Preliminary Investigation of the Use of Electromyographic Signal for the Control of a Prosthetic Ankle

by

Louis Hong Basel

Submitted to the Department of Mechanical Engineering
In Partial Fulfillment of Requirements for the Degree of

Bachelor of Science

at the

Massachusetts Institute of Technology
[June 2006]
May 2006

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ABSTRACT

The overarching goal of this work is to develop a control algorithm that will allow an active prosthetic ankle to emulate its biological equivalent. The current convention for below-knee amputees is to use passive ankles. Previous work exists in active ankles under state machine control and active prosthetic elbows under electromygraphic (EMG) based control. In this paper, an investigation of methods for collecting EMG and ankle angle data are reviewed and a preliminary correlation of the two is developed. Experimental hardware has been designed to facilitate the simultaneous measurement of ankle angle and EMG. Its design and functional requirements are reviewed. Ankle angle is assumed to be linear in EMG, and a correlation is developed and evaluated from collected data. A comparison is made between self-varified data (where one set of data is used to develop a correlation and also to verify it) and naïve data (where one set of data is used to develop a correlation and another is used to verify it). Noise and inaccuracies in the model resulted in correlations that could predict ankle angle at best with a 0.972 correlation coefficient. With naïve data, linearity, as measured by the correlation coefficient fell, but not as significantly as RMS, indicating a relative shift in sensitivity of EMG channels. A lack of repeatability in predicted angle indicates an inaccuracy in the model used or too great a degree of noise. A single position can be produced on multiple instances by significantly different EMG signals indicating an incompleteness of the model or poorly understood factors regarding noise and EMG sensitivity drift.

Thesis Supervisor: Hugh Herr
Title: Assistant Professor of Media Arts and Sciences

INTRODUCTION

A long-term goal of this research is to develop a control algorithm that will allow an active prosthetic ankle to emulate its biological equivalent. Specifically, the system will measure the body's own control signals to determine desired ankle position and force. The immediate goal is to investigate and characterize the relationship between the muscles' electrical potential as measured by electromyography and the associated ankle position in biological human legs. Once an algorithm is developed based on the biological data, one can use it to mimic the body's interpretation of muscle control signals with a prosthetic.

The current convention for below-knee amputees is to use passive prostheses, whose dynamics are not governed by any sort of active control. As these devices are purely passive, users are not able to add energy in the heel-rise and toe-off phases, as do humans with biological legs. Such prostheses result in a gait significantly different from that of biological legs and are inefficient for the user in terms of metabolic costs.

The alternative to a passive ankle is an active prosthesis, which allows the addition of energy during the stride. The implementation used in this research is to drive the ankle joint with an electric motor. One developed control method for active prostheses is State Machine control, where the controller determines a desired ankle position or force from expected orders of states and the recent history of position, orientation and force profiles. While such methods have proven effective, they do not allow the same dynamic behavior as a biological ankle. And while State Machine control

has proven to be a robust control scheme, it is a tool whose behavior has been designed to fit the interpreted user's desires, but is not under the user's control.

In a biological human leg, the motion of the ankle during walking is controlled in part, by a series of muscles that span the ankle. For below-knee amputees, the truncation of the limb occurs between the ends of these muscles, resulting in portions of truncated muscles remaining in the residual limb. As there is no longer an ankle joint for these muscles to control, the muscles are not actively used by the amputee and incur a significant amount of atrophy. However, normal biological pathways still control these truncated muscles allowing their activation level to be monitored by EMG sensors.

Over the past several decades, electromyographic signals have been investigated for use in prosthesis control. Reading EMG allows the controller to interpret the user's desires directly from the user's muscles signal, allowing the controller much more immediate access to the user's intentions. Prior implementations have resulted in limited success and high rates of user rejection. However, this work has largely been in the context of prosthetic elbows, which have dramatically different and more precise requirements than ankles, suggesting the possibility of prosthetic ankles as a suitable application of EMG based control.

THEORY

Muscles are made up of many individual bundles of muscle fibers. Multiple sets of these bundles are functionally grouped into motor units, which are controlled by a single alpha-motorneuron. Muscle commands arrive at the muscle via an action potential. When the alpha-motorneuron fires, the fibers of the muscle motor unit controlled by the neuron contract. Control of the level of contraction in the muscle is governed by the frequency of action potentials and number of motor units activated.[1] EMG senses muscle activation level by 'taping' into the human muscle signal pathway. An EMG electrode placed on the surface of the skin measures action potentials assumed to be proportional to the action potential in the muscle. Through this, one is able to determine muscle activation levels.[2]

There are two types of electrodes commonly used for electromyography, surface electrodes and fine wire electrodes. Surface electrodes are firmly held against the skin by the pressure of an elastic bandage, while fine wire electrodes are embedded into the muscle with a syringe. Fine wire electrodes measure electrical potential from a single muscle fiber while surface electrodes measure data across the while muscle belly. Fine wire electrodes offer a better signal to noise ratio than surface electrodes because they are much closer to the muscle than to sources of noise. However, the process of inserting fine wire electrodes is somewhat painful and carries a risk of infection of the site. For these reasons, a surface electrode deemed more appropriate for the prosthetic ankle.

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[1] Per Brodal, The Central Nervous System, Oxford University Press (2003)
[2] Hogan, N, (1976) A review of the methods of processing EMG for use as a proportional control signal. *Biomedical Engineering* , 83

EXPERIMENTAL METHODS

The immediate goal of this work is to characterize the relationship between ankle position and EMG, so that an algorithm may be developed to determine desired ankle position from EMG. EMG is most simply correlated with muscle activation, and can be associated with both force and position. When ankle position is fixed, the force exerted by relevant muscles is approximately proportional to the activation of the muscle and EMG. When the external force on the ankle is zero, the ankle's displacement from the rest position is approximately proportional to the EMG of contracting muscles. The nature of this relationship is complex, but explicitly assumed to be approximately linear. When both force is nonzero and position is not fixed, both force and displacement influence EMG obscuring the relationship. Thus the influences of position and force are evaluated independently.

