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Ganesh Kumar Hari Shankar Lal Das, Bertrand Tondu, Florent Forget, Jérôme Manhes, Olivier Stasse, et al.. Performing Explosive motion using a multi-joint arm actuated by pneumatic muscles with quasi-DDP optimal control. MSC-2016 IEEE Multi-Conference on Systems and Control 2016, Sep 2016, Buenos Aires, Argentina. hal-01382328

HAL Id: hal-01382328

<https://hal.science/hal-01382328v1>

Submitted on 16 Oct 2016

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Performing Explosive motion using a multi-joint arm actuated by pneumatic muscles with quasi-DDP optimal control

G. Kumar Hari Shankar Lal Das^{1,2}, B. Tondu^{1,2}, F. Forget¹, J. Manhes¹, O. Stasse¹, P. Soueres¹

Abstract—With the rapid evolution of robotic technology, robots are expected to perform various complicated task. Explosive motions like throwing, kicking or jumping are some of the ambitious tasks interesting for researchers. In the present paper, we would like to present a ball throwing task performed by an anthropomorphic arm with each joint actuated by an agonist-antagonistic pair of Mckibben artificial muscles. Pneumatic actuators have inherent compliance and hence they are very interesting for applications involving interaction with environment or human. But controlling such kind of actuators is not trivial. The paper presents an implementation of iterative Linear Quadratic regulator (iLQR) based optimal control framework to control such actuators. The method is applied to positioning tasks and generation of explosive movements by throwing a ball to a maximum distance. It is then compared to traditional control strategies to justify that optimal control is effective in controlling the position in highly non-linear pneumatic systems. Also the importance of varying compliance is highlighted by repeating the tasks at different compliance level. The algorithm validation is reported here by several simulations and hardware experiments in which the shoulder and elbow flexion are controlled simultaneously.

I. INTRODUCTION

With the emerging robotic technology, the robots are expected to perform high performance task in the presence of human. So the safety to human has become a major concern. In order to address this issue while executing high performance task, compliance at actuator level would be required. Pneumatic actuators are inherently compliant and have very high power to weight ratio. These factors motivate researchers to use pneumatic actuation for exoskeleton, prosthesis, rehabilitation or even in walking robot and human robot interaction. The goal of this paper is to use an arm actuated by McKibben muscles to perform explosive task of throwing a ball. Recent works [1] advocates other kind of actuation system which are easier to control but come with a high price tag. Our goal was to demonstrate here that with minimal modification of an existing platform [2], it is possible to perform such kind of explosive motions, and not fine manipulation as in [1]. The McKibben artificial muscle is known for its non-linearities and hence pose a great control challenge. These non-linearities are mainly due to hysteresis, saturation and internal friction between fabrics. So far these challenges were dealt with traditional controllers like high gain PID controller, sliding mode controller for position control [3]. These methods usually lead to stiff system dynamics with higher impedances. Recent developments in pneumatic actuation control [4], [5] are use Model Predictive Control (MPC). For instance in [6], the control scheme is based on a switching Piece Wise Affine

(PWA) system model approximation. The method is able to capture the high non-linearities of the Pneumatic Artificial Muscle (PAM). In [4] a linear formulation of the actuation system is proposed to simplify the algorithm implementation and makes it real-time.

The contribution of this paper is two fold.

- First it proposes a new model which provides a good compromise between accuracy and simplicity.

- The second contribution is to show that, on this model an iLQR control scheme can be used to generate with good precision positioning task and explosive movements.

This is achieved with the introduction of an empirical model of pressure generation from the Intensity-Pressure converter (I/P). Each of the seven Degrees of Freedom (DoFs) of the manipulator arm of LAAS-CNRS is actuated by a pair of agonist-antagonist McKibben muscles. The capabilities of the non-linear iLQR control to execute some simple tasks of reaching a point, maximizing the velocity of joint and end effector are demonstrated on this platform.

The paper is organised as follows: The dynamical model of joints actuated by McKibben muscles is presented in section II. Section III describes the model of the anthropomorphic robot arm. The optimal control formulation and brief introduction to iterative Linear Quadratic Regulator(iLQR) is presented in section IV. Section V presents simulations and experiments.

II. DYNAMIC MODEL OF A JOINT ACTUATED BY MCKIBBEN MUSCLES

There have been several attempts to model the McKibben artificial muscle [4], [7], [8], [9], [10]. The difficulties for getting an accurate model are due to a combination of complex phenomena during static and dynamic contraction: shape changing at the muscle tip which lose their initial cylindrical shape for a conical one, mobility and flexibility of the braided sleeve, elasticity of the inner rubber tube, exotic friction in the textile braided sleeve without forgetting, for the pneumatic version of the McKibben muscle, dynamic fluidic phenomena resulting from the artificial muscle volume variation during contraction. When we want to include such a physical model into the closed-loop control of a McKibben muscle actuator, a compromise must be found between the complexity of an accurate model and the time required for its computation. The need for an efficient but not too complex dynamic muscle model is all the more important in the case of artificial muscles for robot arms. Indeed the preservation of the actuator compliance imposes a joint direct-drive mode and so the consideration of a dynamic robot model, linked to the actuator model. The originality of our approach, described in this section, consists in including an original model of real pressure variation inside a simple McKibben muscle dynamic

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model before proposing a multi-variable pressure control of the actuator made of two similar antagonist muscles.

