system contributes to the fluid energy; in a system lacking fluid energy regeneration, any vented fluid is considered an energetic loss. Assuming negligible wall thickness and cylindrical shape, actuator volume V is modeled in equation (7) as a function of strain and FAM geometry, following the derivations of [11]. Parameters include initial bladder radius r_0 , initial braid angle α_0 , initial length l_0 , actual length l , and strain ε .

$$V = \pi r_0^2 l_0 \left(\frac{1-\varepsilon}{\sin(\alpha_0)^2} - \frac{(1-\varepsilon)^3}{\tan(\alpha_0)^2} \right), \varepsilon = \frac{l_0 - l}{l_0} \quad (7)$$

During operation, the contraction of a FAM solely determines the FAM volume, and therefore the amount of consumed incompressible working fluid. This conclusion has been supported experimentally [11]. Note that although volume is represented as a function of strain and does not explicitly depend on pressure, actuator strain is implicitly coupled with applied pressure and external load. Differentiating equation (7) with respect to time and for concision substituting strain as a function of length, the volumetric flow rate as a function of changing muscle length, $\dot{V}$, is derived in equation (8), where $\dot{l}$ is the time rate of change of the length of the FAM.

$$\dot{V} = \pi r_0^2 \dot{l} \left(\frac{1}{\sin(\alpha_0)^2} - \frac{3l^2}{l_0^2 \tan(\alpha_0)^2} \right) \quad (8)$$

2.3. Mechanical work

Mechanical work is defined in equation (9) as the position integral of torque multiplied by differential rotational position $d\theta$. Via the chain rule, mechanical work is then represented as a time integral of net actuator torque multiplied with the system angular velocity $\dot{\theta}$. FAM braid friction and system damping dissipate a portion of the applied actuator force, introducing path-dependent losses to the calculations. As we are interested in the transduction of fluid energy to purely mechanical work done by the system, the calculated efficiency should not include frictional losses, as accounted for in equation (10) by the mechanical torque producing work τ_{mech} .

$$W_{out,mech} = \int_{\theta_i}^{\theta_f} \tau_{mech} d\theta = \int_{t_i}^{t_f} \tau_{mech} \dot{\theta} dt \quad (9)$$

$$\tau_{mech} = \tau_{actuators} - c\dot{\theta} \quad (10)$$

By disregarding dissipative losses, a key consequence of in equation (9) is that for a given plant model that starts and stops a motion trajectory at static equilibrium, mechanical work is solely dependent on the initial and final positions (i.e., change in potential energy), regardless of the nature or quantity of actuators required to move the system. It is therefore deduced that only a reduction in consumed fluid energy will improve the efficiency of a given task. This result is the motivation for pursuit of a variable recruitment scheme, as has been experimentally demonstrated with offline recruitment [14], [15].

2.4. Actuator force characterization

Researchers have quantified the FAM force-strain-pressure profiles with analytical and empirical methods. A semi-empirical method [11] uses an idealized analytical virtual work model [4] combined with empirical tuning parameters. The virtual work model derivation, resulting in equation (11), has been thoroughly reviewed [5], [11], [14] and is not covered here. Equation (11) uses FAM geometry to relate actuator contraction force, F_{ideal} , to applied pressure, P_a , and actuator strain. Parameters a , b , and strain ε are used to simplify the representation of the modeling equations.

$$F_{ideal} = \pi r_0^2 P_a (a(1 - \varepsilon)^2 - b) \quad (11)$$

$$a = \frac{3}{\tan(\alpha_0)^2}, b = \frac{1}{\sin(\alpha_0)^2} \quad (12)$$

The *blocked force* and *free strain* of the actuator model are of particular interest. The blocked force of the actuator is defined as the force produced at zero-strain, and is the actuator's maximum force output at a given pressure. The free strain of the actuator is defined as the actuator strain corresponding to zero-force, and represents the maximum contraction of the actuator at a given pressure. Although the virtual work model provides a starting point rooted in first principles, experimentally collected force data deviates from the idealized model. This deviation has several causes, including elastic bladder energy storage, non-cylindrical end effects (the model assumes a completely cylindrical shape), and braid friction. Results have shown that, for Latex bladder actuators at a pressure of 300kPa, the ideal model over predicts the free strain by 33% and the blocked force by 10% [11]. A corrected model incorporates a free strain tuning parameter, κ_ε , proposed in [5], and a blocked force tuning

parameter, κ_F , proposed in [16] to account for the model deviation. The blocked force tuning parameter is calculated as the ratio of the pressure-dependent blocked force to the predicted virtual work blocked force, shown in equation (13). The free-strain tuning parameter is calculated as the ratio of the pressure-dependent free strain to the predicted virtual work free strain, shown in equation (14). Collectively, κ_F and κ_ε are referred to as the *force model tuning parameters*. The modified actuator force-strain model is given by equation (15).

$$\kappa_F = \frac{F_{fit}(P_a)}{\pi r_0^2 P_a (a - b)} \quad (13)$$

$$\kappa_\varepsilon = \frac{1}{\varepsilon_{fit}(P_a)} \left(1 - \frac{1}{\sqrt{3} \cos(\alpha_0)} \right) \quad (14)$$

$$F_{mod} = \kappa_f \pi r_0^2 P_a \left(a(1 - \kappa_\varepsilon \varepsilon)^2 - b \right) \quad (15)$$

A procedure is proposed in [11] to experimentally determine the force model tuning parameters. Blocked-force and free-strain data are collected for a range of pressures and curve fit with a high order polynomial or logarithmic function. $F_{fit}(P_a)$ is the curve-fit function of blocked force as a function of pressure, and $\varepsilon_{fit}(P_a)$ is the curve-fit function of free strain as a function of pressure. The blocked-force and free-strain fit equations for a Latex FAM bladder with parameters in Table 1 are given in equation (16) for pressure up to 7 bar [11]. Although inelastic actuator bladders such as Low Density Polyethylene (LDPE) have been shown to improve actuation efficiency, we have chosen the Latex bladder model due to the material's frequent use in literature.