Human muscles have mechanical characteristics such that they can be approximately modeled as springs. Thus, the force required to extend them is approximately proportional to the quasi-static displacement from a rest position. Additionally, the ankle joint has a rest position about which angular displacements are approximately proportional to net muscle activation. Thus, the net torque required to displace the ankle is approximately proportional to displacement from the rest position. Assuming the influence of gravity and any torques from the jig are small compared to that of muscles, the position of the ankle should be approximately correlated to muscle activation.

In this experiment, EMG and ankle displacement will be measured while the ankle exerts zero external force in order to decouple the relationships of these two quantities. The subject kept his ankle as still as possible, so the assumption of a static relation between ankle angle and EMG is valid. Because it is difficult to hold one's ankle precisely stationary, we will consider only angle data whose range remains within a 0.3 degree threshold.

For each trial, the subject first moves his ankle from one extreme to the other to be sure to register the index, which assures that the angle measurement locations of one trial match those of another. The subject will then hold his ankle still for approximately four seconds at a series of different ankle positions in order to collect quasi-static data. Data of ankle position and EMG will be simultaneously recorded. Post-collection, the data of constant position will be extracted and used to determine a correlation between EMG and ankle angle.

APPARATUS - Experimental Hardware Design

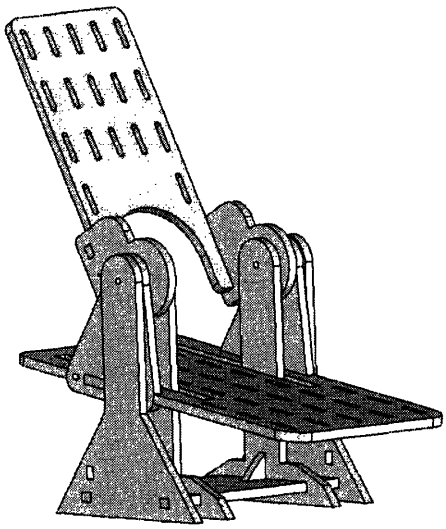

Figure 1. A solid model of the ankle jig

In order to collect EMG and ankle angle data, it was necessary to design and build an ankle jig. The jig has a plate that attaches to the calf of the user and a pedal for the foot. The calf plate is fixed at one of several positions while the foot pedal rotates about an axis lined up with the axis of the ankle. Because the human ankle is a rolling joint, the axis of rotation actually moves with ankle angle. However, this joint is nearly approximated by a rotary joint, as verified by users' experience of minimal slipping in the jig. The jig is supported by a stand that has four vertical struts holding two coaxial shafts. Two separate shafts were used so that the ankle axis could be coaxial with the shaft axes while the ankle rests between the two sets of supports. Each side of the pedal and each side of the calf plate is supported by one shaft or the other. A first test prototype was created by cutting thin acrylic parts on a lasercutter in order to check sizes and motions. After several dimensions were adjusted, a second functional version was cut. Individual

parts were assembled with screws after drilling and taping the parts. An image of the jig in use is shown in figure 2.

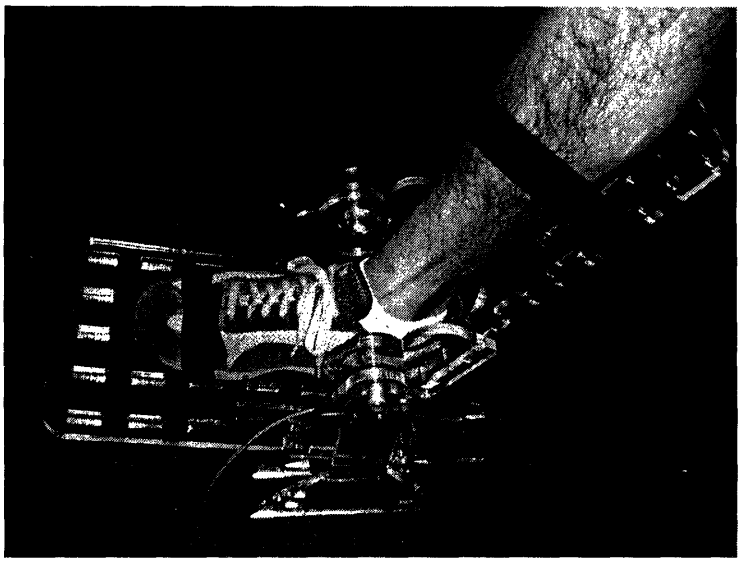

Figure 2. The laser cut acrylic jig designed to collect ankle position data.

For the jig to serve its purpose optimally, there are several functional requirements it must meet. The jig must not obstruct ankle motion and measure ankle angle as it travels through its full range of motion. This will allow the collection of data from the widest possible range of angles and allow exploration of the EMG - ankle angle relationship at the extremes where it is expected to break down.

Additionally, the pedal must exert zero torque on the ankle. For quasi-static use, this means that the center of mass of the pedal and supports must lie on their axis of rotation. This is only true for the quasi-static case as the pedal has a moment of inertia, which would affect kinetic motions. The center of mass of the pedal unit can be found by allowing the unit to come to rest under only the force of gravity. At this point the center of mass is directly below the axis of rotation. A measurement can be made to determine the angle of the part so that a cantilevered beam extending in the opposite direction may be added to support a mass. With an experimentally determined appropriate mass, gravity

will exert zero torque on the pedal in any position. This was not actually implemented in this version of the jig, but is suggested for future iterations.

