Reference Position Estimation for Prosthetic Elbow and Wrist using EMG Signals

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Abstract— **Progress in Bio robotics has provided several ways to mimic the form and function of human limbs, thus allowing the scheme of better prostheses for amputees. This paper presents EMG based Human Machine Interface framework to estimate reference positions of a prosthetic arm for patients suffering from above elbow amputation. In the present study, a set of information about four basic motions regarding elbow flexion/extension along with the twist of radius and ulna referred as pronation/supination is acquired from bicep of a human arm. Upon muscle activation, the numerical data set points representing the electromyographic intentions were recorded using the Thalamic Labs product i.e. Myo Armband. To analyze these acquired signals, feature selection followed by feature extraction was done in order to classify the input data extracted from human muscle. Artificial Neural Network (ANN) is used for classification and the performance of four motion classification is evaluated. A mathematical model of kinematic of a trsanshumeral arm based on Denavit-Hardenberg convention is presented using Matlab®. Analytical results of the forward kinematic model are verified using Matlab® PeterCorke® Robotic toolbox. A physical significance of proposed work is tested through the information of forward kinematics from Matlab® linked with that of Solid works simulated with reference to the EMG intentions captured and classified to generate the reference positions. The classification accuracy obtained from ANN i.e. 91.9% is found significant with p<0.01 for a group of ten healthy subjects. This verifies usability of the proposed technique.**

Keywords—Above Elbow Amputation, EMG, Kinematics, Myo Arm Band, ANN

I. INTRODUCTION

Evolution in the field of engineering has provided numerous solutions to complex problems. Advancements in the technology have revolutionized the concept of prosthesis[1]. The new problem that has emerged is to control such devices according to the dire need of the user i.e. moving the prosthetic arm towards a certain position with some specific speed and time duration[2, 3].

As the arm muscles contract, electrical signals are produced which are referred to as electromyographic signals. In order to capture such information, electrodes are engaged on the surface of the contracting muscles. The signals generated are proportional to the amount of activity detected at the flexed muscle. In the case of a trans-humeral amputee, the only functional muscles for signal acquisition in the arm are biceps, which make it suitable for the sensor to be set. As these fluctuations are different for each person at different position and time intervals, this becomes a disadvantage to work on control command generation, as the reference is non-linear and variable. For such a scenario, the implementation of machine learning techniques helps in determining the motion for the device. Most of the work done for myoelectric prosthetic arm generates a command for go or not go for a fixed type of motions [4]. This does not give an accurate position of a prosthetic arm.

This paper presents a simple approach to estimate a reference position using EMG signals where the prosthetic arm has to reach. A prosthetic arm with 2 degrees of freedom is used to verify the proposed method. A 2 degree of freedom arm is as simple as a 2-R configuration manipulator. It is proposed to first simulate the system and analyze how it behaves in the real world rather than developing a prototype when one can virtually verify the work based on mathematical models and calculations.

The machine learning method compromises supervised & unsupervised learning. For a known set of data, a model is trained such that it makes predictions for the new or incoming data based on the evidence of uncertainties present in the trained set of input data and the known responses. For acquiring EMG data from bicep muscles, Myo arm is used [6] as it is a low-cost consumer-grade EMG based device which integrates an ARM Cortex-M4 based microcontroller unit, eight dry EMG electrodes, a nine-axis inertial measurement unit (IMU) and a Bluetooth Low Energy (BLE) module. These EMG armbands have unlocked new possibilities for myoelectric control applications, which are not restricted to traditional prosthetics market. Applications have incorporated accessible game-based training for myoelectric prostheses [6,7], sport training systems[8, 9] and many others. Supervised learning uses a classification technique that predicts discrete responses whereas regression technique predicts continuous responses to develop predictive models[10, 11]. Feature selection plays an important role in data classification as well as the paradigm followed for data extraction. As soon as the information is received at the controller end, the robotic replacement of human arm is considered to be in a specific position, as the healthy arm would be. For this purpose, the SolidWorks® model along with PeterCorke Toolbox® is used to simulate the reference positions generated using machine learning algorithm.

