2.086 Term Project Report

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# Modeling Kinematics of a Wrist Joint via Electromyography Data

## I. Introduction

One of the most important objectives in active prosthetic technology is to develop intuitive control of a prosthetic limb. Currently, many advanced prosthetic devices utilize pattern recognition techniques to map myoelectric activity to pre-defined states, essentially limiting the limb's range of motion to several gestures. Many users abandon active devices due to this inefficient cognitive control strategy and the limitations it poses on their ability to facilitate natural movement. In addition, reliance on pattern recognition creates poor control over the speed of a gesture or other more nuanced aspects of motion.

Creating a virtual limb model that actuates movement from an individual's own neural activity provides a more direct and intuitive prosthetic control pathway. To accomplish this, mathematical models have been created to compute a joint's state (i.e. position and velocity). Using such a model allows the generation of virtual multiple degree-of-freedom models that can represent the motion of an entire extremity.

## II. Background

In this project, a single degree-of-freedom wrist joint is modeled by the Hogan joint model. The anatomical flexor and extensor muscles shown in Fig. 1 are directly represented as a single agonist-antagonist muscle pair that provides torques in either direction. As with other joint models, the system is spring-like and is influenced by physical parameters of the joint itself.

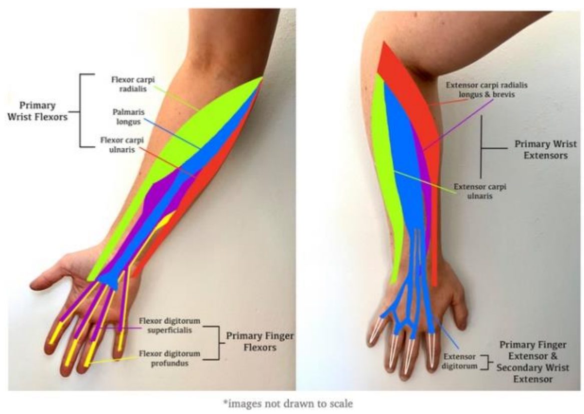


Fig. 1: Wrist flexor and extensor muscle synergists.

Several assumptions are made in the adoption of this joint model for the purposes of simulating a simple, one degree-of-freedom joint. It is assumed:

1. bidirectional torque in the system results only from activation of agonist or antagonist muscle; there is no "pulling" force and only "pushing" force,
2. there is a linear (spring-like) relationship between muscle force and length,
3. and fixed levels of excitation, which ignores any dynamics arising from muscle activation – contraction coupling.

The moment arm will be modeled as a rigid body of mass $m$ and angular inertia $I$ rotating about a fixed axis. Thus, the net sum of muscle torques about this axis is:

$$\boldsymbol{T_n = T(u_1 - u_2) - K(u_1 + u_2)\theta}$$

where *T* is the max torque of the joint at the moment arm's vertical position. *K* represents angular stiffness and is in some sense modulated by the central nervous system (CNS). Neural inputs are represented by floats *u1* and *u2* so that they lie between 0.0 and 1.0, inclusive.

Considering gravity and viscosity effects of muscle, the Hogan model dynamics equations are:

$$\boldsymbol{\dot{\theta} = \omega}$$

$$\boldsymbol{I\dot{\omega} = T(u_1 - u_2) - K(u_1 + u_2)\theta + mgL\sin\theta - B\omega}$$

where B is the viscous coefficient of muscle.