Finally, the jig must be inexpensive, quick to manufacture and precise. Because of the relatively short timeline of this work, it is necessary to minimize the time required to produce the jig. Because of the need to align assembled parts and shafts in bearings a reasonable degree of precision is required. Laser cutting acrylic fit these requirements and because of its availability was chosen as the method of manufacture. There were several significant drawbacks of this choice. Acrylic is a rather brittle material, and assembled parts must be fine tuned for a precise fit. Otherwise, if they are too loose parts may move relative to one another or if they are too tight strains are likely to break one of the parts. A further drawback of laser cutting is that the width of the laser beam varies with height resulting in a slight angle in every cut. When assembled parts are mated on cut surfaces, as is often the case, one must be sure to square up the sides of the part, especially in parts that contain two parallel bearings.

Data was collected with MATLAB Simulink running on a PC104 computer. The PC104 read encoder data through a digital encoder card. Multiple surface EMG sensors run from the user to a Motion System Lab 'Backpack A to D Unit', through a Motion System Lab MA300DTU 'Desktop Unit' to the PC104's A to D board. The EMG signal is converted from analog to digital and back to analog by the Motion System Lab system to prevent signal degradation.

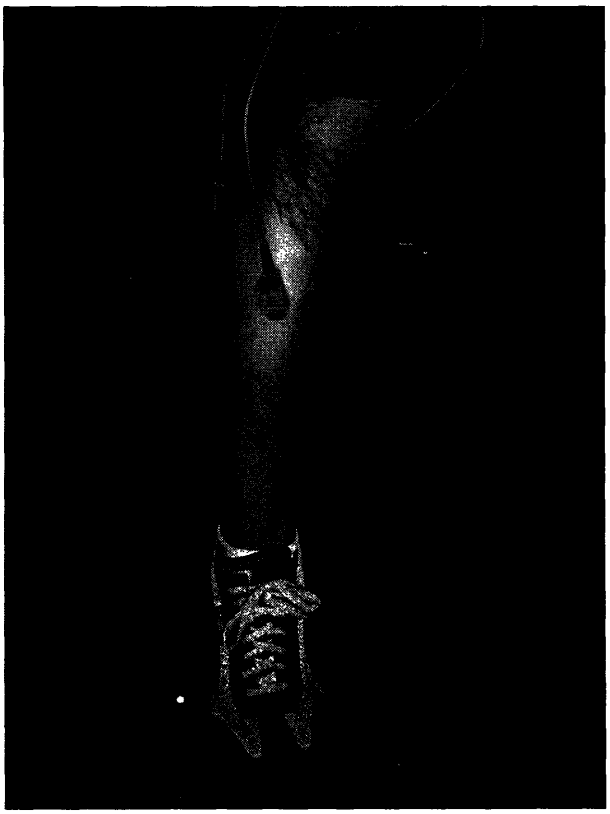

Figure 3. Three surface EMG sensors were placed on the major antagonist muscles of the ankle.

Three sensors were used to detect EMG of muscles controlling the ankle, the tibialis anterior, the medial gastrocnemius and the lateral gastrocnemius. Sensors are oriented parallel to the muscle fibers so that the electrodes are in line with the expected direction of impulses. The location and orientation of the electrode was found to have significant influence on noise and signal strength. It was expected that hairs between the sensor and the skin would degrade the signal, but removal of hairs was found to not have a noticeable effect.

US Digital HEDS encoders were used to measure ankle angle. These quadrature encoders have a resolution of 2000 positions per revolution. HEDS encoders have a

separate reader and disk, which must be accurately aligned. Using the laser cutter to create encoder mounting holes was an easy way to obtain the necessary precision.

EXPERIMENTAL ANALYSIS

Both encoder and EMG data require significant processing before it can be used to develop a reasonable correlation. Data processing was done post-collection in MATLAB.

The HEDs encoders used in the jig are indexed. When data collection begins the encoder assigns the initial position the value zero independent of its location relative to the index. Then, whenever the index is registered the count is reset to zero. As a result, unless the encoder began right on the index, the encoder value will jump to zero the first time the index is registered. If the encoder is properly adjusted and is not 'skipping' ticks, the value should continuously pass through zero at subsequent index registrations, but not jump as it did the first time. Encoder, EMG and time data from before the index registration is unwanted because the encoder data will be shifted, thus it is thrown away.

Next, the EMG data undergoes some processing. Muscle activation shows up in EMG in both the amplitude and frequency of the pulses. Because EMG measures series of zero-summing pulses, if low pass filtered EMG signals will tend to zero, independent of activation. To obtain activation data from EMG, the EMG data is full wave rectified by taking its absolute value.

Because EMG sensors are reading very small electrical signals any noise that is present tends to be large in comparison. Additionally, because the signal is simply electric potential, many sources of electrical potential are present from 60 Hz AC noise to other biological sources to signals picked up on the antenna-like electrode wire. While the frequency of all noise is not obvious upon inspection, there is clearly a component at a frequency much greater than motion of ankle and actual control signals. Thus the signal is passed through a low pass filter to attenuate high frequency noise. Two approaches were considered in attempts to attenuate high frequency noise, low pass filters and time averaging. A simple first order low pass filter and a Butterworth filter were considered, as was averaging a fixed size window of contiguous data points. According to Hogan's work with EMG signal conditioning, a time averaging method yields a 50 percent better signal to noise ratio than either of the low pass filters.[3] Thus, a time averaging method was employed.

Encoder data is evaluated in order to find segments of constant angular position. Only data at constant position meets the desired zero external torque constraint, so encoder data is broken into small two tenth second segments which are logged in an encoder-flat index if variation in position is less than 0.3 degrees. The encoder-flat index is called an index because values in it refer to positions in the encoder data array. It is not to be confused with the zero position index on the encoder disc itself. Segments of EMG, encoder and time data that meet the constant position constraint are saved while those that do not are discarded.