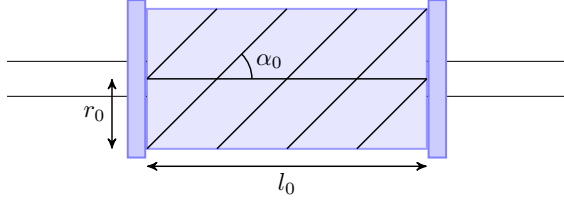


Fig. 1. Muscle geometric parameters: l_0 initial length, r_0 radius and α_0 braid angle

A. Muscles side dynamics

The following model was considered for relating the dynamic contraction force F of the artificial muscle to its control pressure P and contraction ratio.

$$F(\varepsilon, P) = (\pi r_0^2)P[a(1 - k\varepsilon)^2 - b] \quad (1)$$

Where,

$$\begin{aligned} \varepsilon &= \frac{l_0 - l}{l_0} \\ a &= \frac{3}{\tan^2(\alpha_0)} \\ b &= \frac{1}{\sin^2(\alpha_0)} \end{aligned}$$

l being the current muscle length and l_0 , r_0 , α_0 are the muscle geometric parameters corresponding to its initial length, radius and braid angle respectively (see [7] for more details). The parameter k , slightly greater than 1, is empirically chosen for taking into account the conic shape at muscle tips. The viscous coefficient is also experimentally estimated for expressing the naturally damped behavior of the artificial muscle contraction due to the complex kinetic friction inside the braided sleeve. Although hysteresis phenomenon due to dry friction is not included in this model, we think it captures most of the static and dynamic behaviour of the artificial muscle.

B. Pressure side dynamics

Control pressure in a muscle is provided by an Intensity-Pressure (I/P) converter which translates a current value into a desired pressure value that has to be fed to the muscle. In literature, see [11] for a survey, there exist several models of pressure generated in a muscle in terms of the mass of air injected, volume of the muscle and some parameters of servo valves or I/P converter (for an example see [12]). These models are highly non-linear and eventually become too cumbersome for devising control strategies. We propose a somewhat simpler empirical model to cover the dynamics of the pressure generation from the I/P converter. It is derived from SAMSON I/P converters reported in [13]. Following this model the instantaneous pressure p inside a muscle is represented by a damped second order differential function with a control pressure as input as follows:

$$\ddot{p} + 2w_n\dot{p} + w_n^2p = w_n^2P_{des} \quad (2)$$

Note that the input of the intensity converter is a current value which is then scaled to the corresponding pressure control input P_{des} in the pressure unit. The above equation is also non-linear as the natural frequency w_n has been empirically identified as a function of the volume of the muscle, V .

$$w_n = 2\pi f_v(1/V) \quad (3)$$

f_v is the empirically found parameter. The volume of a McKibben artificial muscle can be approached by the following cylindrical volume: $V = \pi r^2 l$, where r and l are the current radius and length of the artificial muscle. By using the relationship Eq.(4) as reported in [14], we deduce an expression for the volume of the muscle.

$$r/r_0 = (1/\sin(\alpha_0))\sqrt{(1 - \varepsilon)^2} \quad (4)$$

$$V = \frac{\pi r_0^2 l}{\sin^2(\alpha_0)}(1 - \cos^2(\alpha_0)(1 - \varepsilon)^2) \quad (5)$$

For a second order system, the rise time is inversely proportional to its natural frequency and in the case of our pressure dynamic model, the natural frequency is inversely proportional to the volume. It implies that the bigger the muscle, the larger the rise time. Fig. 2 depicts a typical variation of w_n with the joint angle at one of the manipulator joints. If the range

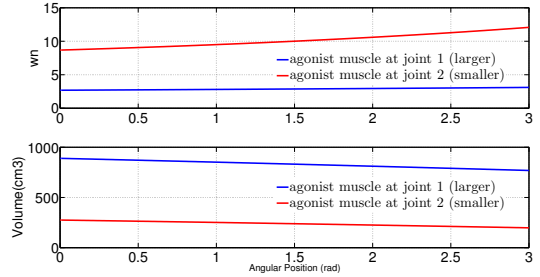


Fig. 2. Natural frequency and volume of the muscle with the joint angle

of operation for a joint is small i.e range of θ is small, then the corresponding changes in the volume of the muscles as θ varies, would be small at that joint. In such case, a constant value for w_n could be chosen for the muscles corresponding to their mean volumes. Here, another interesting point to notice is that for different muscles, pressure dynamics of a larger volume muscle will be slower. The above two points help in trading off between the operating range of the joint and the corresponding easiness of control strategy.

