CPSC 530P 201 – PROJECT

A very first approach of virtual reality for people without forearms using Myo Armband and Leap Motion.

ABSTRACT

The report at hand describes a model that might bring closer virtual reality to people without forearms. The model is identified using two devices, one of them it is the Myo armband to measure the superficial Electromyography (sEMG) of the upper arm of the subject, these signals are used as an input of the model. The second device is the Leap Motion that generates the output of the model, which is used to capture the different position (Pitch, Roll, and Yaw) of the forearm and hand in the three-dimensional space to close the loop of the model. After generating a Look-up-table (LUT) of the input and output signals, a general model is identified using Recursive Least Squares (RLS) to generate a parametric identification of the system. The found model has been tested, and shown that it could be feasible to replace the Leap Motion device by using only the Myo armband, using merely sEMG signals, which gives a hope to people without forearms who want to connect with human machine interfaces for playing games, and undergo virtual reality therapy for prosthesis design, among other applications.

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Contents

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1 Abstract

The report at hand describes a model that might bring closer virtual reality to people without forearms. The model is identified using two devices, one of them it is the Myo armband to measure the superficial Electromyography (sEMG) of the upper arm of the subject, these signals are used as an input of the model. The second device is the Leap Motion that generates the output of the model, which is used to capture the different position (Pitch, Roll, and Yaw) of the forearm and hand in the three-dimensional space to close the loop of the model. After generating a Look-up-table (LUT) of the input and output signals, a general model is identified using Recursive Least Squares (RLS) to generate a parametric identification of the system. The found model has been tested, and shown that it could be feasible to replace the Leap Motion device by using only the Myo armband, using merely sEMG signals, which gives a hope to people without forearms who want to connect with human machine interfaces for playing games, and undergo virtual reality therapy for prosthesis design, among other applications.

2 Introduction

Nowadays, Superficial Electromyography (sEMG) is used widely for many clinical and biomedical applications, especially for developing human machine interfaces to send orders to devices connected to the human body. These devices are mainly developed for assistance, and rehabilitation, e.g. robots, and prosthesis. In addition, technologies as virtual reality have played a very important role for the development of such tools, not only using sEMG but computer vision devices that using the computational power that today computers have can extract different features of the human body to create human machine interfaces aiming to reach the same goal as the sEMG applications. One example, it is the Myo armband, and Leap motion, which use sEMG signal, and Computer Vision respectively to bring people close to virtual reality and better human machine interfaces. However, these devices are meant to be used mainly for people who do not have any disabilities, which creates a firewall between these devices and people without forearms who due a tragical or birth circumstances have no limbs, therefore cannot use these kinds of devices to connect with virtual reality.

Leap Motion has proven to be a powerful tool for video game interfaces for people with forearms, although, “what about those without forearms who want to play video games and connect with virtual reality?”. Moreover, Myo armband has been designed to be used on the forearm of the individual, which generates the same dilemma as the Leap motion device “but what about people without forearms? How can they approach virtual reality using these tools?”. One way to bring these kinds of people close to virtual reality would be to develop from scratch a new device capable of connecting armless (without forearm) people with video games, and this can be done by measuring the muscle potential using sEMG sensors. On the other hand, it is possible to reuse or improve what it is already developed, for instance, the Myo armband, even though, it has not been designed for the upper arm, it is possible to reuse it to acquire the upper arm sEMG signals to build model that makes accessible virtual reality to armless people (without forearm). Notwithstanding, converting EMG to motion signals it is not an easy task.

Firstly, and after measuring the sEMG signals, it is necessary to infer the motion of the forearm from EMG signals, which are well known to be disturbed by lot of noise, that makes harder the recognition of movement, furthermore, and in order to generate a model, it is important to have an output signal, which in this case it is the motion of the forearm. Hence, it is vital to close the loop using sensors to measure the forearm movement, and this can be done initially by using the Leap motion and a person with forearm, to then, port the same model and test it on a person without forearm. Notwithstanding, the scope of this project has been only planned to generate a motion model of the forearm using the sEMG upper arm signals of the Myo armband, and the rotations (Pitch, Roll, and Yaw) of the forearm generated by the Leap Motion. The next stage would be to test the model on a person without forearm to refine the generated model.

3 Methodology

The main goal of this project is to generate model capable of converting sEMG signals into Pitch, Roll, and Yaw signals to replace the Leap motion dependence for people without forearms. As the time is short, the main objective is to identify a model using initially a person with forearm. The Myo Armband and the Leap Motion are used to measure sEMG of the upper arm, and Position of the forearm respectively to create the desired model. In a next stage and not part of this project, it is to test the proposed model on an individual without forearm.