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[3] Hogan, N, (1976) A review of the methods of processing EMG for use as a proportional control signal. *Biomedical Engineering* , 81-86

Finally, a correlation between EMG and ankle angle is developed and used to predict ankle angle from EMG. It is assumed that for a quasi-static ankle angle the relationship between ankle position and EMG is,

$$\theta_{eq}^{*} = B \cdot A \tag{1}$$

where θ_{eq}^{*} is a m x 1 vector of unknown ankle position values. B is an m x n+1 matrix holding m samples from each of n EMG channels and the last column is all ones. A is an n+1 x 1 vector containing n slope values and the rest position.

$$\theta_{eq} \approx \theta_{eq}^{*} = B \cdot A \tag{2}$$

By comparing θ_{eq} to θ_{eq}^{*} one can evaluate the accuracy of the assumed relationship. Using the Moore Penrose pseudo inverse, A can be solved.

$$A = (B^{T} \cdot B)^{-1} \cdot B^{T} \cdot \theta_{eq} \tag{3}$$

The vector A is found using the Moore Penrose pseudo inverse, as demonstrated in equation 3 and used in equation 1 to solve for a predicted ankle angle.

RESULTS & DISCUSSION

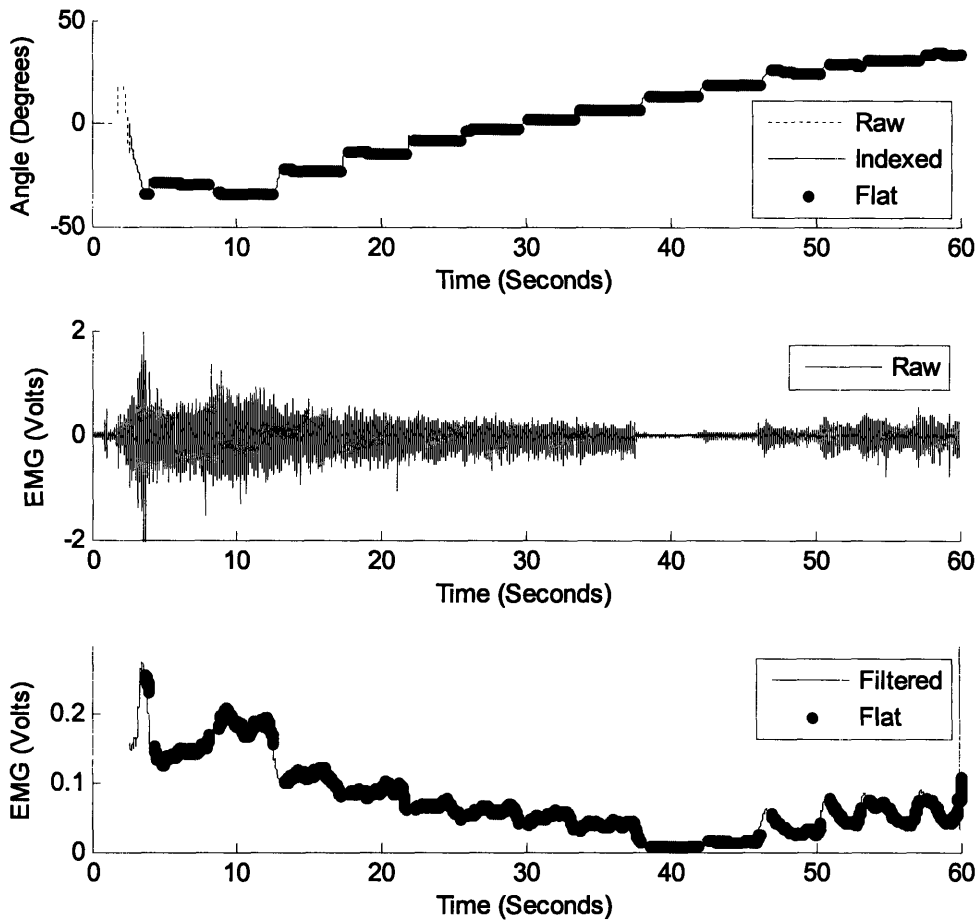

Figure 4. (top) Raw, indexed, and flat encoder data. (middle) Raw EMG data. (bottom) Filtered and flat EMG data. Note that 'flat EMG' data does not necessarily obey any 'flat' constraints; it is EMG data corresponding to encoder data the obeys the quasi static angle constraint. Trial 5. No cocontraction.

As a preliminary evaluation of the EMG to ankle angle correlation, predicted data is compared to measured data which was used to determine the correlation. Using a single set of data to create the correlation and verify it will result in the closest result from the correlation as can be expected. The alternative is to use 'naïve data.' In this case, measured ankle position is compared to ankle position as predicted from EMG and a correlation derived from a different data set.

Cocontraction is where a set of antagonist muscles are both contracting, however, as they oppose each other, their shared force cancel one another and result in zero net force. When flexing like a 'muscle man' to show the size of one's bicep, one is cocontracting the bicep and tricep. R is the correlation coefficient, indicating the linearity of the dataset. RMS is the root mean square.

For each trial shown the first plot is a comparison of measured ankle angle and predicted angle calculated from measured EMG. The second is a comparison the two ankle angles as a function of time.

Trial 5. Self-varified. No cocontraction.

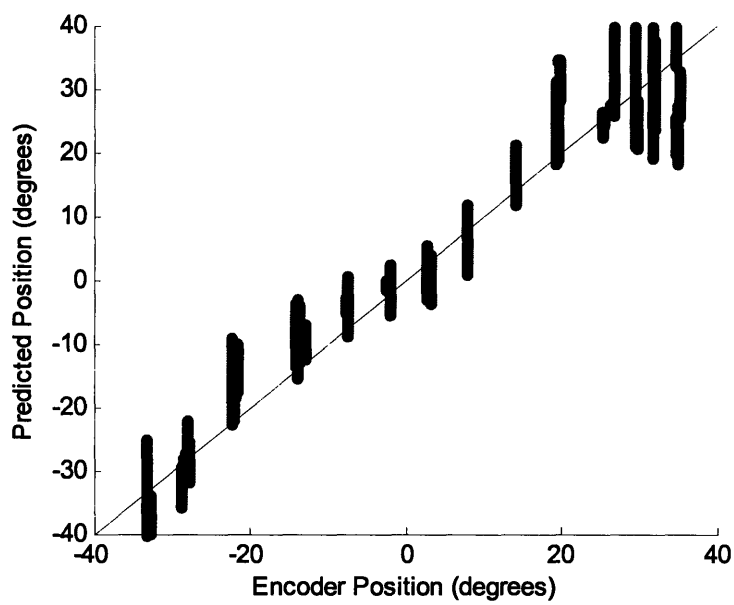

Figure 5. No cocontraction. Measured encoder position vs. predicted encoder position. R=.972 ,