$$\begin{aligned}\varepsilon_{fit}(P_a) &= 1.242 \times 10^{-18} P_a^3 - 2.167 \times 10^{-12} P_a^2 + 1.342 \times 10^{-6} P_a - 0.0377 \\ F_{fit}(P_a) &= 6.239 \times 10^{-4} P_a - 3.479\end{aligned}\tag{16}$$

Note that a FAM, acting only as a tensile actuator, will be in a buckled state and unable to produce contractile force if its strain is greater than the pressure-dependent free-strain, $\varepsilon_{fit}(P_a)$. This notion is important when considering online variable recruitment, as an actuator's inability to produce tensile force in a buckled state must be accounted for in the controller. The semi-empirical model retains the elegance of an analytical approach, while avoiding the excessive amount of data collection necessary for a purely empirical approach. Actuators used throughout the paper are modeled by the data presented in [11] with parameters in Table 1.

Table 1. FAM Parameters

Parameter	Measured Value
Unpressurized length, l_0 (m)	0.16
Unpressurized radius, r_0 (cm)	0.635
Unpressurized braid angle, α_0 (deg)	28.7

3. ONLINE VARIABLE RECRUITMENT ALGORITHMS

Biological musculature relies on altering activation firing rates or recruitment of additional muscles to change operating force regimes, with different activation levels and recruitment states affecting force output and fatigue rate [17]. A similar approach is taken in switching control development by allowing the desired motor unit pressure to drive motor unit recruitment. The block diagram in Figure 2 schematically represents the overall feedback

controller. It is divided into three distinct sections representing the plant/actuator hardware, pressure dynamics and control valves, and controller.

2.1. Motor unit control scheme

Development of an online variable recruitment control strategy first requires creation of a control scheme applicable to a single motor unit. While advanced nonlinear control studies have been developed in the literature [5]–[10], we focus on the variable recruitment aspect and implement a more traditional control scheme. The proposed control scheme and simulation treat the control valves as an idealized system, i.e. a “black box with unity gain” in the control block diagram, leading to desired pressure P_{des} being equal to the actual applied control pressure, P_{act} . Multiple hardware implementation solutions for pressure control exist, including an experimentally validated cascaded PI pressure controller [6], [15] and a model based pressure regulation scheme [18]. It is important to note that poor pressure control can lead to excessive venting of pressurized fluid, and therefore contribute to system losses. Later sections

Figure 2. The block diagram represents the hybrid controller, control valves, actuators, and robotic arm. Position feedback error is input to the PID controller, driving the switching logic and model computations. Bold terms represent vectors, with entries corresponding to distinct motor units within each muscle bundle.

give an overview of necessary control valve hardware required for variable recruitment implementation.

Inspiration for a PID and model-based control algorithm is taken from [18] and altered to include the modified virtual work force-strain profile. Due to the computations performed by the entire switching control algorithm, the PID controller is simulated in discrete time. Position error $e(t)$ at time step k is fed into the PID controller, outputting a representative corrective force control signal U_c in equation (17). K_P , K_I , and K_D represent the proportional, integral, and derivative control gains, respectively.

$$U_c(t_k) = K_P e(t_k) + K_I \sum_{i=1}^k e(t_i) \Delta t + K_D \frac{e(t_k) - e(t_{k-1})}{\Delta t} \quad (17)$$

Known system gravitational forces U_g are calculated in equation (18) using the actual measured system position θ_{act} .

$$U_g = \frac{m_{arm} g \frac{L_{arm}}{2} \cos(\theta_{act}) + M_{ext} g L_{arm} \cos(\theta_{act})}{r_{pulley}} \quad (18)$$

The corrective control signal is then added to the known system gravitational forces to yield equation (19), a representative desired total force F_{tot} .

$$F_{tot} = U_c + U_g \quad (19)$$

Using the representative total force and the desired rotational position θ_{des} of the robot arm, and assuming $F_{tot} = F_{des}$ for the single motor unit case, desired applied pressure can be calculated with equation (20) by inverting the actuator force-strain model.

$$P_{des} = \frac{F_{des}}{\kappa_F \pi r_0^2 (a(1 - \kappa_\epsilon \epsilon_{des})^2 - b)} \quad (20)$$

$$\epsilon_{des} = \frac{l_0 - r_{pulley} \theta_{des}}{l_0} \quad (21)$$

Abstracting the controller from operating a single motor unit to operating an antagonistic pair of motor units presents additional considerations. First, it is desirable for the system to not require an assisted return mechanism, thereby allowing operation in the horizontal and vertical planes. Additionally, a pressurized motor unit acting against motion will provide an increasing resistive force as it is stretched, meaning for effective motion to occur, the agonistic (active) motor unit should increase pressure, while the antagonistic (inactive) motor unit should reduce pressure. Changing the sign of the control signal for the counter-clockwise acting muscle bundle, F_{des+} , and applying it to the clockwise acting muscle bundle control signal, $F_{des-} = -F_{des+}$, allows the controller to create antagonistic motion. Further development leads to inclusion of the switching variable recruitment logic. Using the total desired force and position information, the switching controller dictates the number of active distinct motor units and the applied motor unit pressure. Methods to accomplish this, as well as a comparison baseline, are presented next.

3.1. Single Equivalent Motor Unit (SEMU)

A single equivalent motor unit (SEMU) is a single muscle fiber that replaces the entire muscle bundle to provide a performance baseline for the variable recruitment schemes. The initial cross sectional area of a SEMU is equivalent to the sum of the initial cross sectional areas of all motor units in a variable recruitment muscle bundle, with equivalent initial braid

angle and contraction characteristics. When comparing a SEMU and a fully activated muscle bundle, the cross sectional equivalency yields identical force-strain behavior and incompressible fluid volume consumption. For comparison purposes, a SEMU is assumed to be constructed such that it has the same pressure-dependent blocked-force and pressure-dependent free-strain as the bundle muscle fibers.