Before reaching the main goal of the project, it is important to study the anatomy of the body to have a better insight about the human body limitation regarding the position of the sEMG sensor on the upper arm. In addition, it is necessary to study how to use the Leap Motion, and the Myo arm band to generate a LUT to build the desired model input/output. For that, Nodejs is chosen as a scripting software interface to access both devices in order to store the sEMG signal of the upper arm, and the positions of the forearm into a file(LUT) concurrently. Using the Nodejs, and its modules **myo**, and **leapjs**, it is possible to create a web application to visualize the 3D forearm and hand model, acquire the signals coming from the sEMG sensor of the Myo armband, and the Pitch, Roll, and Yaw given by the Leap Motion. Once the web interface is created, each sEMG is analyzed by observation and according to the Human anatomy to relate each signal with the Leap Motion signals, for that the LUT file is read using MATLAB to plot and observe the data.

Once the LUT file is generated using Nodejs, and sEMG signal has been assigned to a Leap Motion signal, the model can be identified by Recursive least squares (RLS). This kind of identification is used to build an ARMAX equation of the proposed model (sEMG- Motion). Furthermore, this algorithm is well known to converge rapidly, and filter undesirable noise, and it is used widely to model dynamic systems using recorded input/output data, which in this case are sEMG signals(input) of the upper arm, and positions of the forearm(output), making this algorithm suitable for this kind of system. Moreover, RLS uses low computational power which makes the model applicable to real time system in which low consumption embedded system can be used, in the future to create new human machine interfaces. It is important to highlight that by replacing the Leap Motion device by the Myo armband not only brings closer people with disabilities to the virtual reality but reduces the computational power that implies to use the Leap Motion that although, powerful, takes a lot of computational performance of the computer on which it is used.

3.1 Leap Motion.

As it was already mentioned, the Leap Motion device uses Computer Vision to extract features of the hand movement, and forearm positions. This device can be exploited to extract the different positions of the hand, and the forearm(outputs) in order to model the desired system. The Leap motion device is presented in the Figure 1, and Figure 2, as it can be seen, the leap motion extracts from the position of the hand the Roll which corresponds to Pronation and Supination (rotation) movements of the hand and forearm in the Z axis (Figure 3), the Extension and Flexion movements of the hand and forearm correspond to the Pitch also called tilt or X axis(Figure 4), and finally, the medal rotation, the lateral rotation, the flexion and extension of the forearm is related with the Yaw/direction or Y(Figure 5) axis of the Leap motion.

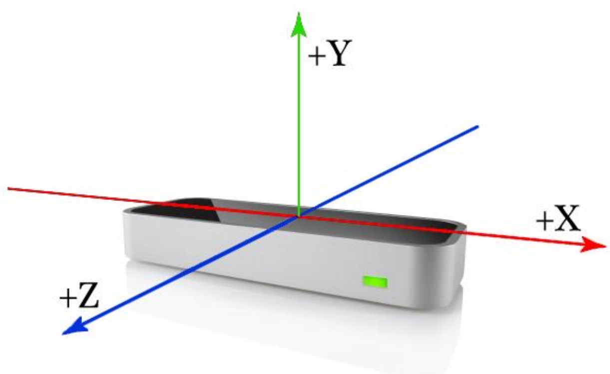

Figure 1 - Physical View and configuration of the Leap Motion Device in the space

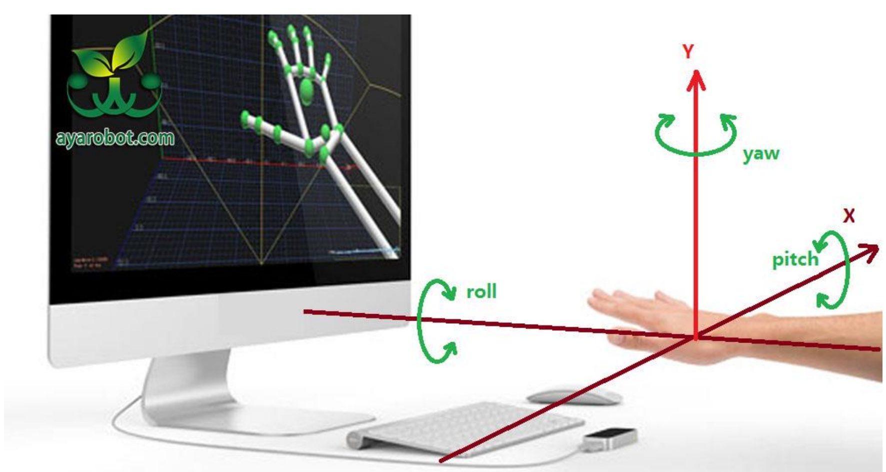

Figure 2 - Pitch, Roll and Yaw using Leap Motion

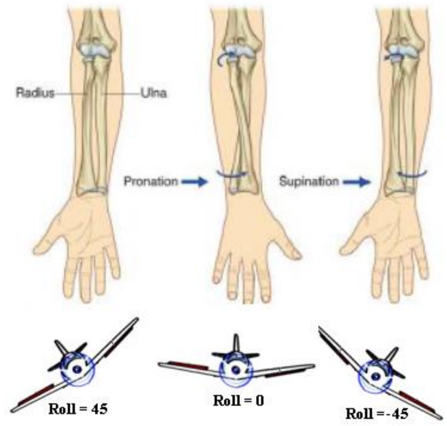

Figure 3 - Leap Motion, Roll Regarding Anatomy.