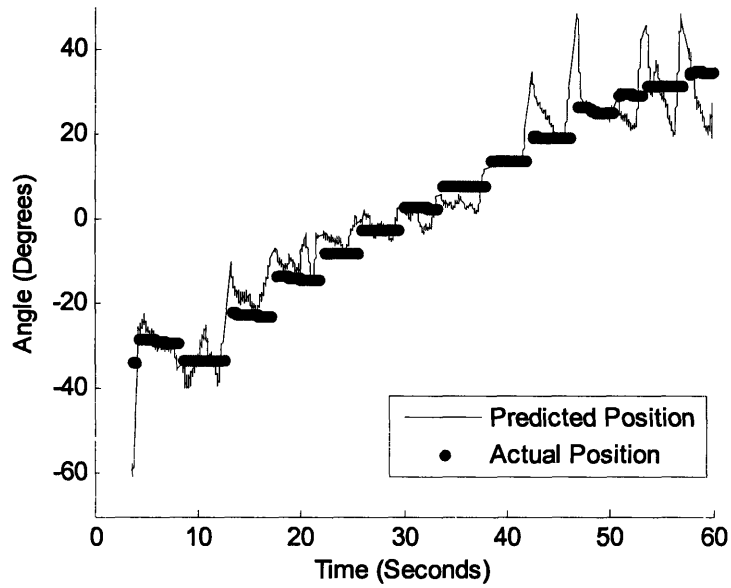

Figure 6. No cocontraction. Actual flat ankle position and predicted ankle position as a function of time. RMS=5.12

For self-verified data, predicted and measured angle data generally follow the expected trend, achieving correlation coefficients of .972 for non-cocontraction data and .943 for cocontraction data. However, naïve data fared much worse with correlation coefficients of .870 and .930. Further, correlation coefficient only addresses the linearity of the data. A better measure of the quality of predicted angle is the root mean square (RMS) of the difference between measured ankle angle and predicted ankle angle. While the RMS for self-verified non-cocontraction and cocontraction data were 5.12 degrees and 7.83 degrees respectively, for naïve data they were 53.05 degrees and 23.81 degrees.

For self-verified data the difference between cocontraction and non-cocontraction is subtle, with the correlation for cocontraction data slightly worse than that of non-cocontraction. Figure 5 shows that often predicted position fell within a tighter band for a given measured position than with non-cocontraction data. Note the predicted positions

for encoder values from 5 to 10 degrees in figure 7. This may be caused by nonlinearities between EMG and contraction at higher activations. It is unlikely, however, that this deviation from measured data is caused by something like noise as predicted position values fell into such a tight range.

Trial 4. Self-verified. Cocontraction.

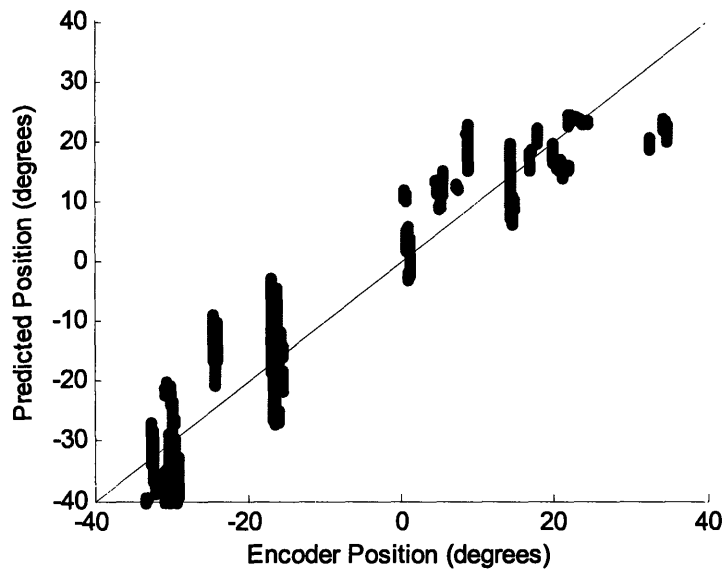

Figure 7. Cocontraction. Measured encoder position vs. predicted encoder position. R=.943

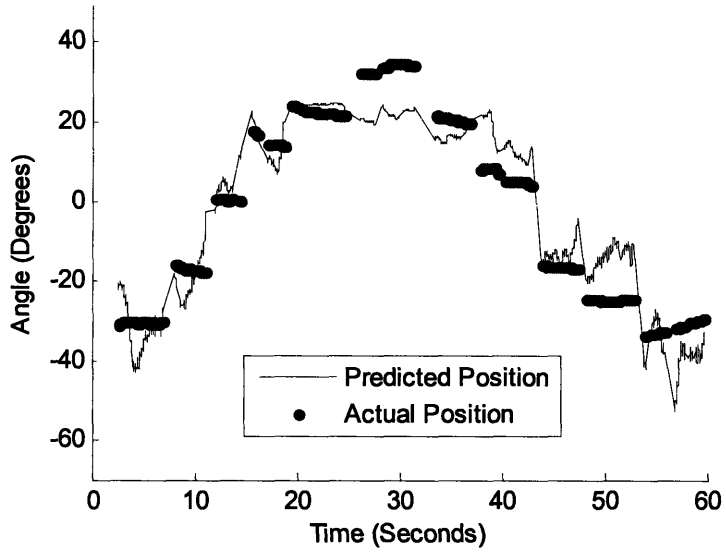

Figure 8. Cocontraction. Actual flat ankle position and predicted ankle position as a function of time. RMS=7.83

Of naïve data, cocontraction produced a better prediction than did non-cocontraction. However, naïve data seems to be fundamentally much worse. Perhaps some of the EMG sensors were shifted between the two trials. As the sensor signal strength was shown to be very sensitive to sensor location, such a physical shift of the sensor would alter the magnitude of EMG signal and thus also alter predicted angle values.