3.2. Batch recruitment

The batch variable recruitment scheme, visually represented in Figure 3, is designed such that all active motor units in a muscle bundle are at the same operating pressure. This procedure is more consistent with the pressure application of the quasi-static variable recruitment approach in [14] and the offline variable recruitment of [15]. A recruitment state change (transition to a different number of active units) is triggered when the desired pressure P_{des} of the active motor units exceeds the maximum system pressure P_{sys} . In order for the switching

Figure 3. The batch recruitment switching transitions are depicted for the system at (a) an initial equilibrium at t_0 , (b) in motion at t_1 , and (c) at a final equilibrium at t_f . When the increasing control pressure, P_{act} , reaches the system pressure, P_{sys} , at t_1 , a new motor unit is recruited, and the pressure is equalized to a new control pressure in the two active motor units. The 5/3 valve allows for continuous pressure control to the motor units, while the 3/2 valves control which motor units are active.

controller to trigger the state change, it must compare its input (F_{tot}) to the maximum force F_{max} generated by a fully activated motor unit at the current position. F_{max} is calculated as

$$F_{max} = \kappa_F P_{sys} \pi r_0^2 \left(a(1 - \kappa_\epsilon \epsilon_{des})^2 - b \right) \quad (22)$$

The number of active motor units n_{batch} needed to produce F_{des} is therefore calculated in equation (23) by dividing the total desired force by the maximum force of a single motor unit and rounding upwards to the next integer,

$$n_{batch} = \text{ceiling} \left(\frac{F_{tot}}{F_{max}} \right) \quad (23)$$

The desired applied pressure for each of the active motor units is calculated as

$$P_{des} = \frac{F_{des}}{n_{batch} \kappa_F \pi r_0^2 \left(a(1 - \kappa_\epsilon \epsilon_{des})^2 - b \right)} \quad (24)$$

A drawback of variable recruitment is the number of control valves associated with implementation. Control valves and sensors increase the size, weight, and cost of a system. Additionally, sensors and actuated valves require electrical energy to operate, a loss that is not explored in this paper. It is therefore prudent to evaluate the number of control valves necessary to implement the recruitment schemes.

Figure 3 shows a valve schematic for batch recruitment implementation. Each muscle bundle requires a single control valve with pressure regulation. Downstream of the control valve, each motor unit within the muscle bundle requires a 3/2 valve, allowing the motor unit to either: i) operate at the controlled pressure, or ii) vent to a low pressure reservoir. For one

bundle with n motor units, batch recruitment requires one proportional control valve, one pressure transducer, and n 3/2 valves.

3.3. Orderly recruitment

The orderly variable recruitment scheme is designed such that when an active motor unit saturates at system pressure, a new motor unit is recruited from atmospheric pressure, while previous active motor units remain at system pressure. This process is visually represented in Figure 4. For $n_{orderly}$ active motor units, $n_{orderly}-1$ motor units are at maximum system pressure, and one motor unit is at a controlled pressure. The event triggering a recruitment state change is again based on the desired controlled pressure being greater than or equal to the maximum operating system pressure. Similar to batch recruitment, the maximum representative force causing a pressure saturation for the current position is calculated using equation (22). The total number of active motor units, $n_{orderly}$, is calculated as before by rounding equation (23)

Figure 4. The orderly recruitment switching state transitions are depicted for the system at (a) an initial equilibrium at t_0 , (b) in motion at t_1 , and (c) at a final equilibrium at t_f . When the increasing control pressure reaches the system pressure at t_1 , a new motor unit is recruited, and the pressure is increased from atmospheric pressure to a new control pressure in the newly recruited active motor unit. The initial active motor unit remains at system pressure after the recruitment state change. The 5/3 valves allow for continuous pressure control to each motor unit.

upwards to the next integer. Finally, the desired pressure of each motor unit is calculated in equation (25), where *rem* denotes the argument's division remainder.

$$P_{des,i} = \begin{cases} P_{sys} & i = 1 \dots n_{orderly} - 1 \\ rem\left(\frac{F_{tot}}{F_{max}}\right) \frac{1}{\kappa_F \pi r_0^2 (a(1 - \kappa_\epsilon \epsilon_{des})^2 - b)} & i = n_{orderly} \end{cases} \quad (25)$$

Orderly recruitment performance will depend on material choice due to elastic bladder energy storage and pressure-dependent free-strain effects. The tensile actuators are in a buckled state until sufficiently pressurized, as described by equation (26). An orderly recruitment hardware implementation requires a proportional valve with a pressure control loop for each motor unit is required.

$$F_i(P_{act}, \epsilon_{act}) = \begin{cases} \kappa_f \pi r_0^2 P_{act} (a(1 - \kappa_\epsilon \epsilon_{act})^2 - b) & \text{if } \epsilon_{act} < \epsilon_{fit}(P) \\ 0 & \text{if } \epsilon_{act} > \epsilon_{fit}(P) \end{cases} \quad (26)$$

Figure 4 shows a valve schematic for orderly recruitment implementation. The most straightforward arrangement uses a pressure regulating control valve for each motor unit, allowing each motor unit to operate at an independent controlled pressure. For one bundle with n motor units, orderly recruitment requires n proportional control valves, and n pressure transducers.