This paper presents a methodology and their results in two steps: *First*, EMG data acquisition & control command generation through data processing as given in section II, *Second*, the development of solid and kinematics model to simulate motion of the arm given the reference positions generated in the form of control commands as given in section III.

II. EMG Data Acquistion and Control Command Generation

The control commands for reference positions are generated through analysis of data acquisited. This section presents the experimental paradigm and setup, data acquisition, feature selection, classification and control command generation as given in following subsections.

A. *Experimental Paradigm*

EMG signals were acquired using MYO armband. It is an application-based wireless wearable device which includes eight EMG sensors and nine-axis IMU sensors. It recognizes muscle movements and raw EMG signals can be extracted using this device. In this research, the signal extraction process was done through the multiple chambers, integrated with the MYO armband. Initially, the patient wore the arm band in such a way that the front plane faces in the downward direction. At that time the armband has to be in sync with a computer through Bluetooth. After the band was properly synced, various chambers showed peaks that means it is collected at different positions respectively. To check whether the pods were activated, MYO diagnostics was used and it reported spikes on the pods when the sensors were triggered.

As this research is explicitly for people suffering from transhumeral amputation so MYO armband was placed on the biceps muscle to capture EMG signals as illustrated in Figure 1. No change in electrode position was followed. Changing the electrode positions causes a disturbance as different muscles are activated which further gives information to predict the human arm motion. The change in electrode position also causes activation of the wrong electrode while the arm is in motion. EMG signals were captured using the MYO Armband in a defined range of elbow and wrist motion. The signals were then acquired using MYO Data Capture.

The data of 10 healthy persons (7 males & 3 females) was extracted at arbitrary angles which include -80°, 0°, 80° span for extension and flexion movement of the elbow joint. This was conducted by analyzing bicep & triceps signals. The experimental paradigm used is shown in table 1.

A sample of data is shown in Figure 2. This data is shown as EMG graphs . EMG graphs are active EMG signals at Mayo diagonostics.

B. *Signal Analysis*

A Microsoft Excel sheet was automatically generated as the sensor was synchronized followed by signal capturing application of the armband as soon as it was executed. The extracted signals were analyzed in MATLAB for further processing. Figure 3 represents the raw electromyographic signals extracted from healthy subjects. It also shows the electrodes activity upon any muscle action.

Every instant, a reading at each electrode is plotted together in a graphical form. Each peak represents the different peak value obtained at that very instance on a certain electrode.

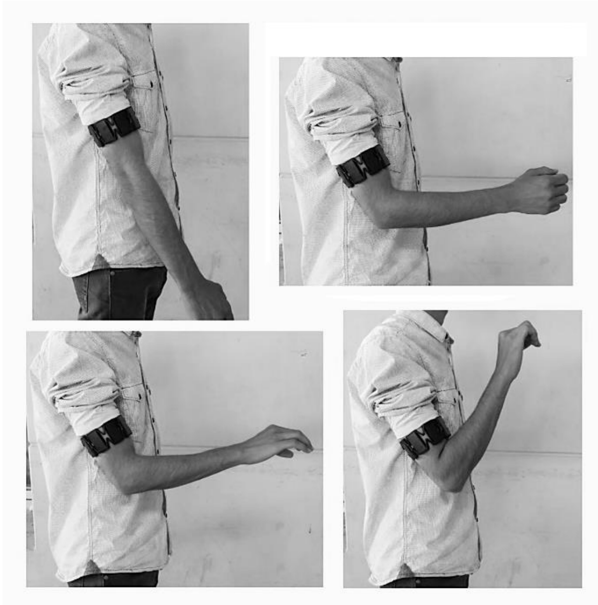

Figure 1.Sensor Placement at Biceps to Acquire Signals and Calibration of four different motions including Elbow Extension, Elbow Flexion, Wrist Pronation and Supination