C. Agonistic-antagonistic joint actuator

Following the human arm model, a pair of artificial muscles can be set up in antagonistic fashion to drive a chained wheel of radius R . According to Fig. 3, the resulting actuator torque T can be written as follows:

$$T = R[F_1(\varepsilon_1, P_1) - F_2(\varepsilon_2, P_2)] \quad (6)$$

where F_1 and F_2 are the forces of muscles 1 and 2 respectively, defining the antagonist muscle pair. As illustrated in Fig. 3, the relationship between θ , the actuator angle and the contraction ratios for each muscle can be expressed as follows: $\varepsilon_1 = \varepsilon_{10} + \frac{R\theta}{l_0}$ and $\varepsilon_2 = \varepsilon_{20} - \frac{R\theta}{l_0}$, where ε_{10} and ε_{20} are the

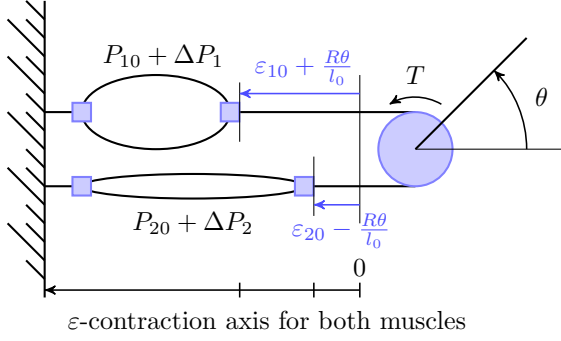


Fig. 3. Pulley-chain driven antagonist muscle actuator made of two identical McKibben artificial muscles. It has the possibility to adapt initial torque at initial zero θ -position by means of P_{10} , P_{20} , ϵ_{10} and ϵ_{20}

initial contraction ratios for muscle 1 and muscle 2 respectively corresponding to the zero-angular position. Moreover, we propose to specify the pressures in muscle 1 and muscle 2 as follows: $P_1 = P_{10} + \Delta P_1$ and $P_2 = P_{20} + \Delta P_2$ where P_{10} and P_{20} are respectively the initial pressure in the agonist-antagonist muscle and related to zero positioning of the joint. ΔP_1 and ΔP_2 , are the control pressures.

Using Eq.(1), and neglecting the terms ϵ_1^2 and ϵ_2^2 , the torque at the joint can be expressed as

$$T = K_1 \Delta P_1 - K_2 \Delta P_2 - K_3 (P_1 + P_2) \theta - K_4 \dot{\theta} + K_5, \quad (7)$$

where,

$$\begin{aligned} K_1 &= (\pi r_o^2) R [a(1 - 2k\epsilon_{10}) - b], \\ K_2 &= (\pi r_o^2) R [a(1 - 2k\epsilon_{20}) - b], \\ K_3 &= 2(\pi r_o^2) R^2 k a / l_o, \\ K_4 &= (\pi r_o^2) R^2 f_v / l_o, \end{aligned}$$

$$K_5 = (\pi r_o^2) R [(a - b)(P_{10} - P_{20}) - 2ka(P_{10}\epsilon_{10} - P_{20}\epsilon_{20})].$$

If $P_{10} = P_{20}$ and $\epsilon_{10} = \epsilon_{20}$, K_5 is equal to zero. The details of our robot-arm including the dimensions of muscles are given in [2]. The antagonist muscle actuator is now considered as a MIMO-system whose inputs are the control pressures $\Delta P_1, \Delta P_2$, and outputs are both the θ and the actuator stiffness which is defined as the instantaneous ratio between the current torque variation and the current angular position variation (see Eq.(9)). When no gravity effect is considered, the static equilibrium position of the actuator can be directly derived from Eq.(7) with zero angular velocity.

$$\theta_{equ} = (K_1 \Delta P_1 - K_2 \Delta P_2 + K_5) / (K_3 (P_1 + P_2)) \quad (8)$$

With associated stiffness σ_{equ} expressed as

$$\sigma_{equ} = -\frac{\partial T}{\partial \theta} = K_3 (P_1 + P_2) \quad (9)$$

From Eq.(8) and Eq.(9), it is possible to remark that the equilibrium position can be changed while keeping the same stiffness by modulating ΔP_1 and ΔP_2 with a constant $\Delta P_1 + \Delta P_2$. In the case of a symmetrical pressure variation in both muscles: $\Delta P_1 = -\Delta P_2 = \Delta P$, the actuator becomes a SISO-system

whose corresponding torque T_{SISO} , is now given by the following relationship:

$$T = (K_1 + K_2) \Delta P - K_3 (P_{10} + P_{20}) \theta - K_4 \dot{\theta} + K_5 \quad (10)$$

where stiffness at equilibrium position is now constant and equal to $K_3 (P_{10} + P_{20})$. When the joint angle θ varies, and assuming that the actuator chain is inextensible, the contraction ratio of each muscle is known and, consequently, the pressure dynamic model, proposed in II-B, can be applied to each muscle. It is important to note that, in the case of relatively small joint muscles, the effect of volume variation with joint angle on pressure dynamics could be negligible. If the range of operation is small, a constant w_n could be chosen for that joint. As previously noted, pressure dynamics of a larger volume muscle will be slower which is, especially, the case of the muscles at the shoulder joint compared to the muscles at the elbow joint.