3.4. Bundle force sensitivity to pressure

Because the pressure is applied to the actuators differently in batch and orderly recruitment, the sensitivity of the muscle bundle output force to a change in actual applied control pressure (P_{act}) or system pressure (P_{sys}) will differ. The output force of a batch recruitment muscle

bundle, F_{batch} , is described in equation (27), whereas the output force of an orderly recruitment muscle bundle, $F_{orderly}$, is described in equation (28).

$$F_{batch} = n_{batch} F_{mod} (P_{act}, \varepsilon) \quad (27)$$

$$F_{orderly} = F_{mod} (P_{act}, \varepsilon) + (n_{orderly} - 1) F_{mod} (P_{sys}, \varepsilon) \quad (28)$$

Differentiating the batch and orderly bundle forces with respect to control pressure yields equations (29) and (30), respectively.

$$\frac{\partial}{\partial P_{act}} [F_{batch}] = n_{batch} \frac{\partial}{\partial P_{act}} [F_{mod} (P_{act}, \varepsilon)] \quad (29)$$

$$\frac{\partial}{\partial P_{act}} [F_{orderly}] = \frac{\partial}{\partial P_{act}} [F_{mod} (P_{act}, \varepsilon)] \quad (30)$$

Comparing equations (29) and (30), the batch recruitment force output is n_{batch} times as sensitive as orderly recruitment force output with respect to the control pressure. In other words, a small deviation in control pressure will affect a batch recruitment bundle's force output n_{batch} times as much as an orderly recruitment bundle. Therefore, a well-formulated downstream pressure control system (i.e. control valves, sensors, and closed-loop pressure controller logic) is imperative to batch recruitment performance, as small fluctuations in control pressure cause a greater system-level effect in force output. Similarly, differentiating the batch and orderly bundle forces with respect to system pressure, in equations (31) and (32) respectively, yields

$$\frac{\partial}{\partial P_{sys}} [F_{batch}] = 0 \quad (31)$$

$$\frac{\partial}{\partial P_{sys}} [F_{orderly}] = (n_{orderly} - 1) \frac{\partial}{\partial P_{sys}} [F_{mod}(P_{sys}, \epsilon)] \quad (32)$$

A comparison of equations (31) and (32) shows that the force output of a batch recruitment bundle is insensitive to deviations in system pressure (assuming the bundle is not fully activated). However, an orderly recruitment bundle is sensitive to fluctuations in system pressure by a factor of $n_{orderly} - 1$. This implies that components with a direct impact on source pressure (e.g., upstream motors, pumps, accumulators, and regulators) are of greater importance to maintaining orderly recruitment force output than batch recruitment force output.

4. SWITCHING CONTROLLER EFFECTS ON THE FORCE-STRAIN SPACE

A FAM's force-strain space is a visual representation of all possible combinations of tensile force production, position, and applied pressure. While a variable recruitment bundle has a continuous force-strain space [14], the controller can introduce discontinuities that lead to imperfect recruitment transitions. The transitions are investigated in this section by first developing relationships between modeling inaccuracies and actuator force output. Next, the relationship between the control signal and the muscle bundle output force at a fixed position in the presence of modeling inaccuracies is analyzed, revealing a potential for force discontinuities. The effects of modeling inaccuracies on the force-strain space are then examined, providing intuitive reasoning for the transition imperfections. Finally, the developed relationships are used to identify design tradeoffs for modeling and creating a variable recruitment system.

4.1. Force sensitivity to empirical tuning parameters

Developing sensitivity relationships between the empirical coefficients (ε_{fit} and F_{fit}) and modeled force allows us to understand how changes in the empirically fit functions affect the controller's predicted force output. The virtual work force model is differentiated with respect to κ_F and κ_ε in equations (33) and (34). Assuming an unbuckled contractile FAM,

$$\frac{\partial F}{\partial \kappa_F} = \pi r_0^2 P_a (a(1 - \kappa_\varepsilon \varepsilon)^2 - b) > 0 \quad (33)$$

$$\frac{\partial F}{\partial \kappa_\varepsilon} = -2\kappa_F \pi r_0^2 P_a a \varepsilon (1 - \kappa_\varepsilon \varepsilon) < 0 \quad (34)$$

Furthermore, the force model tuning parameters are differentiated with respect to the empirically fit functions

$$\frac{\partial \kappa_F}{\partial F_{meas,max}} = \frac{\partial}{\partial F_{meas,max}} \left[\frac{F_{meas,max}(P_a)}{\pi r_0^2 P_a (a - b)} \right] = \frac{1}{\pi r_0^2 P_a (a - b)} > 0 \quad (35)$$

$$\frac{\partial \kappa_\varepsilon}{\partial \varepsilon_{meas,max}} = \frac{\partial}{\partial \varepsilon_{meas,max}} \left[\frac{1}{\varepsilon_{meas,max}} \left(1 - \frac{1}{\sqrt{3} \cos(\alpha_0)} \right) \right] = \frac{-1}{\varepsilon_{meas,max}^2} \left(1 - \frac{1}{\sqrt{3} \cos(\alpha_0)} \right) < 0 \quad (36)$$

Via the chain rule, we arrive at

$$\frac{\partial F}{\partial F_{meas,max}} = \frac{\partial F}{\partial \kappa_F} \frac{\partial \kappa_F}{\partial F_{meas,max}} = \frac{a(1 - \kappa_\varepsilon \varepsilon)^2 - b}{(a - b)} > 0 \quad (37)$$

$$\frac{\partial F}{\partial \varepsilon_{meas,max}} = \frac{\partial F}{\partial \kappa_\varepsilon} \frac{\partial \kappa_\varepsilon}{\partial \varepsilon_{meas,max}} = \frac{2\kappa_F \pi r_0^2 P_a a \varepsilon (1 - \kappa_\varepsilon \varepsilon)}{\varepsilon_{meas,max}^2} \left(1 - \frac{1}{\sqrt{3} \cos(\alpha_0)} \right) > 0 \quad (38)$$

Because equations (37) and (38) are positive, if the data of ε_{fit} or F_{fit} are slightly overestimated when empirically curve fit (i.e., ∂F_{fit} or $\partial \varepsilon_{fit} > 0$), the modeled force will be

overestimated with respect to the physical actuator, and vice-versa. This is an important conclusion as it provides a guideline for balancing variable recruitment control design tradeoffs. Furthermore, computing equations (37) and (38) with values in Table 1, it is calculated that the force output is more sensitive to changes in ε_{fit} than F_{fit} – at a pressure of 300 kPa and a strain of 0.15, a 10% increase in ε_{fit} leads to nearly 3 times more expected force production as compared to a 10% increase in F_{fit} .