Table 1: Experimental Paradigm

No. of Persons (7 male & 3 females)	10
No. of trials	4 each person
Resting Time (For the Arm Band)	5 minutes
Time for signal extraction	20 sec (max)

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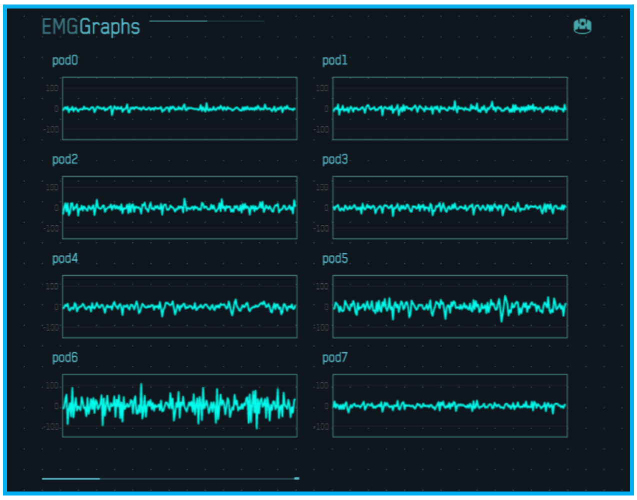


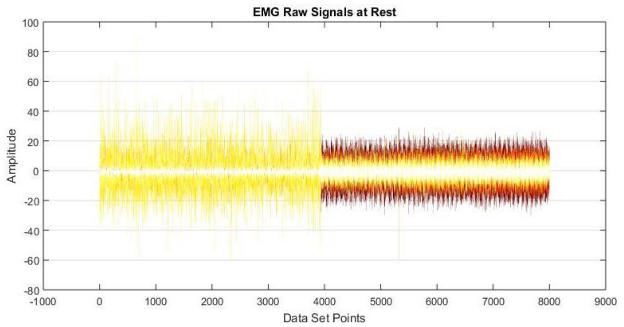
Figure. 2. Active EMG Signals at Myo Diagnostics

Due to the muscle contraction and relaxation, different peaks were created which were caused by an action potential in which different results are generated which the MYO armband reads the electrical activity of their muscles. At every angle, about 8000 set points were collected, plotted, and analyzed. These steps were repeated repeatedly for every patient. A large number of results were collected. A larger number of data sets points aids in acquiring higher accuracies.

These signals were then validated by finding the turning points i.e. where the signals peak or maximum threshold values were checked and analyzed if all the motions performed during signal acquisition were traceable or not.

C. Feature Selection

EMG signals extracted from muscles need advanced methods for detection, decomposition, processing, and classification. Figure 4 represents the entire algorithm that was responsible for the signal acquisition until the control command generation. These signals represented raw data and contained noises and disturbances. It could not to be used directly to get accurate results. Instead, features were extracted from the acquired signals and they contribute to classify the signals. The extracted features included Mean Absolute Value, Variance, Waveform Length, Kurtosis and Peak among which only peaks & wavelength showed different behavior and significance checked using p-test.



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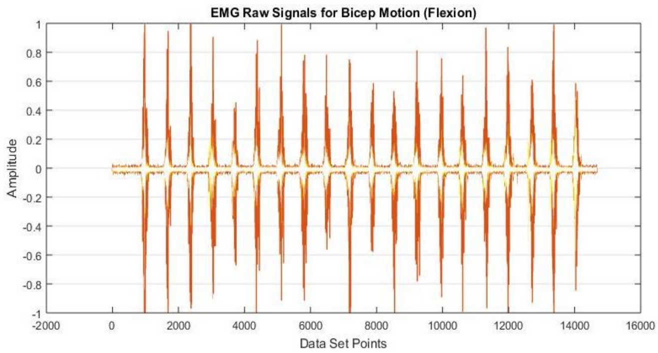