III. ROBOT DYNAMICS

This section presents the robot model formally including the rigid body model of the robot with its pressure dynamics. Let us consider a n degrees of freedom robot with generalized joint angle coordinates $q \in \mathbb{R}^n$. Each joint is actuated by 2 pneumatic muscles, so there will be $2n$ muscles, each one with a pressure $P_i \in \mathbb{R}^{2n}$. The robot dynamics can be represented in standard form as below:

$$M(q)\ddot{q} + C(q, \dot{q}) + G(q) = T(q, P) \quad (11)$$

$$\dot{P} + 2C_p \dot{P} + G_p P = G_p P_{des} \quad (12)$$

$M(q) \in \mathbb{R}^{n \times n}$ is the mass inertia matrix of the robot, $C(q, \dot{q}) \in \mathbb{R}^{n \times 1}$ is the coriolis and centrifugal terms, $G(q) \in \mathbb{R}^n$ is the gravity related terms, $T(q, P) \in \mathbb{R}^n$ is the torque generated by pneumatic muscles as described in Eq.(6). $C_p = \text{diag}[w_{n_1}, w_{n_2}, \dots, w_{n_{2n}}]$ and $G_p = \text{diag}[w_{n_1}^2, w_{n_2}^2, \dots, w_{n_{2n}}^2]$ are the collection of coefficients of the pressure dynamics of each muscle and w_{n_i} is the natural frequency of the pressure dynamics at the i^{th} muscle. $P = [P_1, P_2, \dots, P_{2n}]^T \in \mathbb{R}^{2n}$ is the vector of current muscle pressure and $P_{des} = [P_{des_1}, P_{des_2}, \dots, P_{des_{2n}}]^T \in \mathbb{R}^{2n}$, is the vector of desired pressure P_{des_i} , the control input in pressure unit given to the I/P converter of the i^{th} muscle. Any reference trajectory in q given to the robot has to respect the pressure dynamics whose bandwidth depends on w_n . As discussed in the previous section, if the joint is actuated by larger muscles (having smaller bandwidth) and higher rise time, rapidly varying trajectory would be difficult to track and pose a limiting factor in performing explosive tasks. Limits to the operating range of the joints are obviously decided by the maximum contraction of the spanning muscles. In addition to that, w_n could be reasonably considered as constant in a limited operating range, removing in this way the non-linearity in pressure dynamics. Apart from this, due to hardware limitation of I/P converter, the control input P_{des} is bounded as follows:

$$U = P_{des} \in \mathbb{R}^{2n} : P_{des} \in [P_{min}, P_{max}] \quad (13)$$

Where, P_{min}, P_{max} are the lower and upper bound on control input P_{des} .

IV. OPTIMAL CONTROL FORMULATION

This section presents the optimal computational framework used to find the control sequences to perform a desired task. The optimal control problem is the minimization or maximization of a performance criterion with respect to the control under a set of constraints that arise from the physical limitation of the control action and from the plant dynamics.

A. State space representation

Let us represent the dynamics stated in Eq.(11) and Eq.(12) in state space form considering the state vector as $x = [q, \dot{q}, P, \dot{P}]^T$.

$$\dot{x} = f(x, u) = \begin{bmatrix} \dot{q} \\ M^{-1}(-C(q, \dot{q}) - G(q) + T(q, P)) \\ \dot{P} \\ -C_p \dot{P} - G_p P + G_p u \end{bmatrix} \quad (14)$$

where, f is the non-linear function given by Eq.(14) in state x and control u that gathers Eq.(11) and Eq.(12). In the present work, we consider the constraints on the state in the optimal control formulation which is discussed in the following subsection.

B. Treatment of Constraints

There exists a mechanical limit to each degrees of freedom of the arm. To have safe operation, we have introduced these limits as constraints on the state space inside the cost function of the optimal control formulation. The chosen cost function for the state space constraints are expressed in the following equations:

$$\begin{aligned} \max &= 1 - \lambda(x_{\max} - x) \\ \min &= 1 - \lambda(x - x_{\min}) \\ C_s &= e^{\lambda * \max} + e^{\lambda * \min} \end{aligned} \quad (15)$$

where x_{\min}, x_{\max} are lower and upper limits on the state and λ is a constant. The above consideration for the cost function will ensure that the cost near the limits will be very high as evident in the Fig: 4 and hence the optimal solution will keep the system within the operating limits. Also, the control action

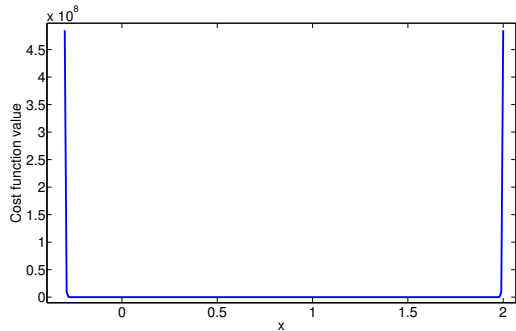


Fig. 4. Cost function of the state constraints

has to be admissible, i.e $u \in U = [P_{\min}, P_{\max}]$. In order to handle

the constraints on the control, the control limited Differential Dynamic Programming (DDP) approach reported in [15] is used. The control problem formulation is then expressed as determining an open-loop control input $u = u(t, x) \in U$ which can minimize or maximize a cost function along a given time interval $t \in [0, T]$ and with initial state $x(0) = x_0$. The most generic expression for the cost function can be written as follows:

$$J(x_0) = C_f + C_r + C_s \quad (16)$$

where $C_f = h(x(T))$ is the final cost, $C_r = \int_0^T c(x(t), u(t, x(t))) dt$ is the integral of the running cost $c(x, u)$ which encapsulates the task objectives and C_s is the cost value imposed by the constraints. For a non-linear dynamics Eq.(14) and non-quadratic cost Eq.(16), optimal control solutions can be obtained using full DDP. However, as DDP is computationally expensive, an iterative LQR (iLQR) approach is considered [16]. The iLQR method is relying on linearizing the dynamics and approximating the cost function to quadratic form along the x trajectory. This control approach is briefly summarized in the next section.