4.2. Controller effects on output force

Introducing the model-based switching controller and observing the input/output relationship of the system, as shown in Figure 5, lends insight into the variable recruitment transitions effects. Specifically, if any modeling inaccuracies between the controller model and physical actuators exist, output force discontinuities or dwells with respect to an input control signal are observed at variable recruitment transitions. In the case of a controller model and actuator behavior mismatch, the controller will not request the correct post-transition pressure to actually create the desired continuous force.

Figure 5. Input/output relationship of the variable recruitment switching controller.

The relationship between the control signal and output force is shown in Figure 6 for batch recruitment and Figure 7 for orderly recruitment at a constant strain, $\varepsilon = 0.15$. Each figure depicts eight controller scenarios, where the controller uses:

1. Corrected virtual work model (with force-strain tuning parameters)
2. Parameter-less uncorrected virtual work model
3. 10% overestimate of both ε_{fit} and F_{fit}
4. 10% overestimate of only ε_{fit}
5. 10% overestimate of only F_{fit} ,
6. 10% underestimate of both ε_{fit} and F_{fit} ,
7. 10% underestimate of only ε_{fit}
8. 10% underestimate of only F_{fit} .

For all scenarios, the actuator force output is simulated by the corrected virtual work model. Markers denote variable recruitment transitions. A fully recruited muscle bundle (three motor units) is capable of exerting 403.7 N at $P_{max} = 600$ kPa.

Figure 6 and Figure 7 reveal the potential for a discontinuity or dwell in output force when the variable recruitment state changes, dependent upon both the recruitment scheme and the type of model inaccuracy. When control model mismatch is present in ε_{fit} , the batch recruitment force output exhibits a jump discontinuity at recruitment transitions. As the pre- and post-transition forces are therefore not equivalent, a jump discontinuity will create a physical jerk on a considered system. The orderly recruitment force output exhibits a jump discontinuity when ε_{fit} is underestimated, and a short dwell at constant force in the case of an overestimated ε_{fit} or parameter-less controller model. For both batch and orderly recruitment, modeling

Figure 6. Relationship of control signal and muscle bundle force output for batch recruitment at strain = 0.15, shown for (a) the entire force range, and (b) a detailed inset at first the transition event. Markers denote recruitment transitions. When discrepancies exist between the controller model and actuator output, discontinuities in the force output at variable recruitment transition events are observed.

inaccuracies in F_{fit} only affect the slope of the plotted relationship. Because modeling inaccuracies in F_{fit} do not create discontinuities or dwells at transition events, this change in slope will not cause adverse variable recruitment transition effects, and can be accounted for by the PID controller's integrator term.

In general, a curve-fit function will be greater than some data points, and less than others. For our applications, this implies that the controller will either over-predict or under-predict the output force as a function of pressure. Therefore, if proper care is not taken when constructing the curve fit, different transition effects can occur (varying in type and severity), dependent upon whether the pressure at the time of transition leads to the control model over-predicting or under-predicting the actuator force output. The implications of the jump discontinuity directions (i.e., increasing or decreasing) are next explored by analyzing the force-strain space.

Figure 7. Relationship of control signal and muscle bundle force output for orderly recruitment at strain = 0.15, shown for (a) the entire force range, and (b) a detailed inset at the first transition event. Markers denote recruitment transitions. When discrepancies exist between the controller model and actuator output, discontinuities in the force output at variable recruitment transition events are observed.

4.3. Force-strain space analysis

The discontinuities observed in Figure 6 and Figure 7 can be further visualized over the entire force-strain space, shown in Figure 8 and Figure 9. The jump discontinuities result in the force-strain space exhibiting either gaps or overlaps, depending on the nature of the jump discontinuity. If the discontinuity jumps to a decreased force output, an overlap in the force-strain space is observed, as the system is capable of producing the force-strain combination at multiple recruitment levels. Physically, an overlap in the force-strain space will lead to the post-transition output force being less than the pre-transition output force.

If the discontinuity jumps to a greater force output, a gap in the force-strain space is exhibited, as the system is incapable of producing the force-strain combinations jumped by the discontinuity. Physically, if the controller desires to produce a force-strain combination residing in a gap, chatter (fast switching between different recruitment states) may result. The

Figure 8. Force-strain space for a batch recruitment bundle with model-based switching controller for (a) the corrected virtual work model, (b) the uncorrected virtual work model, (c) 10% overestimates of empirical data, and (d) 10% underestimates of empirical data.

gaps tend to become more pronounced as the muscle bundle approaches its free strain, implying that it is preferential for muscle bundles to operate with as low of a strain as possible.

In the case of the force output dwelling at a constant value while the control signal increases, the system will lag at a constant position until output force again increases. Although no overlap or gap in the force-strain space exists, a degradation in physical system performance

Figure 9. Force-strain space for an orderly recruitment bundle with model-based switching controller for (a) the corrected virtual work model, (b) the uncorrected virtual work model, (c) 10% overestimates of empirical data, and (d) 10% underestimates of empirical data.

occurs due to the constant force dwell. An overview of the potential variable recruitment transition effects are presented in Table 2.