Trial 5 trained on trial 11. Naïve. No cocontraction.

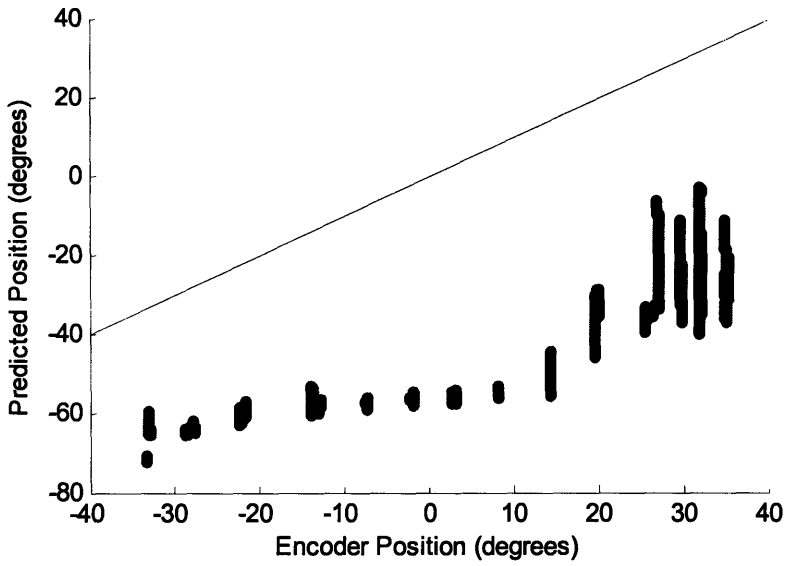

Figure 9. No cocontraction. Naïve R=.870

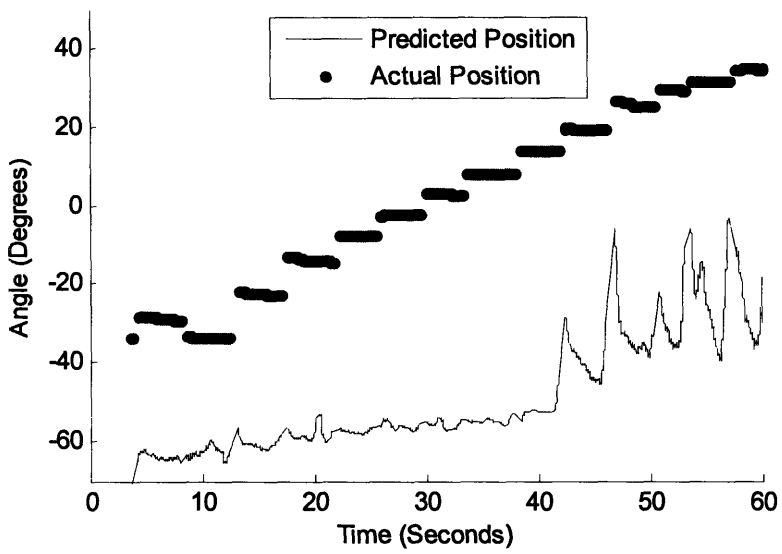

Figure 10. No cocontraction. RMS=53.05

Trial 4 trained on trial 8. Naïve. Cocontraction

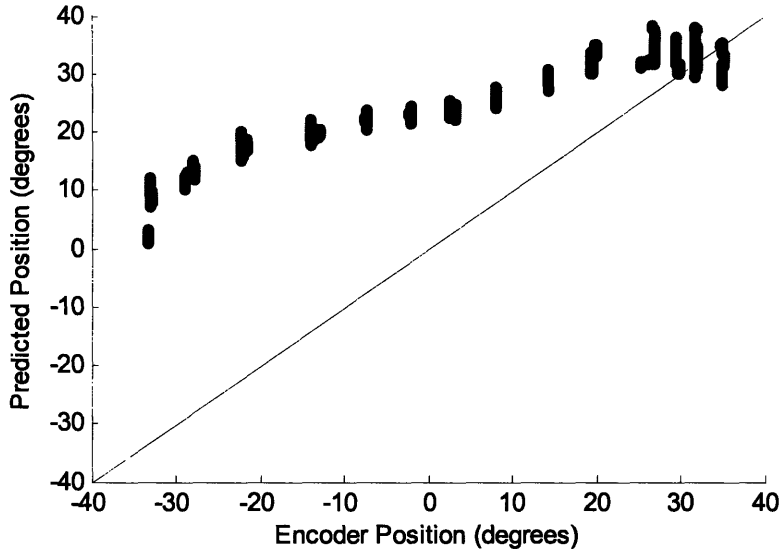

Figure 11. Cocontraction. Naïve data. R=.930

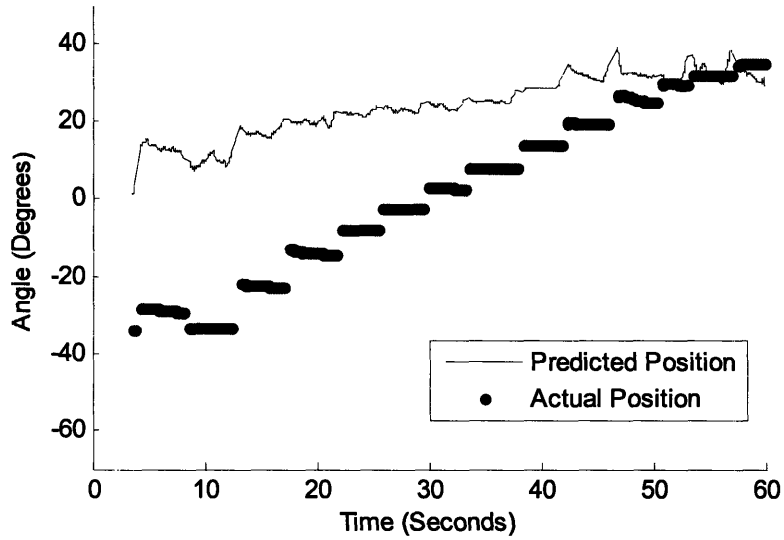

Figure 12. Cocontraction. Naïve data. RMS=23.81

Alternatively, the differences between the naïve cocontraction and non-contraction may not have to do with cocontraction at all. The cocontraction trials 4 and 8 occurred in closer temporal proximity than did the non-cocontraction trials 5 and 11. Perhaps a slow drift is constantly occurring making greater variations more likely when more time has passed between the collection of correlation data and its use. Such a theory could be validated or disproved by recording time delays between trials used to create a correlation and a naïve data set with which the correlation is used.

While such influences as slow EMG sensitivity drifts are possibilities for causes of error or noise, what is certain is that there is some factor which influences EMG that we are not considering. If the ankle goes to a certain position and later returns to the same position, the body is interpreting two sets of biological signals with an identical result. Experimental trials, however, have shown that two identical ankle positions can be produced by significantly different sets of EMG. This difference may be caused by an addition of external sources of noise to the biological signal or actual different biological signals, which the body interprets as the same position. Either way, to produce a model capable of better interpreting EMG one must find ways of further reducing noise or better understand what factors affect how the body interprets biological electrical signals.

CONCLUSION

While Hogan and others had limited success using EMG for the control of a prosthetic elbow, the functional requirements for an ankle are significantly different and leave the potential for greater success with ankle prostheses. Arms are involved in a diverse set of dexterous tasks that require a high level of precision. On the contrary, ankles are involved in variations of one single type of motion, that of walking. Although there are variations of ankle torque and angle profiles at different speeds of walking, it would be possible to use EMG inputs to determine a desired gait profile and at what point the user is the gait cycle, but use this information only to choose from a known set of safe ankle motions.