C. Iterative Linear Quadratic Regulator (iLQR)

iLQR is initialized with a nominal control sequence and the corresponding state trajectory (x_0, u_0) . the dynamical system is then linearized as in Eq.(17) and the cost function is approximated by the quadratic form Eq.(18) and a local LQR problem is then solved. Using this solution, the states and the control sequence are improved iteratively.

$$\dot{\delta x} = A \delta x + B \delta u \quad (17)$$

$$\begin{aligned} \Delta J &= h_x^T \delta x(T) + \delta x^T(T) h_{xx} \delta x(T) \\ &+ \int_0^T c_x^T \delta x + c_u^T \delta u + \delta x^T c_{xx} \delta x + \delta x^T c_{xu} \delta u + \delta u^T c_{uu} \delta u \end{aligned} \quad (18)$$

where $A = \frac{\partial f}{\partial x}$ and $B = \frac{\partial f}{\partial u}$. In Eq.(17) and Eq.(18) subscript x and u indicate that the function is partially derivated with respect to x and u . At every iteration, Eq.(17) and Eq.(18) are solved and $(\delta x, \delta u)$ are deduced from the resolution of a modified Ricatti-type system. Then the new improved sequence is generated by $x \leftarrow x + \delta x$ and $u \leftarrow u + \delta u$. When $\Delta J \approx 0$, the iLQR converges and gives an optimal control sequence $u^* \in U$ and the corresponding optimal state trajectory x^* .

V. SIMULATION AND EXPERIMENTAL RESULTS

The experimental set up considered here is the manipulator of LAAS CNRS which is an anthropomorphic arm of seven degrees of freedom (DoF), where each joint is pneumatically actuated by a pair of Mckibben muscles. In the experiment presented in this paper, only two joints are controlled. These joints are the flexion θ_1 at the shoulder and the flexion θ_2 at the elbow. (see Fig. 5). So, for the experiments, the robot can be viewed as a 2 DoF manipulator with state defined by $x = [\theta_1, \dot{\theta}_1, \theta_2, \dot{\theta}_2]^T$. Each muscle is pressurized by an IP converter which converts a current command to a reference pressure value. The objective of the experiments is to evaluate the performance of the iLQR control to achieve the following tasks with our multi-link pneumatic robot.

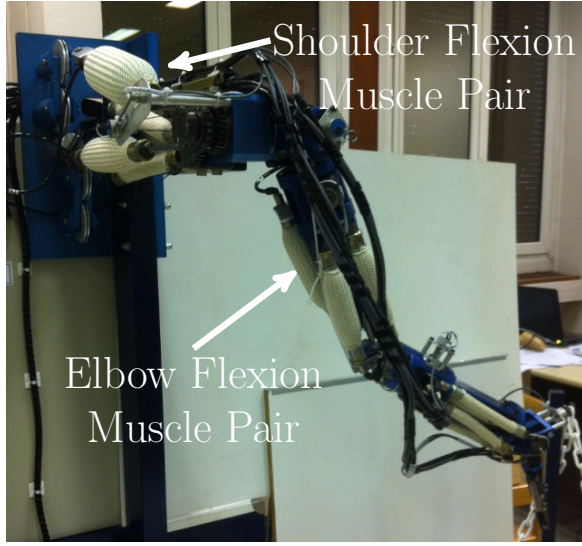


Fig. 5. Picture of the robot-arm showing the two pairs of muscles, in shoulder and elbow flexion.

1) Final position control: We aim to compare the quality of the positioning control in the presence of different loads with the iLQR approach and with the feed-forward proportional control. For this task, we analyze the stiffness modulation and we show that the optimal control approach enhances the explosive motion capabilities by simultaneous modulation of position and stiffness. In order to do that, simulations and experiments are done in two cases. Case-I: When the sum of the pressure in agonist-antagonist pair of muscles at each joint is kept constant, i.e. $P_1 + P_2 = Constant$. Case-II: When P_1 and P_2 are left independent. In this case, there will be two inputs for each joint.

2) Capability to execute explosive movements by throwing a ball to a maximum distance. For this second task we compare simulation results with the results of experiment executed with the real robot.

A. Task 1: Position control

The manipulator is given a final position with a load mass of $m_l = 0.1kg$ at the end effector. iLQR is used here to find the optimal path to reach the final goal $(\theta_1, \theta_2) = (28.8, 57.6)$ degrees. The same task is repeated with different load masses of $m_l = 0.1kg$ and $m_l = 1.0kg$ which is shown in Fig. 6.

The following cost function is considered for this task.

$$C_f = Q_f(x_{ref}(T) - x(t))^2, \quad (19)$$

$$C_r = Q \int_0^T ((x_{ref}(T) - x(t))^2 + u^2(t))dt,$$

where, x_{ref} is the final position for the two joints. The iLQR control uses Eq.(14) and Eq.(19) to solve for optimal control sequence u^* . This optimal control sequence in forward application to Eq.(14) will yield the needed trajectory. To compare the effectiveness of the iLQR approach, the task is executed using a Proportional-Integral controller with a feed-forward term. The feed-forward term gives a desired pressure

for each muscle at the joint needed to maintain a desired joint angle. Thus, the control action of the feed-forward PI controller can be defined as follows:

$$u(t) = P_{feed} + K_p(e(t)) + K_i \int_0^t (e(t))dt \quad (20)$$

where, $e(t) = x_{ref} - x(t)$, K_p and K_i are proportional and integral gains respectively. The simulation results are shown in Fig. 7. Response of feed-forward PI controller is shown in black dashed line is compared with the responses of optimal position control in Case-I when $P_1 + P_2 = Constant$ (blue lines) and in Case-II when P_1 and P_2 are independent (magenta lines)(See Fig. 7).