## III. Methodology

To map neural inputs to joint kinematics, normalized EMG data from an individual flexing and extending the wrist joint was obtained from the wrist flexors (represented as *u1*) and extensors (represented as *u2*). This data was extracted from .pkl files and entered into a .csv file. Angular stiffness was initially calculated as the partial derivative of muscle torque with respect to angle using finite differences. An average was taken and used later as a constant estimate to simulate the joint motion more smoothly.

```
function [ss] = fwd(old_ss, alphas, params, dt)
    tau_max = 100; % max torque at vertical position
    I = params(5);
    a = [0, 0.5, 0.5, 1]; % RK coefficients
    b = [1/6, 1/3, 1/3, 1/6];

    old_theta = old_ss(1);
    old_omega = old_ss(2);

    %calculating slope approximations

    k1_th = old_omega*dt;
    k1_om = dt*model(old_theta, old_omega, tau_max, alphas, params)/I;

    k2_th = dt*(old_omega + a(2)*k1_om);
    k2_om = dt*model(old_theta + a(2)*k1_th, old_omega + a(2)*k1_om, tau_max, alphas, params)/I;

    k3_th = dt*(old_omega + a(3)*k2_om);
    k3_om = dt*model(old_theta + a(3)*k2_th, old_omega + a(3)*k2_om, tau_max, alphas, params)/I;

    k4_th = dt*(old_omega + a(4)*k3_om);
    k4_om = dt*model(old_theta + a(4)*k3_th, old_omega + a(4)*k3_om, tau_max, alphas, params)/I;

    theta = old_theta + b(1)*k1_th + b(2)*k2_th + b(3)*k3_th + b(4)*k4_th;
    omega = old_omega + b(1)*k1_om + b(2)*k2_om + b(3)*k3_om + b(4)*k4_om;

    ss = [theta, omega];
end
```

Fig. 2: Calculating RK4 approximations of position and velocity.

Calculation of system states according to the nonlinear dynamics equations was accomplished with the Runge-Kutta method, as shown in Fig. 2. This method was chosen as it exhibited higher precision than a Forward Euler computation. After iteratively approximating these state values via dynamics, an animation of the wrist joint's position over 753 time steps of length .0167 seconds, as well as position and velocity plots, were created.

## IV. Results

Shown below in Fig. 2-4 are visuals created in MATLAB of the position and velocity of the wrist joint. Plots of EMG data, normalized between 0 and 1, are shown comparatively to demonstrate the physical actuation of the joint in response to muscle activation.

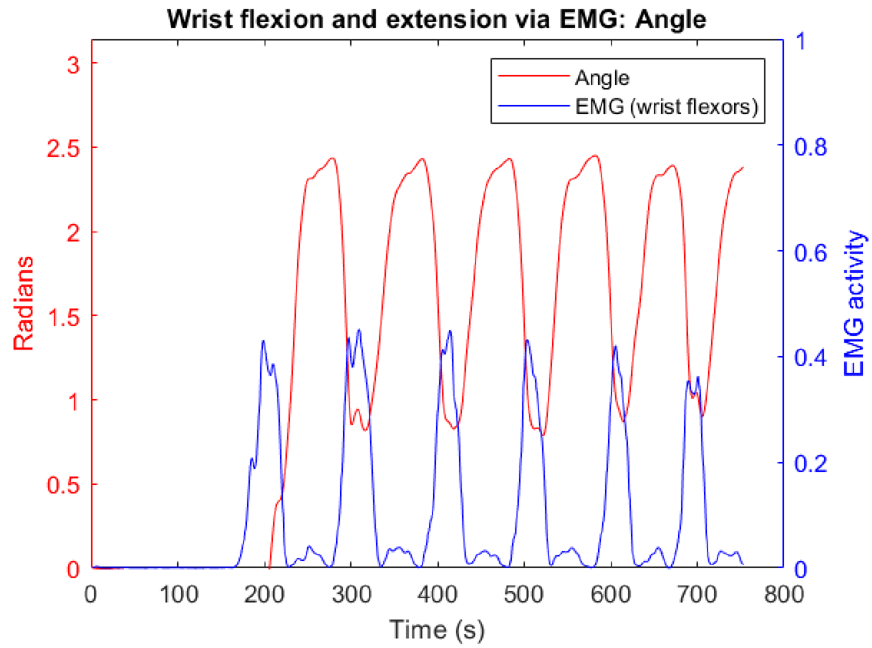


Fig. 3: Predicted angle values (measured from horizontal) from the MATLAB model and activation signals from wrist flexors.