Somewhat similar to this idea is Hogan's concept of threshold control.[4] In order to avoid both jittering due to low frequency noise and time lag due to filtering, Hogan suggests a nonlinear control scheme. In this case small variations from the rest EMG are ignored all together and the joint is actuated only when EMG surpass a given threshold. This scheme is proposed in the context of an elbow for which precise motion is integral to the usability of the prosthesis. However such concepts like thresholding could be applied to the motion of ankles allowing them to retain the more biologically inspired approach while avoiding the pitfalls of dealing with such a noisy input. However, while such systems may provide greater usability, they are straying from the initial goal of creating a system capable of accurate mimicry of the biological human equivalent.

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[4] Hogan, N, (1976) A review of the methods of processing EMG for use as a proportional control signal. *Biomedical Engineering* , 85

Biological human control systems have a major advantage over prosthetic systems. That is, biological systems are closed loop because sensory systems pass information about the location of the ankle back to the brain. However, the prosthetic does not have a means for communicating any information back to the controller or user. This fundamental difference between the two systems is part of what makes designing a successful controller difficult.

While building a successful correlation between EMG and ankle position is a fundamental challenge in the large-scale goal of using EMG to control an active prosthesis, there are also other challenges. All data collected for this work was from a subject with healthy biological legs. While truncated muscles are present in the residual limbs of amputees, these muscles have not only been truncated but are not actively used and are subject to atrophy. Such considerations were not involved in the preliminary level development of this work, but will be come relevant as work continues.

Finally, for future work, I suggest the investigation of nonlinear correlations. Filtered EMG data seems to have a somewhat linear relationship with position while the muscle is in contraction, but a constant relationship when it is being extended. This is somewhat intuitive as muscles can only exert tensile forces. Employing a higher order correlation would allow an approximation to this observed nonlinearity.