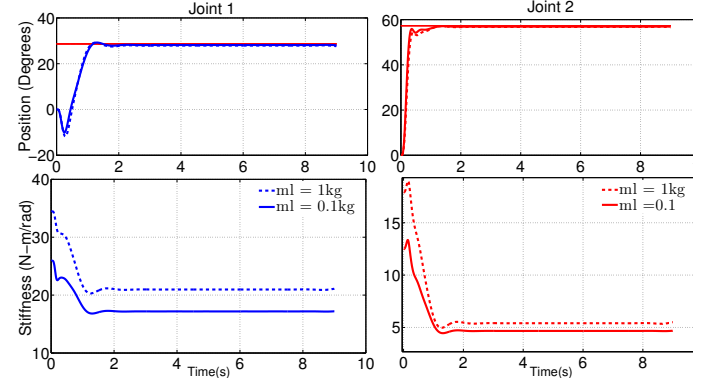


Fig. 6. Figures on the left side represents the position response and stiffness variation at joint 1 and the figures on the right side represents the same for joint 2 in order to reach the target $(\theta_1, \theta_2) = (28.8, 57.6)$ degrees. The plots compare the response of the joints and the stiffness profile when the end effector is loaded with mass 0.1kg (solid line) and 1.0kg (dashed line). For the heavier load, optimal control gives a stiffer stiffness profile.

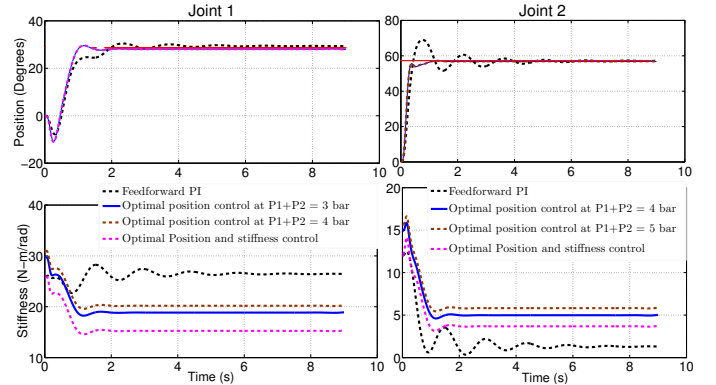


Fig. 7. Figures on the left side represents the position response and stiffness variation at joint 1 and the figures on the right side represents the same for joint 2.

From the position plots in Fig. 7, it appears that the iLQR approach gives a good compromise between keeping the stiffness low and minimizing the oscillations which results into a smooth motion. However, the feed-forward PI controller makes joint 1 very stiff and joint 2 very flexible leading to an overshoot and oscillations.

As discussed in section II-C, the stiffness can be adjusted for the same equilibrium position by changing the sum of pressures in the agonist-antagonist pair of muscles. As the

sum increases, stiffness at the equilibrium increases which is evident at each joint (blue and brown lines in stiffness plots).

In order to find the most compliant position trajectory, i.e. to find the best sum of pressure in the agonist-antagonist pair, P_1, P_2 are left independent and Eq.(7) has two independent inputs for each joint. In this case, the optimal solution gives the similar optimal position trajectory but with better stiffness profile (magenta line in stiffness plot in Fig. 7).

B. Task 2: Maximizing the link speed

The objective is to execute some explosive motions with the aim to perform in the future tasks such as ball throwing, kicking or hammering a nail. Such motions would require either maximizing the joint/link speed or end-effector speed [17], [18]. So the task considered here is maximizing the angular speed of the elbow joint. The task is first simulated and then executed by the real robot. A comparison between simulation and the experimental results are shown in Fig. 8.

For maximizing the elbow joint's angular speed at final time $T = 1$, the task requires only the terminal cost, C_f . But to minimize the control effort, a running cost C_r involving only control pressures is used.

$$\begin{aligned} C_f &= -Q_f(x_4(T))^2, \\ C_r &= Q_u \int_0^T u^2(t)dt, \end{aligned} \quad (21)$$

where, $x_4 = \dot{\theta}_2$ is the angular velocity of the elbow joint which constitutes the fourth state variable. Q_f and Q_u are weights for the terminal cost and the running cost. The simulation results are shown in Fig. 8

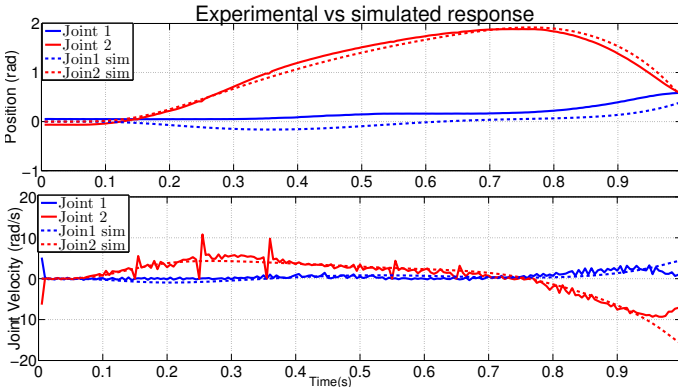


Fig. 8. Plots on the top compare the robot response (solid lines) with simulated response (dashed lines) at joint 1 (blue line) and joint 2 (red line). Bottom plots compare the velocity response of the robot and the simulation.