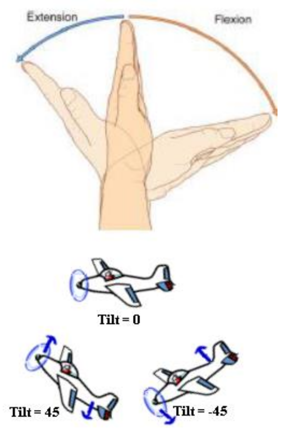

Figure 4 Leap Motion, Pitch Regarding Anatomy.

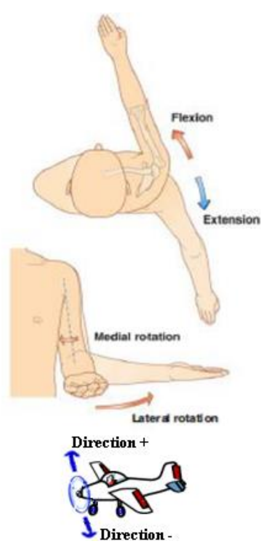

Figure 5 - Leap Motion, Yaw regarding Anatomy.

As it was highlighted before, this device requires a lot of computational power, and it is recommended to have it connected to a USB connector of at least 1 Ampere to keep it working properly, and as it is going to be shown in the Experimental setup section, this was connected to an external hub to guarantee that the device was properly supplied.

3.2 Myo Armband

As it was discussed previously the Myo armband was designed to be positioned on the surface of the forearm. However, for this project, and taking as advantage the geometry of the Myo armband, the devices is repositioned on the upper arm at 5 cm of the albow. The Myo is capable of measuring 8 channels of sEMG that are streamed through low power consumption Bluetooth to a computer or any other device, such a cellphone device.

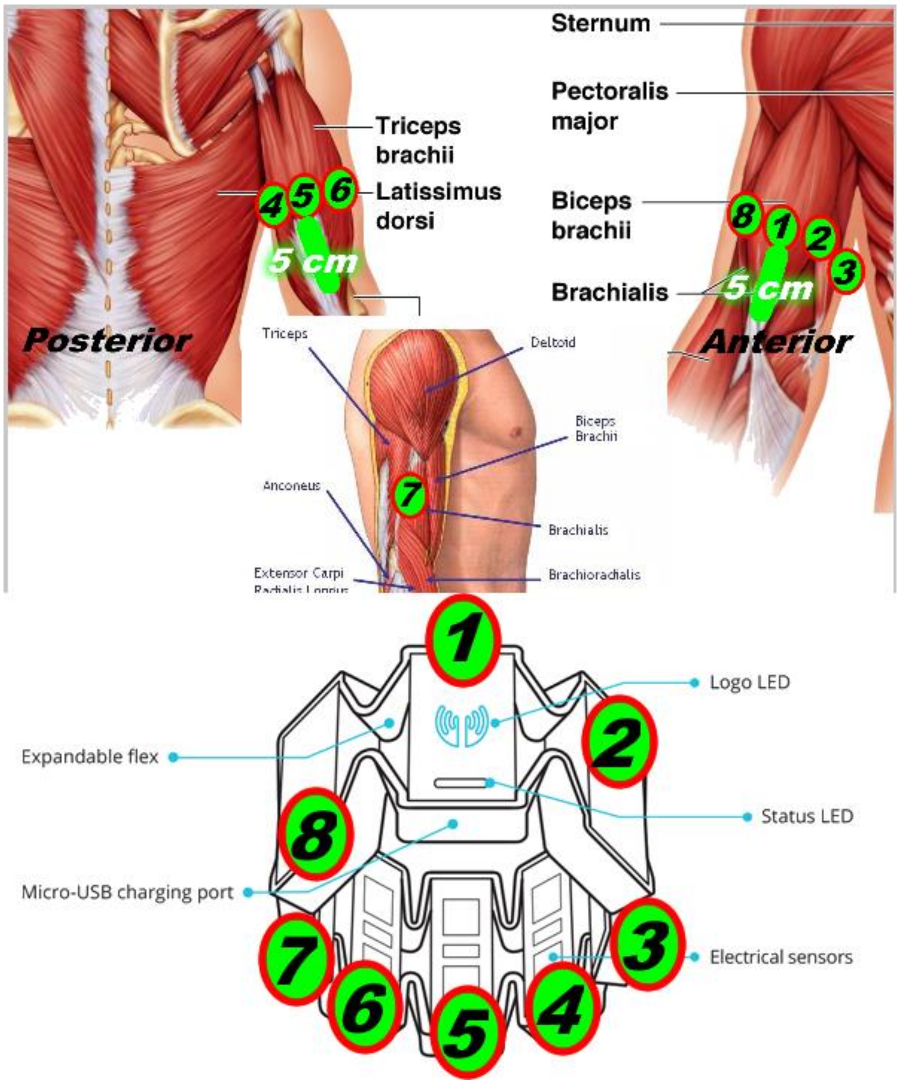

Figure 6 - Positioning the Myo Armband on the Upper Arm.