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APPENDIX

MATLAB data processing script

```
%nofn=[];
%Rofn=[];
chunk = 1000;
%for n = 1001:1000:19001

%    disp(['n = ',num2str(n)])

%n must be ODD
n = 3001;
%close
close
close
close
%clear
load LouisData501_11

%encoderdata= encoderdata(1:150000);
%EMGdata=EMGdata(1:150000,:);
%Time=Time(1:150000);


figure (2)
subplot(3,1,1)
hold on
plot (Time, encoderdata(:,2),'b:')

subplot(3,1,2)
hold on
plot(Time,EMGdata(:,1))
legend('Raw')
axis([0 60 -2 2])
xlabel('Time (Seconds)')
ylabel('EMG (Volts)')

%4, 5, 8 11 are ok trials

%find the index
encoderindexedat=0;
for i=1:length(encoderdata)-1
    if abs(encoderdata(i+1,2)-encoderdata(i,2))>1
    encoderindexedat=i+1;
    end
end

%cut off data before index and
%make encoderdata one channel/get rid of encoder 1
dataindex = length(encoderdata);
encoderdata=encoderdata(encoderindexedat:dataindex,2);
EMGdata=EMGdata(encoderindexedat:dataindex,:);
Time = Time(encoderindexedat:dataindex);

figure(2)
subplot(3,1,1)
plot (Time, encoderdata,'-k')


%EMGdata=EMGdata(8000:end,:);
```

```
%Time=Time(8000:end);
%encoderdata=encoderdata(8000:end,:);



%%figure(3)
%%subplot(3,1,1)
%%plot (EMGdata(:,1))

%rectify
EMGrectified=abs(EMGdata);

%time averaging
%%%n=5000;
%EMGcumsum=cumsum(EMGrectified);
%EMGcumsumshifted=EMGcumsum(n:end,:);
%EMGcumsum=EMGcumsum(1:end-n+1,:);
%EMGTA=(EMGcumsumshifted-EMGcumsum)/n;

N = length(EMGrectified);
windowLength = n;
halfLength = (windowLength-1)/2;
%ypadded = [zeros(1,windowLength), y, zeros(1,windowLength)];
%tpadded = [-windowLength:1:-1, t, t(N)+1:1:t(N)+windowLength];
%Npad = length(ypadded);
EMGcumsum = cumsum(EMGrectified);
EMGforwardshift = [EMGcumsum', zeros(3, windowLength)]';
EMGbackwardshift = [zeros(3, windowLength), EMGcumsum']';
EMGwindowed = ( EMGforwardshift - EMGbackwardshift );

% get average without accounting for padded ends
EMGTA = EMGwindowed(halfLength+1:N+halfLength,:)/windowLength;
% get average at edges
for i = 1:halfLength + 1
    EMGTA(i,:) = EMGwindowed(halfLength+i,:)/(halfLength + i);
end
for i = 1:halfLength
    EMGTA(N-halfLength+i,:) = sum(EMGrectified(N-
halfLength+i:N,:))/(halfLength-i+1);
end


 %EMGTA = EMGwinavg;
 %encoderdataTA=encoderdata(n:end);
%TimeTA = Time(n:end);

%hold on
%plot(Time, EMGrectified(:,1),'r')
%plot(Time,EMGTA(:,1))

%%figure(3)
%%subplot(3,1,2)
%%plot (EMGTA(:,1))
%%hold on
%%subplot(3,1,3)
%%plot (encoderdata)

%create index of flat portions
%chunk=3000; %size of data chunk that must be within delta 'jiggle'
jiggle=.3; %degrees.
flatindex=[];
for i=1:chunk:length(encoderdata)-chunk
    if range(encoderdata(i:i+chunk))<jiggle
```

```
        flatindex=[flatindex; i];
    end
end

%concatinate flats in encoderdata
encoderdataflat=[];
EMGflat=[];
Timeflat = [];
for i= 1 : length(flatindex)
    slice=encoderdata(flatindex(i):flatindex(i)+chunk);
    encoderdataflat=[encoderdataflat;slice];
    slice=EMGTA(flatindex(i):flatindex(i)+chunk,:);
    EMGflat=[EMGflat;slice];
    slice = Time(flatindex(i):flatindex(i)+chunk);
    Timeflat = [Timeflat;slice];
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%EMGflat=[EMGflat;EMGflat2];
%encoderdataflat=[encoderdataflat; encoderdataflat2];
%Timeflat=[Timeflat;Timeflat2];

figure(2)
subplot(3,1,1)
plot (Timeflat, encoderdataflat,'k.')
legend('Raw','Indexed','Flat')
xlabel('Time (Seconds)')
ylabel('Angle (Degrees)')

subplot(3,1,3)
hold on
%plot(Time,EMGdata(:,1))
%plot(Time,EMGwindowed(1:length(Time),1)./2239,'-k')
plot(Time, EMGTA(:,1),'r')
plot(Timeflat,EMGflat(:,1),'k.')
%plot([0:60],zeros(61),'k')
legend('Filtered','Flat')
xlabel('Time (Seconds)')
ylabel('EMG (Volts)')
axis([0 60 0 .3])



%temp check time average code
%%figure(6)
%%subplot(2,1,1)
%%plot (EMGflat(:,1))
%%subplot(2,1,2)
%%plot (encoderdataflat)

%normalize again so 2 and 3 are normalized also.
EMGflat(:,1)=EMGflat(:,1)/max(EMGTA(:,1));
EMGflat(:,2)=EMGflat(:,2)/max(EMGTA(:,2));
EMGflat(:,3)=EMGflat(:,3)/max(EMGTA(:,3));

%find coorilation
A=[EMGflat,ones(length(EMGflat),1)];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
answer=inv(A'*A)*A'*encoderdataflat;

%%plot(encoderdataflat,'r-')
```

```
ang= -40:1:40;

%%figure (2)
%%subplot(3,1,1)
%%plot (encoderdataflat, EMGflat(:,1),'.')
%plot(ang, ang/answer(1)-answer(4)/answer(1))

%%subplot(3,1,2)
%%plot (encoderdataflat, EMGflat(:,2),'.')
%plot(ang, ang/answer(2)-answer(4)/answer(2))

%%subplot(3,1,3)
%%plot (encoderdataflat, EMGflat(:,3),'.')
%plot(ang, ang/answer(3)-answer(4)/answer(3))


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%use corrilation to predict angle from EMG with another set of data.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

anglepredicted= EMGflat*answer(1:3) + answer(4)*ones(length(EMGflat),1);

figure (5)
hold on
plot(Timeflat,anglepredicted,'b-')
plot (Timeflat, encoderdataflat,'b.')
axis([0 60 -70 50])
legend( 'Predicted Position','Actual Position')
xlabel('Time (Seconds)')
ylabel('Angle (Degrees)')


figure(1)
hold on
plot (encoderdataflat, anglepredicted,'b.')
axis([-40,40,-40,40])
plot([-40,40],[-40,40])
xlabel('Encoder Position (degrees)')
ylabel('Predicted Position (degrees)')

%%figure(7)
%%plot(encoderdataflat,anglepredicted,'.')


rms=(sum((anglepredicted-encoderdataflat).^2)/length(anglepredicted)).^.5

R=corrcoef(encoderdataflat,anglepredicted);
%nofn=[nofn,n];
%Rofn=[Rofn,R(2,1)];
%end
%plot (nofn,Rofn,'.')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%
%EMGflat2=EMGflat;
%encoderdataflat2=encoderdataflat;
%Timeflat2=Timeflat;
```