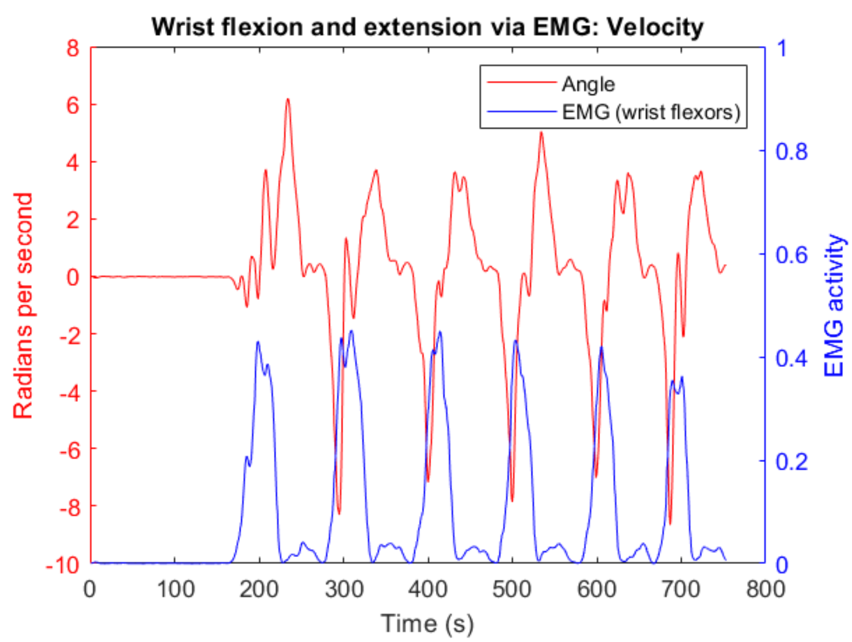


Fig. 4: Predicted velocity values from the MATLAB model and activation signals from wrist flexors.

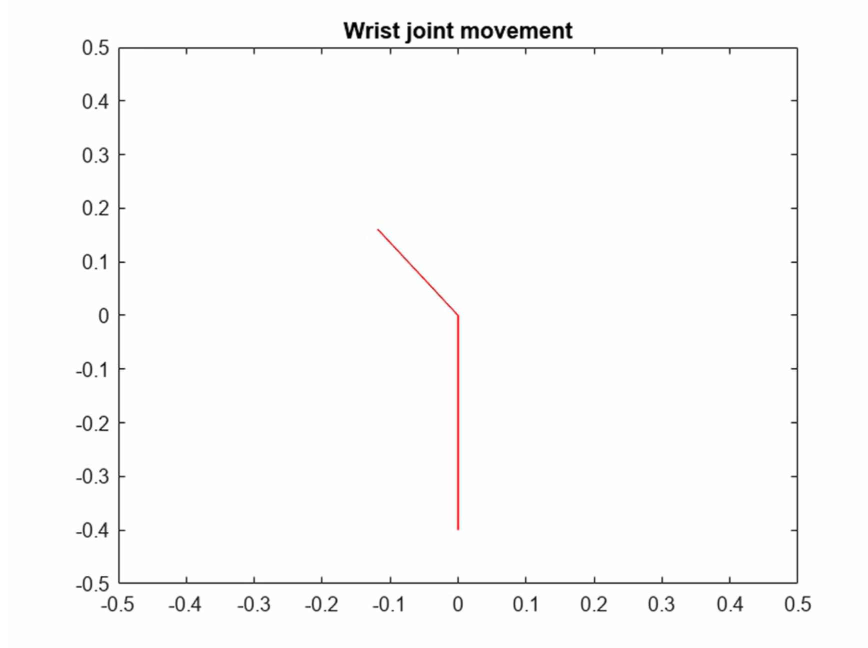


Fig. 5: An arbitrary frame from an animation of the wrist joint's movement. Axes are measured in meters but serve only to orient in space.

## V. Scope and further use

The scope of this model does not extend to raw data, as it uses processed real-time EMG data interpreted as "muscle activation signals." However, it is possible to modify this script to process raw data. This model applies solely to single degree-of-freedom joint kinematics, in which synergistic qualities of the hand and forearm muscles can be ignored. The modification of this script to link several degrees of freedom would create a more complex model that cannot be constrained under physical simplifications made here. As a result, a more reasonable approach may imply using machine learning to optimize certain parameters governing the interaction of one agonist-antagonist muscle pair with another.

## VI. References

Hogan, Neville. "Adaptive control of mechanical impedance by coactivation of antagonist muscles," IEEE Transactions on Automatic Control, vol. AC-29, no. 8, pp. 681-690, 1984. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=1103644&tag=1.