The Figure 6 shows in detail the connection of the Myo armband to the upper arm band, in which each sEMG channel is connected to a different muscle in the following way.

1. **sEMG 1**: This sensor measures the potential of the Biceps muscle.

2. **sEMG 2:** This sensor measures the potential between the Biceps and the Brachialis muscles of the proximal part of the arm.
3. **sEMG 3:** This sensor measures the potential of the brachialis muscle of the proximal part of the arm.
4. **sEMG 4:** This sensor measures the potential between of the brachialis and triceps muscles of the proximal part of the arm
5. **sEMG 5:** this sensor measures the potential of the triceps muscle.
6. **sEMG 6:** this sensor measures the potential between the brachialis and triceps muscles of the distal part of the arm.
7. **sEMG 7:** this sensor measures the potential of the brachialis muscle of the distal part of the arm.
8. **sEMG 8**: this Sensor measures the potential between the biceps and the brachialis muscles of the distal part of the am.

This device can run for hours (long lasting battery ~ Approx. 8 hours), and it is portable, which in comparison with the Leap Motion, makes it suitable for use as a human machine interface for prosthesis, and in this case for long videogames sessions.

3.3 Experimental Setup.

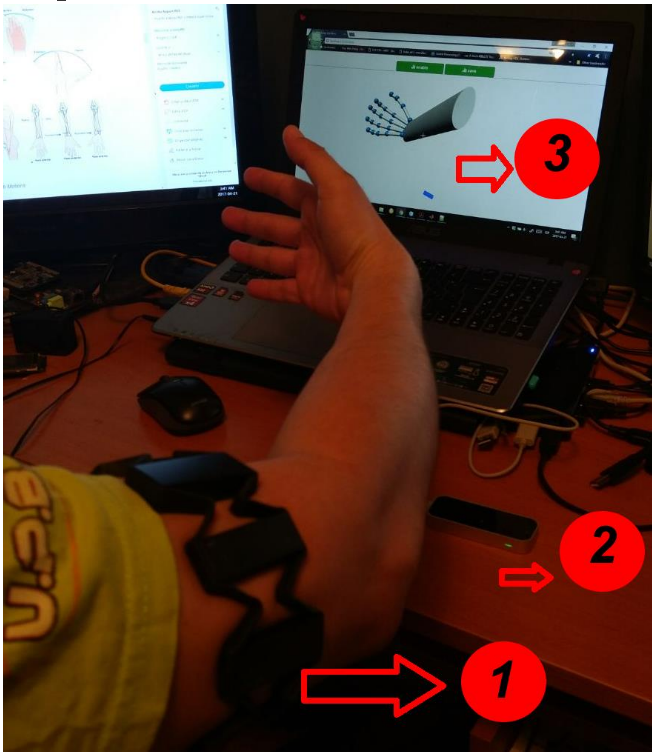

Figure 7 Experimental Setting.

As it is shown the Figure 7, there are 3 main parts for the experimental setup, the first one (1) it is the positioned Myo armband on the upper arm, the second one (2) is the Leap Motion, and the third one (3) is the web application based on Nodejs Scripting. This experimental setup is used to generate the LUT to posteriorly process the input/output data using RLS algorithm using

MATLAB to generate the model, to them plug the model back into the Nodejs interface to remove the leap motion from the experimental setup, leaving only the Nodejs interface and the Myo armband.

As it can be observed in the Figure 7, the leap motion is connected to an external USB hub which supplies the Leap motion with the proper amount of current to avoid wrong functionalities of this device. The Nodejs interface (Figure 8), as already mentioned, uses two important modules which are the **myo**, and **leapjs** modules, which allows the Nodejs to have access to the hardware layer to communicate with the Myo armband, and Leap Motion respectively.