In simulation, the maximum joint velocity is reached at terminal time which is around -15 rad/sec. The robot response and the simulation response in position and speed show a good match. However, some discrepancies can be observed.

C. Task 3: Ball throwing and kicking

The objective is to throw a ball to a maximum distance. The distance to be thrown is related to the kinematics of the arm and hence is a function of the states of the arm. The cost function, thus, comprises the terminal cost C_f involving

the distance and the running cost C_r involving only control efforts. Also the time of motion is taken as $T = 4$ seconds.

$$\begin{aligned} C_f &= d = kf(x) \\ C_r &= Q_u \int_0^T u^2(t)dt, \end{aligned} \quad (22)$$

where, $kf(x(t))$ is the function which computes the maximum distance that the ball will be thrown. This function relates the projectile motion of the ball with the robot kinematics. We have used the same cost function to extend the task to kick a ball stationed at a point. Snapshots of the video of both the experiments are presented in Fig. 12 and Fig. 13.



Fig. 9. Two experiments have been performed. Left picture is the set-up for the task of kicking the ball while the picture in right is the set-up for throwing the ball.

Simulations are done where the sum of pressures in the agonist-antagonistic pair is kept constant at the joint 1 to 4 bar and at the joint 2 to 5 bar. We present the simulation results when there are no constraints on the state of the robot (Fig. 10). However, the robot has limits at its joints which is typically between $[-28.5, 114.6]$ degrees. It is evident from Fig. 10 that it is necessary to include the constraints in order to make the real robot execute the task.

Plots in Fig. 11 compare the response of the real robot with the simulated response of the model when optimal control inputs are applied in the open-loop. It is interesting to note that the optimal solution given by the iLQR is somewhat intuitive to the human behaviour. It takes few swings to attain the maximum speed of the end effector before launching the ball. The maximum distance achieved by the ball was 2.3m against 3m predicted by the simulation. The observed discrepancies between simulated and the real robot response can be justified by the fact that the system is controlled in open-loop without feedback. Also we have not model various effects of hysteresis and dry friction. Since modeling all the aspects of pneumatic muscles actuators seem to be difficult, we would reply on the

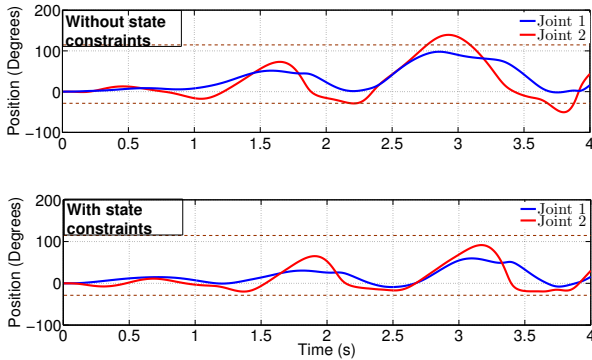


Fig. 10. Plots on the top show the simulated position response of joint 1 (blue line) and Joint 2 (red line) under no constraints and the plot below presents the same after applying the state constraints. Brown lines are the limits on the state

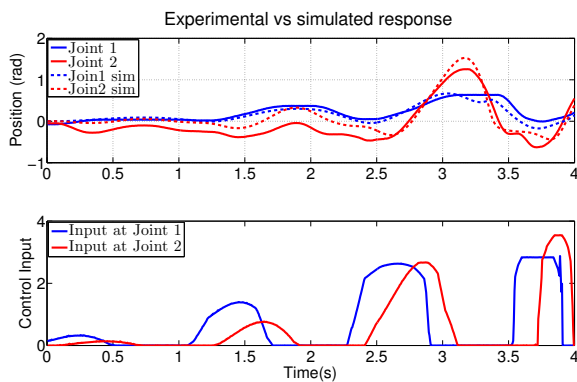


Fig. 11. Plots on the top show the simulated position response of joint 1 (blue line) and Joint 2 (red line). Control effort is shown in the bottom plots. The control inputs, Input 1 and Input 2 are applied on joint 1 and joint 2 respectively.

close loop control. This is an improvement that we plan to do in future work.