There are many ways that modeling inaccuracies may be introduced to a system, e.g. measurement error, material degradation, variation between actuators, and unmodeled dynamics. It is also currently unclear how the actuator tuning parameters change over a life cycle. Because modeling inaccuracies are unavoidable in a model-based controller, a system

Table 2. Overview of variable recruitment transition effects

<i>Scheme</i>	<i>Controller model</i>	<i>Discontinuity type</i>	<i>Discontinuity direction</i>	<i>Physical effect on plant</i>
<i>Batch</i>	<i>Corrected</i>	<i>None</i>	<i>None</i>	<i>Smooth transition</i>
	<i>Uncorrected</i>	<i>Jump discontinuity</i>	<i>Decrease</i>	<i>Jerk downward, efficiency reduction</i>
	<i>110% Both</i>	<i>Jump discontinuity</i>	<i>Decrease</i>	<i>Jerk downward, efficiency reduction</i>
	<i>110% ϵ_{fit}</i>	<i>Jump discontinuity</i>	<i>Decrease</i>	<i>Jerk downward, efficiency reduction</i>
	<i>110% F_{fit}</i>	<i>None</i>	<i>None</i>	<i>Smooth transition</i>
	<i>90% Both</i>	<i>Jump discontinuity</i>	<i>Increase</i>	<i>Jerk upwards, potential for chatter</i>
	<i>90% ϵ_{fit}</i>	<i>Jump discontinuity</i>	<i>Increase</i>	<i>Jerk upwards, potential for chatter</i>
	<i>90% F_{fit}</i>	<i>None</i>	<i>None</i>	<i>Smooth transition</i>
<i>Orderly</i>	<i>Corrected</i>	<i>None</i>	<i>None</i>	<i>Smooth transition</i>
	<i>Uncorrected</i>	<i>Dwell</i>	<i>None</i>	<i>Dwell at constant position</i>
	<i>110% Both</i>	<i>Dwell</i>	<i>None</i>	<i>Dwell at constant position</i>
	<i>110% ϵ_{fit}</i>	<i>Dwell</i>	<i>None</i>	<i>Dwell at constant position</i>
	<i>110% F_{fit}</i>	<i>None</i>	<i>None</i>	<i>Smooth transition</i>
	<i>90% Both</i>	<i>Jump discontinuity</i>	<i>Increase</i>	<i>Jerk upwards, potential for chatter</i>
	<i>90% ϵ_{fit}</i>	<i>Jump discontinuity</i>	<i>Increase</i>	<i>Jerk upwards, potential for chatter</i>
	<i>90% F_{fit}</i>	<i>None</i>	<i>None</i>	<i>Smooth transition</i>

designer must weigh the tradeoffs between model accuracy and performance. Slight errors in F_{fit} can be compensated for by the PID controller, and therefore no modifications are necessary

for the curve fit function describing F_{fit} . In applications where chatter must be avoided, it is recommended to modify κ_ε in equation (14) with a chatter prevention safety factor c_{SF} slightly greater than one to create a slight overlap or dwell in the force-strain space, resulting in a modified tuning parameter of

$$\kappa_{\varepsilon,SF} = \frac{1}{c_{SF}\varepsilon_{fit}(P_a)} \left(1 - \frac{1}{\sqrt{3} \cos(\alpha_0)} \right) \quad (39)$$

5. NUMERICAL SIMULATION OF ONLINE VARIABLE RECRUITMENT CONTROLLER

To validate modeling effects and further illuminate behaviors associated with variable recruitment, a trajectory tracking simulation is developed, where reference position spline trajectories of varying amplitude and duration are used as an illustrative parametric case study. For the considered lifting task, actual position θ_{act} is the only necessary measured variable in the simulation, however pressure measurements for each motor unit are necessary for hardware implementation and efficiency calculations. An ideal pressure source is assumed, removing limitations from source pressure reduction and volumetric flow restrictions. Motor units act only as tensile actuators and do not apply force until sufficiently pressurized, as determined by the pressure dependent free-strain of the FAMs as shown in equation (26). Simulations use control gains of $K_P = 1090$ [N/rad], $K_I = 648$ [N/(rad*s)], and $K_D = 47$ [N*s/rad] tuned via the Tyreus-Luyben criteria [19] and refined with hand tuning.

At a constant pressure, the blocked force of a FAM is dependent upon the resting FAM bladder radius (0.635 cm), the braid angle (28.7°), and the bladder material. The blocked force at maximum pressure of the considered Latex FAM is 371 N. Whereas output force is

independent of FAM initial length, the maximum system rotation is dependent on FAM initial length (16 cm) and pulley radius (5 cm). At maximum pressure (600 kPa) the Latex FAM has a maximum strain of 0.26 with a maximum no-load rotation of 46.84 degrees. Because pulley radius, torque output, and maximum rotation are coupled, a system designer must weigh tradeoffs between FAM length (required space) and the torque amplification/rotational range of the pulley. The system is described by the parameters in Table 3.

Table 3. System parameters

Parameter	Value
r_{pulley} (m)	0.05
m_{pulley} (kg)	0.01
m_{arm} (kg)	0.5
L_{arm} (m)	1
M_{ext} (kg)	0.25
b (Ns/m)	5
P_{sys} (kPa)	600
CSF	1.1

5.1. Switching transition analysis

The simulations presented in Figure 10 represent different combinations of variable recruitment logic and levels of modeling inaccuracies tracking a spline position command. A long duration spline is presented, as it represents a worst-case scenario for chatter and recruitment transitions; when faster signals and motions are used, the momentum of the rotating arm can carry the system through transition events, hiding the transition effects or

presence of possible chatter. Figure 10(c) and Figure 10(d) result from using a $c_{SF} = 1.1$, successfully avoiding chatter with minimal recruitment transition effects. Figure 10(e) and Figure 10(f) utilize a 10% underestimate ε_{fit} , clearly resulting in the system chattering between recruitment states at the recruitment transitions. Figure 10(c) and Figure 10(e) show the applied pressure for the batch recruitment scheme, whereas Figure 10(d) and Figure 10(f) show the applied pressure for the orderly recruitment scheme. Position data markers are also presented in Figure 10 for an optimally matched controller and actuator, where no modeling inaccuracies exist. Figure 10 shows that either the batch or orderly scheme can easily track the slow trajectory with an optimally matched model. Realizing that models will realistically always have some level of uncertainty, and by understanding how the uncertainty affects performance, we can proactively make design decisions to mitigate chatter with minimal performance sacrifice.