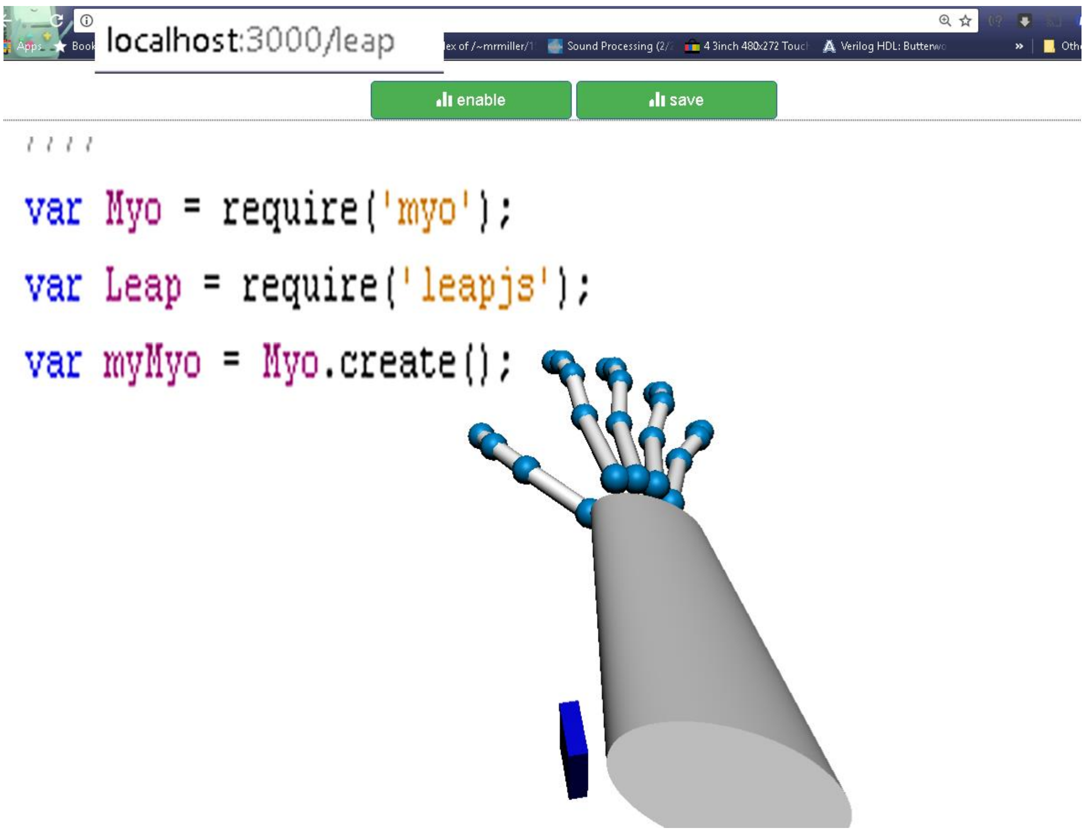

Figure 8 - Nodejs web application to get the Myo arm band sEMG and Leap Motion Pitch, Roll, and Yaw.

As default, every time that the user wears the Myo, and positions the forearm on the leap motion the Nodejs acquires the 8 sEMG signals, and the Roll, Pitch and Yaw, then by pressing the button “save” at the front-end, the data is stored in four different files at the back–end (emg_data, pitch_data, roll_data, and yaw_data), which are read by MATLAB to be modeled using the RLS algorithm. In addition, the Nodejs interface has an extra button which is called “enable”, this allows the user to get rid of the Leap Motion to use the found model by MATLAB, although, this must be done manually, that is the use of the enable button at the front-end. The front-end always shows the user the forearm position in a three-dimensional space using a 3D visualization, and this arm can be driven either by the Myo or the Leap Motion, depending on the mode it is configured.

The MATLAB code, and the Nodejs code are attached to this report and can be analyzed in detail.

3.4 RLS Algorithm

Based on the paper “parametric identification of handwriting system based on RLS algorithm” by Inés CHIHI, in which it is implemented RLS to identify handwriting using sEMG signals. It was decided to use this algorithm for its practicability, and as it was already mentioned because it can be used on low power consumption embedded system using low computational power. Furthermore, by having a differential equation it is easier to model any king of controller in the future, and to study in depth the model.

The RLS algorithm finds an ARMAX model of the system which has the following structure (Equation 1):

$$A(q^{-1})y(t) = B(q^{-1})u(t) + C(q^{-1})e(t)$$

Equation 1 - ARMAX model.

Where the coefficients A, B, and C are found by using the following structure (Kalman Filter).

$$\underbrace{\hat{\theta}(t+1)}_{\text{new}} = \underbrace{\hat{\theta}(t)}_{\text{old}} + K(t+1)\underbrace{\left[y(t+1) - x^T(t+1)\hat{\theta}(t)\right]}_{\text{correction}}$$

Equation 2 - RLS Algorithm.

$$\begin{aligned} \theta &= [a_1, \ldots, a_n, b_1, \ldots, b_n, c_1, \ldots, c_n]^T \\ x^T(t) &= [-y(t-1), \ldots, -y(t-n), u(t-1), \\ &\quad \ldots, u(t-n), e(t-1), \ldots, e(t-n)]^T \end{aligned}$$

Equation 3 - Theta, and Previous Samples of the input and output.

Where θ is the concatenation of the coefficients A, B, and C, and it has a vector form, where K is the Kalman gain which has a matrix form, and the correction factor which is composed by previous samples of the input and output with the old values of the coefficients and it has a vector form.