The hardware set up used for the experimentation is the robot mentioned in [2] whose control modules have been upgraded recently. The important components of the current set up are I/P converters, encoders, NI data acquisition devices and the development computer running real time control software. 1) I/P converter : It is a Samson I/P 6111 manufactured by Samson Corporation, Frankfurt. This I/P is rapid and produces output pressure in range 0 to 5 bar. The bandwidth of the I/P is volume dependent. There are 7 joints and a gripper. Each joint and the gripper are actuated by a pair of Mckibben muscles and each muscle is controlled by one I/P so, there are 16 IP converters. 2) Encoders/Potentiometers: There are seven potentiometers, one at each Dof to get the joint angle data. 3) The data Acquisition device: CompactRIO from National Instruments is used for this purpose. This is a reconfigurable and embeddable chassis, integrating an intelligent real-time controller. It has NI9205 module which is an Analog-to-Digital-Converter (ADC) with up to 32 channels, selectable acquisition range (200mV, 1V, 5V and 0V) and a max sampling frequency of 250kS/s. This device samples the seven potentiometers dedicated to the positioning of the arm. There is a NI9265 card which has three modules of Digital-

to-Analog-Converters (DAC). They have the particularity to provide analog current outputs. Each module is able to manage up to 4 channels in the 0 to 20mA range at 100kS/s. 4) The development computer: The development computer runs the high level control algorithm for the robot. It communicates via the NI module using standard UDP protocol at a frequency of 1kHz in real time. The computer has linux 14.04 with Xenomai real time kernel running in parallel. For the present experimentation, control software are running at 200Hz frequency.

VI. CONCLUSION AND FUTURE WORK

We addressed the problem of modeling and controlling a robot manipulator actuated by the pneumatic Mckibben muscles in an optimal control framework. Our first contribution is to propose a model which encapsulates the pressure dynamics in an efficient way. It is done by using a second order differential function whose bandwidth is dependent on the instantaneous volume of the muscles. Even though, the model does not include the effect of dry friction and hysteresis, it covers most of the static and the dynamic behavior. Using this model, along with the robot manipulator model, our second contribution is to show that the implementation of iLQR allows to perform efficient position control and also preserves the inherent compliance of the Mckibben muscles with respect to the more conventional control approaches. We have embedded the constraints on the state and the optimal control formulation with this new model is used to perform various tasks like positioning control under different loads and maximizing the link speed. We also have shown the capability of the robot arm to perform explosive motions by throwing a ball. The results were reported in simulation first and then these results were validated on the hardware platform. In future work, we plan to extend the application on the real robot in order to perform explosive movements such as hammering a nail. This will be done in real time optimal control in the close loop. A detailed analysis of stiffness variation and possibilities of stiffness control will then be possible.

VII. ACKNOWLEDGEMENTS

This work was partially supported by the European FP7 Project EUROOC under Grant Agreement 608849 and the ERC Advanced Grant Actanthrope. We also thank Kevin Giraud Esclasse for their help in software development.

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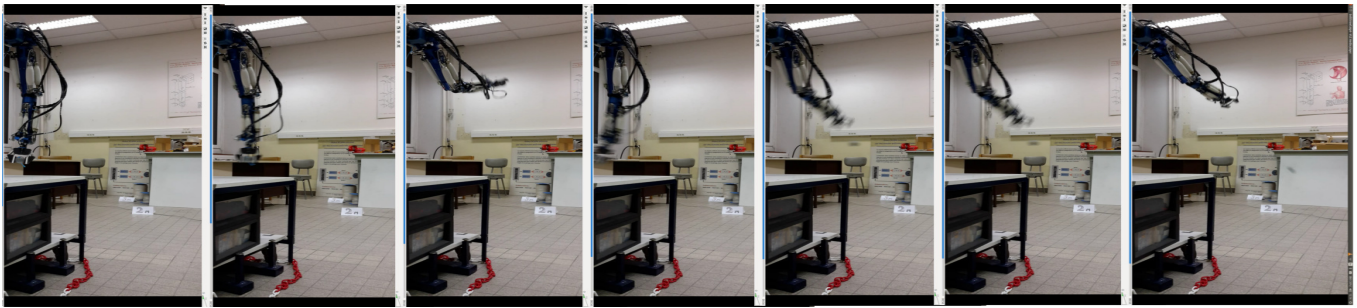


Fig. 12. The pneumatic manipulator arm executing the task of throwing the ball.

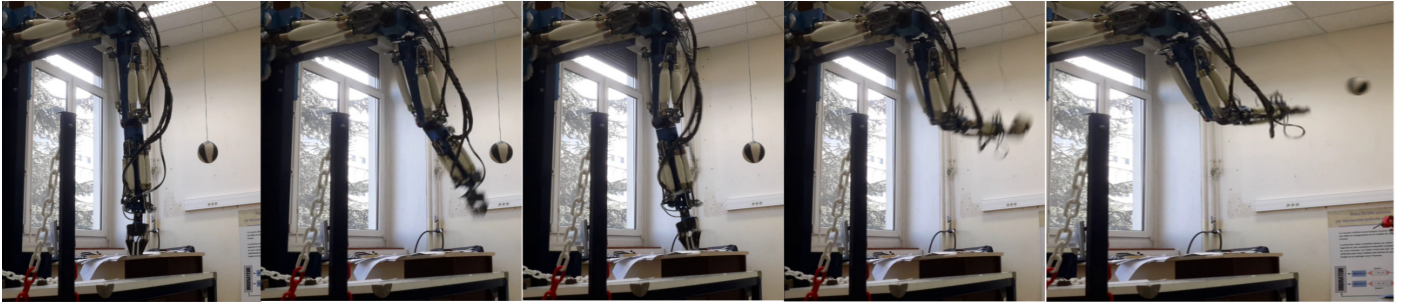


Fig. 13. The pneumatic manipulator arm executing the task of kicking the ball

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