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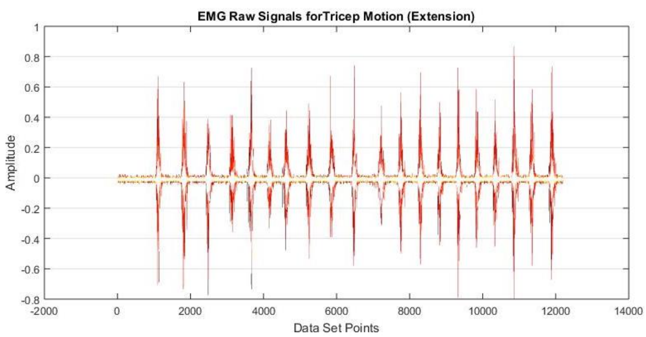

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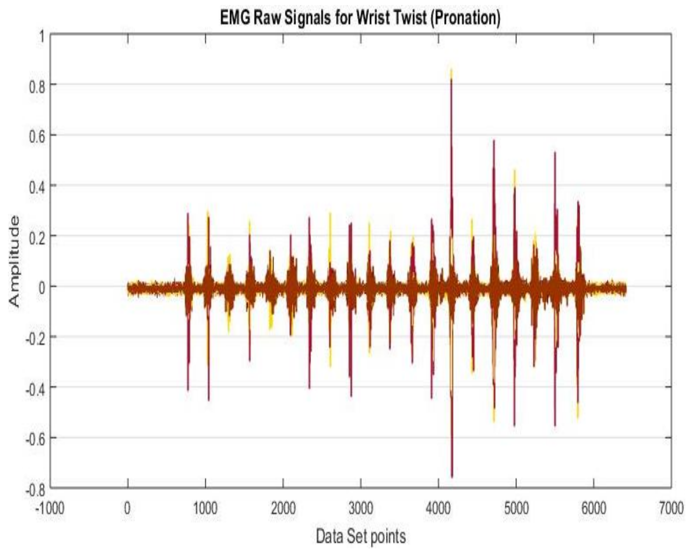

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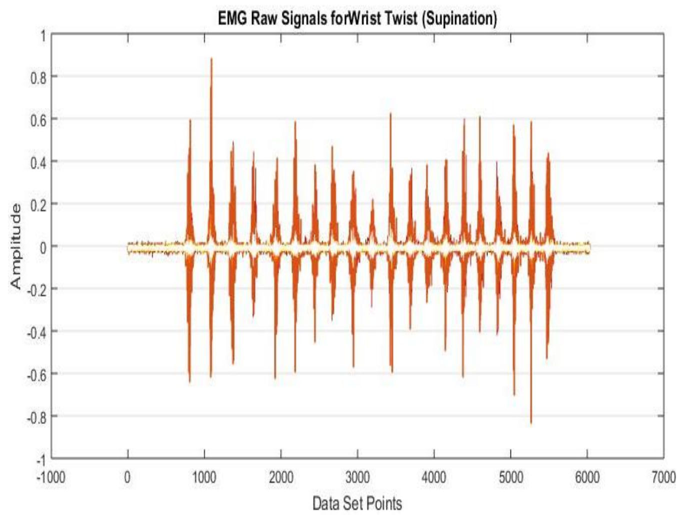

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Figure 3. Raw EMG signals of a healthy subject at a) rest position b) Elbow extension c) Elbow flexion d)Wrist Pronation e) Wrist Supination