The implemented RLS algorithm has the following form:

$$
\begin{aligned}
\hat{\theta}(t+1) &= \hat{\theta}(t)+K(t+1)[y(t+1)-x^T(t+1)\hat{\theta}(t)] \\
K(t+1) &= \frac{P(t)x(t+1)}{1+x^T(t+1)P(t)x(t+1)} \\
P(t+1) &= P(t)-\frac{P(t)x(t+1)x^T(t+1)P(t)}{1+x^T(t+1)P(t)x(t+1)}
\end{aligned}
$$

Equation 4 - RLS algorithm

Where P is the covariance matrix, and x is the concatenation of past samples input and output, of the system, where u is input, and y is output, as it can be observed in the Equation 3.

```
function [thetaest,P]=rls(y,x,thetaest,P)
% RLS
% y,x: current measurement and regressor
% thetaest, P: parameter estimates and covariance matrix
K= P*x/(1+x'*P*x); % Gain
P= P- (P*x*x'*P)/(1+x'*P*x); % Covariance matrix update
thetaest= thetaest +K*(y-x'*thetaest); %Estimate update
end
```

Equation 5 - MATLAB Algorithm for RLS.

3.5 Model Identification and verification.

For the model identification (Figure 9**Error! Reference source not found.**), it was determined by observation, and by the anatomy, that the Roll rotation (Pronation and supination of the forearm, and hand) in the Z axis of the Leap motion is related with the sEMG - 4 signal of the Myo Armband (Figure 11). The Pitch rotation (Hand extension and Flexion) in the X of the Leap motion is related with the sEMG – 1 of the Myo Armband (Figure 13). The Yaw rotation (Medial rotation, flexion and extension forearm) is related with the sEMG – 5 of the Myo Armband (Figure 15). Thus, three different models compose the model, one for each rotation, Roll, Pitch and Yaw, based on three different sEMG signals. Furthermore, for each model it was used different sections of the LUT files, 70% of the data was used to identify each model, and the other 30% was used to verify it. In all cases, the sampling rate was assumed as 200 Hz, according to the specification manual of Myo device.

For the case of the sEMG-4 to Roll model, it was required to used 50 coefficients for A, and 50 coefficients for, and this was chosen by observing the similarity of each estimated signal with regard the original signal in the verification process, and the results are shown in the Figure 12. It is important to highlight that the more coefficients, the more delay of the signal is obtained, which for this case at rate of 200 Hz it is approximately 0.5 seconds of delay to obtain the first result.

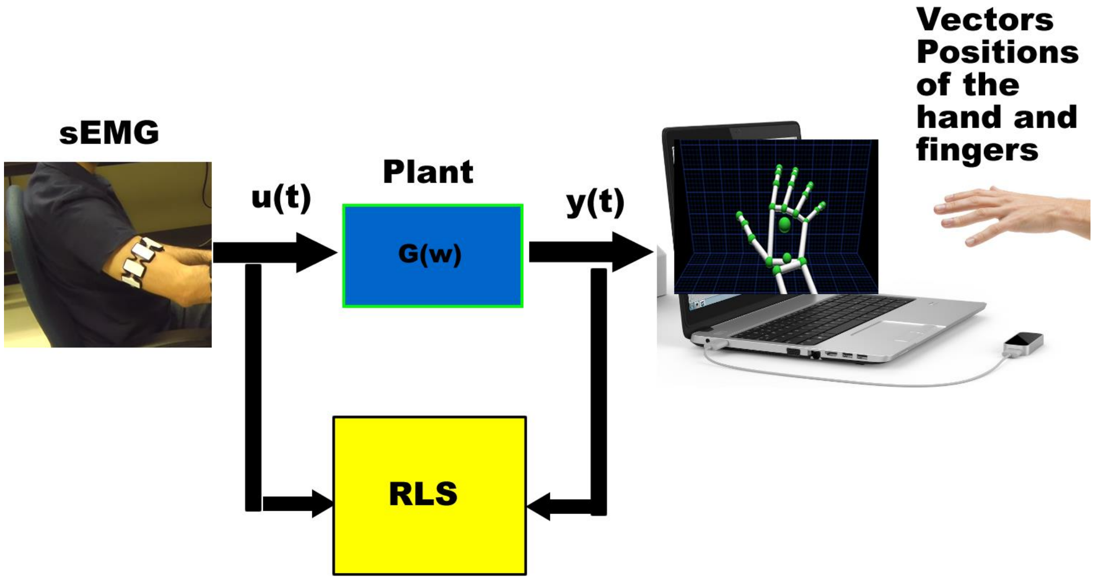

Figure 9 - Model Identification.

For the estimation of the second model, using the sEMG-1-Roll, which determines the hand flexion, and extension, it was hard to use less than 80 coefficients for A, and B, because the signal seems to be more perturbed by noise and, also because the generated potential at the upper arm is not that high, and the results are shown in the Figure 14. Finally, for the third model, sEMG-5-Yaw, or the forearm extension and flexion, only 50 coefficients for A and B were used because the sEMG signal potential was strongly clear an evident for this kind of motion, due to the relation of movement between the forearm with regard the upper arm muscles, and the results are shown in the Figure 16.