Observing the inset position plot of Figure 10(d), the transition effects can be more clearly observed. The batch recruitment pressure data shows two recruitment transitions occurring at 14.6 and 19.5 seconds. Although the system has enough speed and inertia to avoid a position drop at the first transition, this is not true for the second transition, resulting in a small drop of 0.25 degrees. The orderly recruitment position data of Figure 10(e) shows an approximately 0.5s lag at the second transition. Note that despite the position lag, the orderly recruitment controller requires a much smaller step pressure change as compared to batch recruitment. Although batch recruitment requires less expensive hardware for implementation, orderly

recruitment offers better transition effects, places less demand upon the system due to smaller step pressure changes, and is less sensitive to fluctuations in control pressure.

5.2. Performance analysis

The performance of the switching controller is next quantified by calculating the average efficiency (5) and integrated absolute error (IAE). IAE is commonly used as a quality metric for control signal tracking. To be practical, a variable recruitment bundle should provide improved or equivalent efficiency over the entire range of motion of the robotic arm, while

Figure 10. Simulation results using actuators with Latex bladders and a spline input trajectory of $\Delta t = 20$ s displaying (a) angular position versus time and (b) an inset at the second transition event. The applied pressure is displayed for a counter-clockwise acting motor unit (+ MU) for (c) batch recruitment with a chatter prevention safety factor of 1.1, (d) orderly recruitment with a chatter prevention factor of 1.1, (e) batch recruitment with a 10% underestimate of ϵ_{fit} , and (f) orderly recruitment with a 10% underestimate of ϵ_{fit} .

maintaining similar tracking performance as a baseline SEMU. Simulations are performed for various combinations of reference position spline trajectory durations and angular ranges, with duration Δt ranging from 0.1 s to 10 s, and angular range $\Delta\theta$ ranging from 10 degrees to 40 degrees. The trajectory, simulating a lifting task, commands the arm to move an equal distance above and below horizontal; e.g., when $\Delta\theta = 40$ degrees, the plant sweeps from -20 degrees to 20 degrees, with 0 degrees corresponding to horizontal.

The efficiency and IAE values over the range of durations and ranges are compiled into 3D surface plots, shown in Figure 11. Figures are presented for batch recruitment, orderly recruitment, and a SEMU with Latex bladders, all utilizing a $c_{SF} = 1.1$ to avoid chatter. The inset plots indicate the shape of the trajectory signal, with step-like signals demanding high acceleration of the system, and ramp signals demanding less acceleration, but potentially revealing chatter.

The variable recruitment systems show higher operating efficiency over a much larger combination of trajectories as compared to the SEMU. As intended, the variable recruitment bundles maximize efficiency by minimizing consumed fluid volume, increasing the efficiency when only partially active, and matching the SEMU efficiency when fully recruited. Sharp changes in efficiency are also observed to correspond with variable recruitment transitions, visually separating the figure into distinct plateaus. Although the plateaus have a slight gradient demonstrating a small change in efficiency within a constant recruitment state, the efficiency value is dominated by the variable recruitment state. This observation further validates the

necessity of chatter avoidance – when chatter is present and repeated switching occurs, the efficiency of the system will plummet.

It is also observed that, even for the same angular range, the more demanding short duration signals can cause recruitment changes. This implies that the presented switching control schemes will recruit actuators in an attempt to match the high force demands of the system,

Figure 11. Average efficiency and Integrated Absolute Error (IAE) for (a) a batch recruitment bundle with a chatter prevention safety factor = 1.1, (b) an orderly recruitment bundle with a chatter prevention safety factor = 1.1, and (c) a SEMU. Simulations are performed over a range of trajectories and durations.

maintaining tracking performance. It is expected that tracking performance will degrade as the reference trajectory becomes more demanding and the actuators approach their free-strain, however the degradation occurs slightly differently for the variable recruitment schemes and SEMU. As angular range increases, the IAE increases very gradually for the SEMU, whereas it appears to exhibit a sharper jump at the variable recruitment transition. Despite this sharper jump, the tracking performance is very comparable.

Finally, while numerical differences between batch and orderly recruitment exist, they are nearly imperceptible in the figure. Although not addressed here, including a compressible working fluid model, valve dynamics, and flow rate limitations may further differentiate the recruitment schemes by exacerbating transition effects. Because the performance differences with an incompressible fluid do not differentiate the recruitment schemes, the recruitment scheme should be chosen based on jump/dwell transition behavior and physical hardware considerations (e.g., number and type of required valves and transducers).

6. CONCLUSION

Variable recruitment of fluidic artificial muscles has been shown to be an efficient alternative to traditional actuation methods, necessitating the development of an online switching controller. Therefore, two bio-inspired hybrid switching controllers were created and applied to a simulated robotic manipulator, allowing for performance characterization of online variable recruitment. FAM variable recruitment was previously only investigated with offline, manual switching. The created hybrid controllers, deemed “batch” and “orderly” recruitment,

integrate switching logic with a PID and model based controller to change recruitment state in response to the desired force output, resulting in improved system efficiency and versatility.