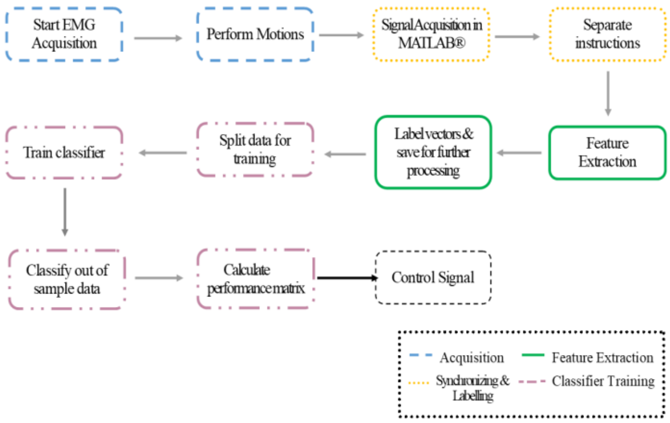


Figure 4. EMG Signal Acquisition and Processing Algorithm

D. Classification Algorithm (Artifical Neural Network)

These two features were selected for classification. Different classifying techniques such as Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), ANN (Artificial Neural Networking) are used in different applications to obtain good accuracies. Among such techniques, ANN is precisely experimented to obtain greater accuracy, more effective offline training and accurate classification.

ANN is a technique that utilizes multiple neuron layers to map data from one distribution to another to allow for better and optimized classification [12]. This technique is implemented to yield state of the art results while using several layers giving rise to a deep neural network in its place. Figure 5 is a step by step representation of working boundaries of Artificial Neural Network [3].

A set of data was entered which passed through hidden nodes/layers before providing a certain output. Initially, it passed through hidden nodes, which comprises different activation functions. They made a decision based on certain input or some predicted value. Mostly, activation functions are non-linear. For this research, Relu was employed as an activation function for neurons. The weights were initialized using the Xavier distribution, the network utilized the Adam optimizer function for gradient descent and categorical cross entropy was used as a loss measure.

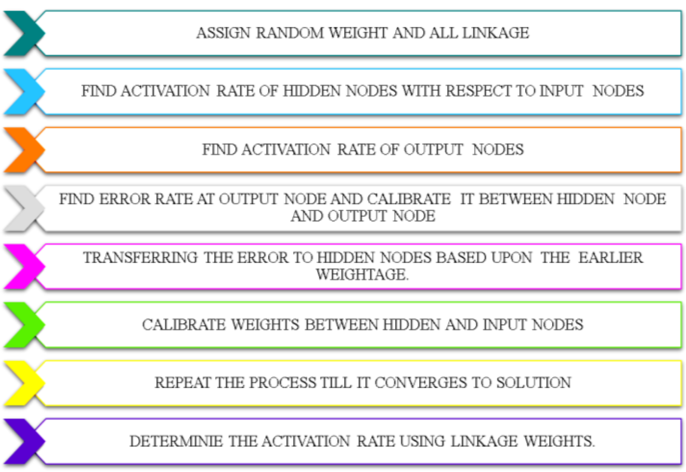


Figure 5. Algorithm for Artificial Neural Networking

For repeated validation, these activations were then directed back as input and cross check. This iterative process is referred to as *Training*. In the training segment, the exact class for each record was known by the supervised training & the output nodes, therefore, gave correct value i.e. "1" for the node corresponding to that particular class and "0" for the others. Table 2 represents the structure of raw data encoded.

Error term was calculated from the correct output term. In order to adjust the weights in the hidden layers, error terms came into action so that all being well, the next time around the output values was closer to the correct values.

A confusion matrix was plotted which compare the input data set points. All the activation functions and their rates were tested and compared against different classifiers to acquire higher accuracy.

After labeling the data as inputs & output by one hot encoding method, furthermore, these labeled signals were cruised to the classification steps as discussed earlier. These were then fed to the classifiers. The offline training accuracy obtained from ANN was presented in Matlab® and generated confusion matrix. The ANN was 91.9% accurate for the data of 10 healthy subjects.

E. Control Command Generation

The control commands were generated as soon as the signals were classified depicting the position of the arm. The controller, after classifying the signals, generated control commands to actuate the motors so that the elbow and wrist joint motion provides the desired position.