3.6 Structure of the model.

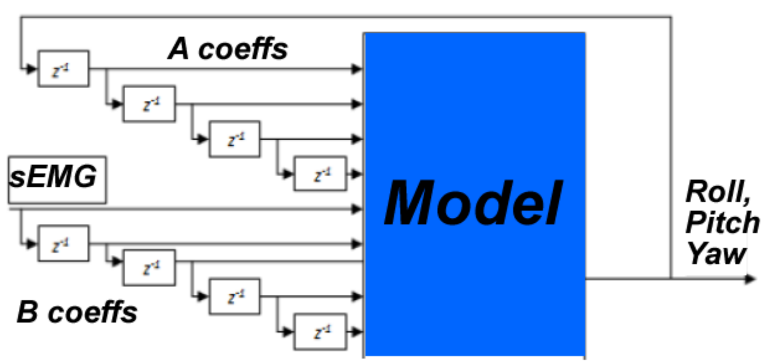

Figure 10 - Model architecture after finding the coefficients.

As it can be observed in the Figure 10, the architecture of the model after identifying the coefficients A, and B, of the system. For this case, there are three models, therefore, there are three set of A's, and B coefficients, hence, three models, one for estimating the Roll, the other one to estimate Pitch, and finally Yaw, as it was mentioned in the section "Model Identification and verification.

4 Results

4.1 EMG channel 4 to Leap Motion Roll

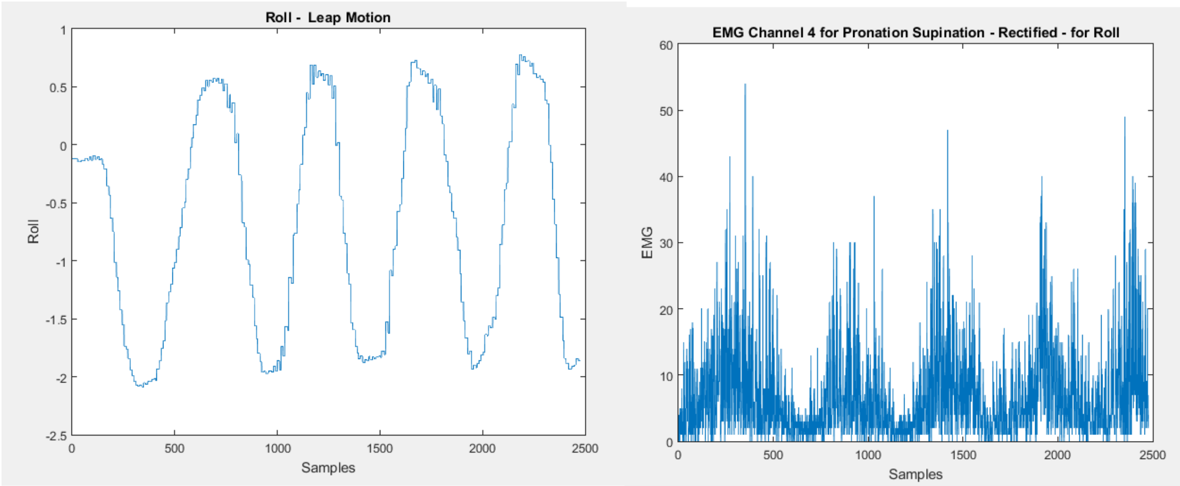

Figure 11 - Roll and EMG 4

4.2 Leap Motion Roll Estimation

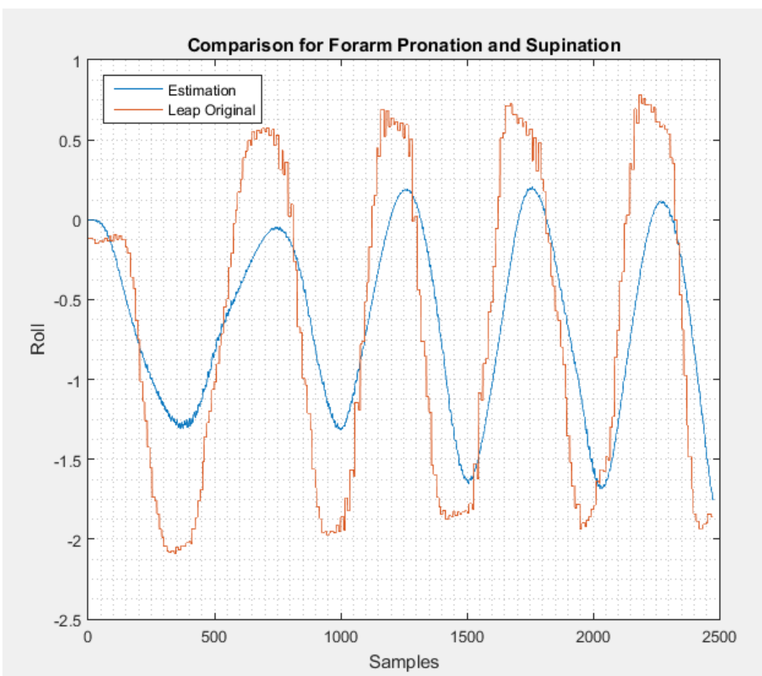

Figure 12 - Roll Estimation, Comparison.