To characterize recruitment transition effects, a controller model sensitivity analysis was developed, leading to less-than-obvious, yet intuitive conclusions. The switching controllers were shown to affect the actuator force-strain space in the presence of modeling inaccuracies. Batch recruitment, which is more synonymous with the recruitment schemes in literature to date, shows less desirable transition effects when compared to the orderly recruitment scheme. By utilizing a “chatter reduction safety factor” in conjunction with orderly recruitment, chatter and an associated reduction in efficiency can be prevented from occurring. Overall, a variable recruitment FAM bundle is able to quickly recruit additional actuators when load, system dynamics, and trajectory necessitate high-force output, while minimizing the sacrifice of control quality.

Although research continues to support the viability of variable recruitment, the body of knowledge is still lacking in various areas. The expected FAM life-cycle shortening and model evolution due to repeated pressurization and associated venting is currently unclear. An incompressible working fluid, which has proven to be more efficient than a compressible working fluid, is the focus of this paper. However, quantifying the energetics of the presented control scheme utilizing a compressible working fluid is of future interest. Finally, interesting future work could consider control improvements, including implementation of the switching control schemes in conjunction with nonlinear controllers, adaptive controllers, and time dwell switching methods.

REFERENCES

- [1] Z. Zhang and M. Philen, "Pressurized artificial muscles," *J. Intell. Mater. Syst. Struct.*, vol. 23, no. 3, pp. 255–268, 2012.
- [2] S. F. Ramsey, R. W. & Street, "The isometric length-tension diagram of isolated skeletal muscle fibers of the frog," *Protoplasma*, vol. 36, no. 1, pp. 157–190, 1941.
- [3] F. Buchthal and H. Schmalbruch, "Motor unit of mammalian muscle," *Physiol Rev*, vol. 60, no. 1, pp. 90–142, 1980.
- [4] B. Tondu, "Modelling of the McKibben artificial muscle: A review," *J. Intell. Mater. Syst. Struct.*, vol. 23, no. 3, pp. 225–253, 2012.
- [5] B. Tondu and P. Lopez, "Modeling and control of McKibben artificial muscle robot actuators," *IEEE Control Syst. Mag.*, vol. 20, no. 2, pp. 15–38, 2000.
- [6] T. V. Minh, T. Tjahjowidodo, H. Ramon, and H. Van Brussel, "Cascade position control of a single pneumatic artificial muscle-mass system with hysteresis compensation," *Mechatronics*, vol. 20, no. 3, pp. 402–414, 2010.
- [7] D. Cai and Y. Dai, "A sliding mode controller for manipulator driven by artificial muscle actuator," *Electron. Commun. Japan, Part III Fundam. Electron. Sci. (English Transl. Denshi Tsushin Gakkai Ronbunshi)*, vol. 86, no. 11, pp. 57–64, 2003.
- [8] H. Aschemann and D. Schindele, "Sliding mode control for a high-speed linear axis driven by pneumatic muscles," *Lect. Notes Control Inf. Sci.*, vol. 407, no. 11, pp. 31–40, 2010.
- [9] K. K. Ahn and T. D. C. Thanh, "Nonlinear PID control to improve the control performance of the pneumatic artificial muscle manipulator using neural network," *J. Mech. Sci. Technol.*, vol. 19, no. 1, pp. 106–115, 2005.
- [10] K. K. Ahn and H. P. H. Anh, "Design and implementation of an adaptive recurrent neural networks (ARNN) controller of the pneumatic artificial muscle (PAM) manipulator," *Mechatronics*, vol. 19, no. 6, pp. 816–828, 2009.
- [11] M. A. Meller, M. Bryant, and E. Garcia, "Reconsidering the McKibben muscle: Energetics, operating fluid, and bladder material," *J. Intell. Mater. Syst. Struct.*, vol. 25, no. 18, pp. 2276–2293, 2014.

- [12] B. Vanderborght, B. Verrelst, R. Van Ham, M. Van Damme, P. Beyl, and D. Lefeber, "Development of a compliance controller to reduce energy consumption for bipedal robots," *Auton. Robots*, vol. 24, no. 4, pp. 419–434, 2008.
- [13] G. Mathijssen, D. Lefeber, and B. Vanderborght, "Variable recruitment of parallel elastic elements: Series-parallel elastic actuators (SPEA) with dephased mutilated gears," *IEEE/ASME Trans. Mechatronics*, vol. 20, no. 2, pp. 594–602, 2015.
- [14] M. Bryant, M. a Meller, and E. Garcia, "Variable recruitment fluidic artificial muscles: modeling and experiments," *Smart Mater. Struct.*, vol. 23, no. 7, p. 074009, 2014.
- [15] R. M. Robinson, C. S. Kothera, and N. M. Wereley, "Variable Recruitment of Pneumatic Artificial Muscles for Robotic Manipulators," *IEEE/ASME Trans. Mechatronics*, vol. PP, no. 99, pp. 1–11, 2014.
- [16] R. W. Colbrunn, G. M. Nelson, and R. D. Quinn, "Modeling of braided pneumatic actuators for robotic control," *Proc. 2001 IEEE/RSJ Int. Conf. Intell. Robot. Syst. Expand. Soc. Role Robot. Next Millenn. (Cat. No.01CH37180)*, vol. 4, no. FEBRUARY 2001, pp. 1964–1970, 2001.
- [17] C. J. De Luca, "Control properties of motor units.," *J. Exp. Biol.*, vol. 115, pp. 125–136, 1985.
- [18] S. Ganguly, A. Garg, A. Pasricha, and S. K. Dwivedy, "Control of pneumatic artificial muscle system through experimental modelling," *Mechatronics*, vol. 22, no. 8, pp. 1135–1147, 2012.
- [19] W. Luyben, "Tuning proportional-integral-derivative controllers for integrator/deadtime processes," *Ind. Eng. Chem. Res.*, vol. 5885, no. 96, pp. 3480–3483, 1996.