According to the human anatomy, when the biceps are activated, the brain is been told to move the elbow upward & when the triceps comes in action, it indicates that the arm is moving downwards from the elbow joint. Same as the human anatomy, the controller classified the signals by separating these two classes i.e. if the arm is moving upwards or downwards. It then commands the motors to move in a clockwise direction or anti-clockwise direction. The pronation & supination command generation was carried out in the same way, but it was observed that the signals for this motion changed as the elbow joint was displaced more than 30 degrees.

Table 2. Raw Data Encoding/Masking

Class Label	Encodings
Class A (Extension)	0 0 0 0 1
Class B (Flexion)	0 0 0 1 0
Class C (Pronation)	0 0 1 0 0
Class D (Supination)	0 1 0 0 0
Class E (Rest)	1 0 0 0 0

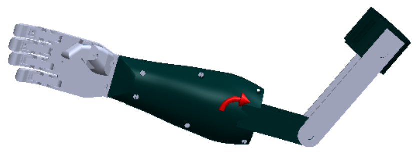
For such control commands to be generated, the offline training was done so that in real time the classifier will know what motion is to be performed.

III. Modeling and Simulation

In order to verify reference positions generated through EMG data analysis, simulation was performed on a solid model using kinematics model of the trans-humeral arm. For the purpose, the SolidWorks model along with PeterCorke Toolbox® comes in action providing the reference position by using the information of forward kinematics.

A. Solid Model

A SolidWorks model was developed in SolidWorks® for the system. Simulation of different motion types of the elbow and wrist are shown in Figure 6. This SolidWorks model window was used for the visual verification of the reference positions generated as given earlier in Section II-D. The SolidWorks model receives the generated reference values from a workspace that is imported from the kinematics model developed in Matlab, and both the virtual windows were linked together.



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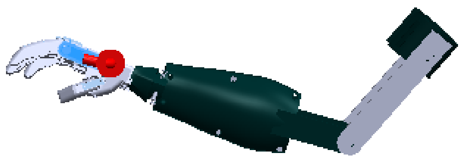

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Figure 6. a) Elbow Flexion b) Elbow and Wrist at rest c) Wrist Pronation in SolidWorks®. A virtual representation of the device for how it is actuated physically. Matlab® providing the coordinates at a certain angle with reference to forward kinematics already linked with Solidworks® motion to study the error

B. Kinematics Model

Forward kinematics helps in determining the position of the end effector by using different values of angles [13]. The desired position would not be just suggested by electromyographic signals but also through kinematics equations. In this research, one Degree of Freedom (DOF) each for elbow and wrist joint has been considered. The objective of the forward kinematic analysis is to determine the cumulative effect of the entire set of joint variables. A commonly used convention for selecting frames of reference in robotic applications is the Denavit- Hartenberg, or D-H convention [14]. The DH parameters for the proposed prosthetic elbow and wrist are given in Table 2. The kinematics model developed in MATLAB® was used to verify five reference positions, given in table 3.

These reference positions were generated for rest and four types of motions. The generated results in PeterCork are shown in Figure 7 for two selective positions. The Solid Works® design was imported in Matlab® for processing through SimMechanics which was used to produce a mechanical model. It contains all the physical aspects such as weight, gravity etc. so that the real environment parameters are virtually tested/validated.

Table 3: DH Parameters

Link Length a_i(mm)	Link Twist α_i (deg)	Joint Distance d_i(mm)	Joint Angle θ_i(deg)
0	90^0	d_1	θ_1
0	90^0	d_2	θ_2
0	-90^0	0	θ_3

Table 4: Reference positions of the prosthetic elbow and wrist for different motion types

Arm Part	Motion Type	Angular Position
Elbow	Extension	-80^o
	Flexion	80^o
	Rest	0^o
Wrist	Pronation	-85^o
	Supination	85^o

The transformation matrix represents the general mathematical form of special linkages within a robot [15]. The general transformation equation is written as (1).

