A bio-inspired limb controller for avatar animation

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1. Introduction

In the field of computer animation, producing a realistic procedural avatar animation based on dynamics remains challenging.

Recent advances in musculoskeletal simulation have enhanced drastically the limb controllers in direct dynamics and the final animation by taking into account the muscular redundancy and the muscular viscoelasticity in the motion dynamics of avatars (Geijtenbeek, Van de Panne & Van der Stappen, 2013). Nevertheless, such optimisation based animation is costly in terms of computation time and does not handle the real-time constraint – mandatory for video-games, serious-games or virtual reality applications.

In the current abstract, we introduce a new musculoskeletal-based limb controller including a linearizing feedback of the musculoskeletal structure and a PID control of the limb position with the objective to enhance virtual avatar animation.

2. Methods

Let us consider a simple 1-dof limb actuated with two antagonist muscles.

The control inputs of the system are the muscular neural excitations (ε) and the control output is the angular position of the limb (q).

Our control strategy is based on a feedback linearization of the musculoskeletal dynamics which will allow us to conceive a joint space controller. Similarly, to (Bonnet et al., 2009) the pulling muscle is determined based on the error in the system.

The classical Hill-type muscle model, force-length (f_l) and force-velocity (f_v) relationships featured in (Rengifo, Aoustin, Plestan & Chevallereau, 2010) were used to determine the total force (f_{tj}) of muscle j,

$$f_{tj}\left(l_{tj}\right) = f_{pj}\left(l_{mnj}\right) + a_j f_{lj}\left(l_{mnj}\right) f_{vj}\left(\dot{l}_{mnj}\right) f_{oj} \quad (1)$$

Where f_{pj} is the passive force, a_j is the muscle activation and f_{oj} is the maximum isometric force. The normalized length (l_{mnj}), tendon length (l_{tj})

and rate of change in length ($\dot{l}_{mnj}$) of both muscles are dependent on the joint position and joint velocity.

Consequently, one can represent the dynamics of this system through the time progression of the joint position and velocity.

Considering this and the torque imposed at the joint by the muscles and external forces we obtain the following state space representation,

$$x_1 = q \quad \dot{x}_1 = x_2$$
$$x_2 = \dot{q} \quad \dot{x}_2 = \frac{1}{I}\left(r_1 f_{t1}\left(l_{t1}\right) + r_2 f_{t2}\left(l_{t2}\right) + \Gamma_g\right) \quad (2)$$
$$y = q$$

Where r_1 and r_2 are the constant muscle moment arms, I is the inertia of the system and Γ_g is the torque produced by gravity.

The relative degree of the system, proves that the output can be controlled via a feedback linearization,

$$(3)$$
$$y^{(2)} = \ddot{q} = \frac{1}{I}\left(r_1\left(f_{p1} + a_1 f_{l1} f_{v1} f_{o1}\right) + r_2\left(f_{p2} + a_2 f_{l2} f_{v2} f_{o2}\right) + \Gamma_g\right) = v$$

Where,
$$a_j = \varepsilon_j\left(1 - e^{-t/\tau}\right) + a_{oj} e^{-t/\tau}$$

The initial conditions on the activation are expressed through the terms a_{oj}, τ is the time constant representing the activation dynamics.

The feedback linearization is done by assigning to eq.(3) a new control input v.

Inverting the system as in eq.(4), we find an expression for the neural excitations in terms of the new control input v,

$$u = A^{-1}(x)(v - b(x)) \quad (4)$$

$$(5)$$

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} = \begin{bmatrix} \dfrac{\alpha I}{\left(1 - e^{-t/\tau}\right)\left(\alpha^2 + \beta^2\right)} \\ \dfrac{\beta I}{\left(1 - e^{-t/\tau}\right)\left(\alpha^2 + \beta^2\right)} \end{bmatrix} \left(v - \frac{1}{I}\left(\alpha a_{o1} e^{-t/\tau} + \beta a_{o2} e^{-t/\tau} + r_1 f_{p1} + r_2 f_{p2} + \Gamma_g\right)\right)$$

Where, $\alpha = r_1 f_{l1} f_{v1} f_{o1}$ and $\beta = r_2 f_{l2} f_{v2} f_{o2}$.

The system has been reduced to an integrator chain that can be easily commanded through the new control input v. Consequently, classical control techniques can be used to command the position of the limb, such as a PID controller.

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3. Results and Discussion

The elbow extension task described in (Osu et al., 2004) was simulated with the parameters in Table 1, taken from (Stroeve, 1999). The limb was commanded to move from an initial position of 97° to a desired position of 41°.

Parameter	Value
Length to center of mass (m)	0.16
Inertia ($Kg.m^2$)	0.013
Forearm mass (Kg)	1.6
Forearm length (m)	0.32
Joint rest angle (rad)	$\pi/2$
Constant Moment arms (m)	+/-0.03
Max. isometric force (N)	900
Slack/Tendon length (fixed) (m)	0.02
Optimal fiber/Resting length (m)	0.13
Activation/Deactivation time constant	0.04

Table 1 Parameters

The resulting angular position of the limb, neural excitations and activations are illustrated in Fig. 1 and Fig. 2.
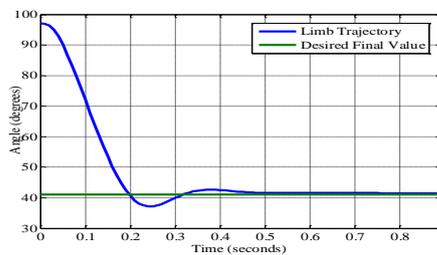

Figure 1 Limb Extension

Both position and excitations are satisfying in terms of shape, magnitude, occurrence and are coherent with a fast extension movement. As in the experimental measurements presented in (Osu et al., 2004), the excitation of the extensor muscle is initially high, decreases as the limb approaches the goal and achieves a steady state in order to hold the position. Thanks to the predictive action of the controller, the flexor muscle is excited to reduce the velocity of the limb and make final corrections in position.
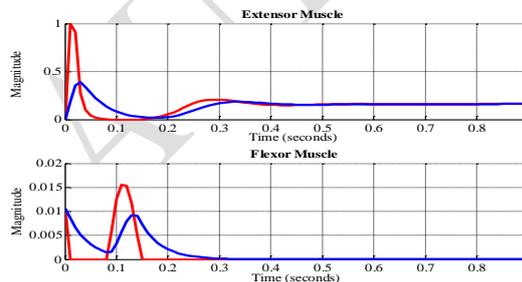

Figure 2 Excitations/activations

Note that the movement presented above is faster than those recorded in the experiments and that the flexor is only activated for preventive or corrective actions. This difference is due to the fact that other aspects that are present and controlled during human motion such as the stiffness and desired joint velocity were not considered in our model.

4. Conclusions

We have introduced a simple limb controller that partially reproduces the neural excitation signals that satisfy a specific kinematic behaviour. Complex articulated bodies such as those of avatars could be controlled by assigning a pair of antagonist muscles and a controller to each degree of freedom. A finite state machine and a target generator would then produce desired poses which the controllers would use for muscle excitation regulation. In our future work we intend to produce more realistic, human-like motions through the consideration of new control variables, such as the velocity and impedance of the limb. We also intend to explore optimal control techniques to minimize external perturbation effects, followed by a model simplification for real time implementation.

Acknowledgments

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