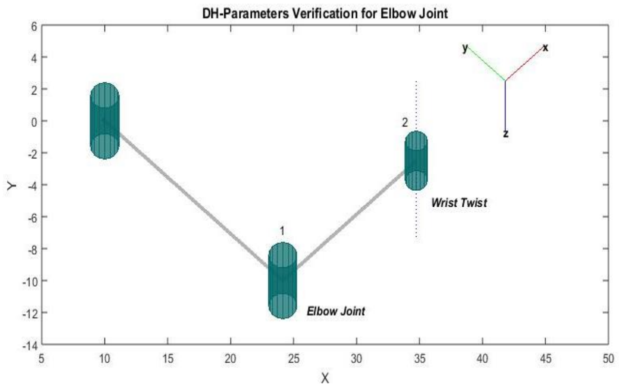
$$ {}^0_iT = \begin{bmatrix} c\theta_i & -s\theta_i c\alpha_i & s\theta_i s\alpha_i & a_i c\theta_i \\ s\theta_i & c\theta_i c\alpha_i & -c\theta_i s\alpha_i & a_i s\theta_i \\ 0 & s\alpha_i & c\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1) $$

According to the DH-table, the link transformation matrices of proposed two DOF prosthetic arm (elbow and wrist) is given in (2).

$$ {}^0_2T = \begin{bmatrix} c_2 c_1 & s_1 & s_1 c_1 & s_1 d_2 \\ s_1 c_2 & -c_1 & s_1 s_1 & -c_1 d_2 \\ s_2 & 0 & -c_1 & d_1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2) $$

C. Simulation Results

The kinematics model was simulated for all five reference positions i.e. Extension (-80°), Flexion (80°),Rest (0°),Pronation(-85°) and Supination(85°). Sample results for extension and supination are shown in Figure 7 for reference. The results show that extension is terminated at -80° (Figure 7a) while supination is terminated at 85° (Figure 7b).



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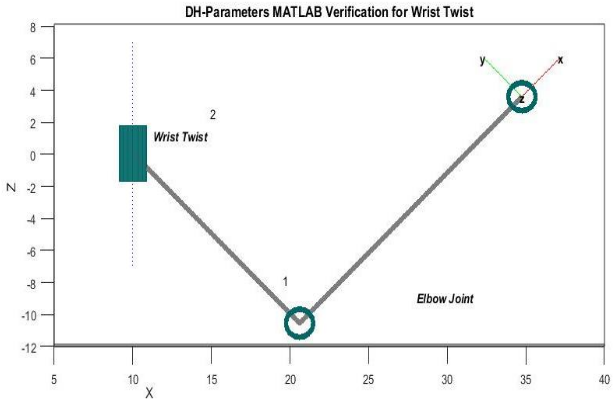

(b)

Fig. 7. a)Elbow Joint at 80° representing Flexion b) Wrist Joint at 85 ° representing Pronation in PeterCorke Robotics Toolbox Matlab®

IV. CONCLUSIONS

The electromyographic signals were acquired (extracted & recorded) for elbow joint extension and flexion movement along with the wrist twist i.e. supination and pronation. After analyzing the obtained data, feature selection played an important role in data classification. Different features and their combinations helped to classify the raw signals. Artificial neural network (ANN) was used for offline training. A CAD model of two DOF prosthetic arm was developed in Solid works® and its Kinematic Model was built in Matlab®. Afterward, both were linked to check the output of the system virtually rather than developing a real-life model. It verified that the arm joints move and reach the desired position as soon as the control signals from classified EMG data were attained. Unlike forearm, upper arm has minor muscle activity & motions for the elbow joint and forearm twist can't be predicted very easily. Therefore, signal processing is a big challenge for above elbow amputation but more experimentation & better feature and classifier selection may help in resolving such problem.

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