4.3 EMG channel 1 to Leap Motion Pitch

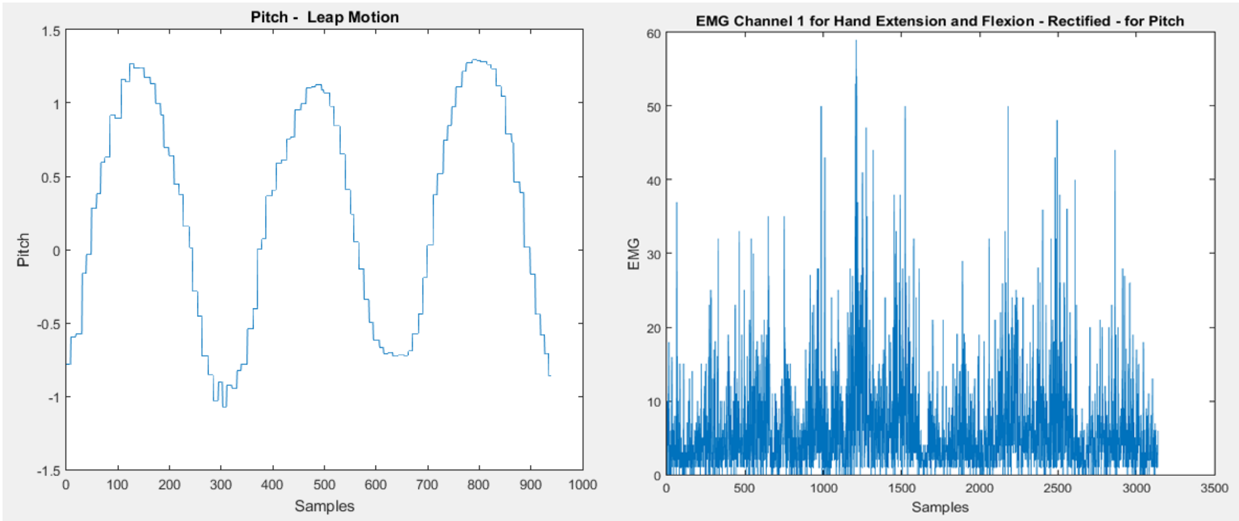

Figure 13 - Pitch and EMG 1

4.4 Leap Motion Pitch Estimation

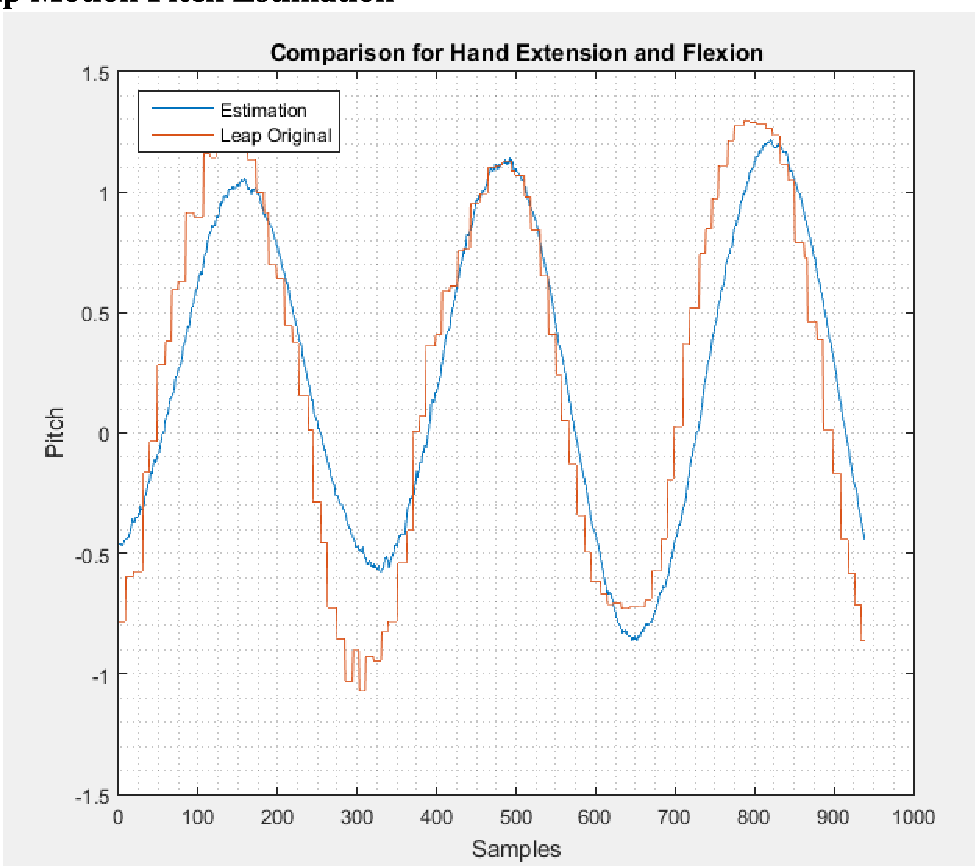

Figure 14 - Pitch Estimation, Comparison.

4.5 EMG channel 5 to Leap Motion Yaw

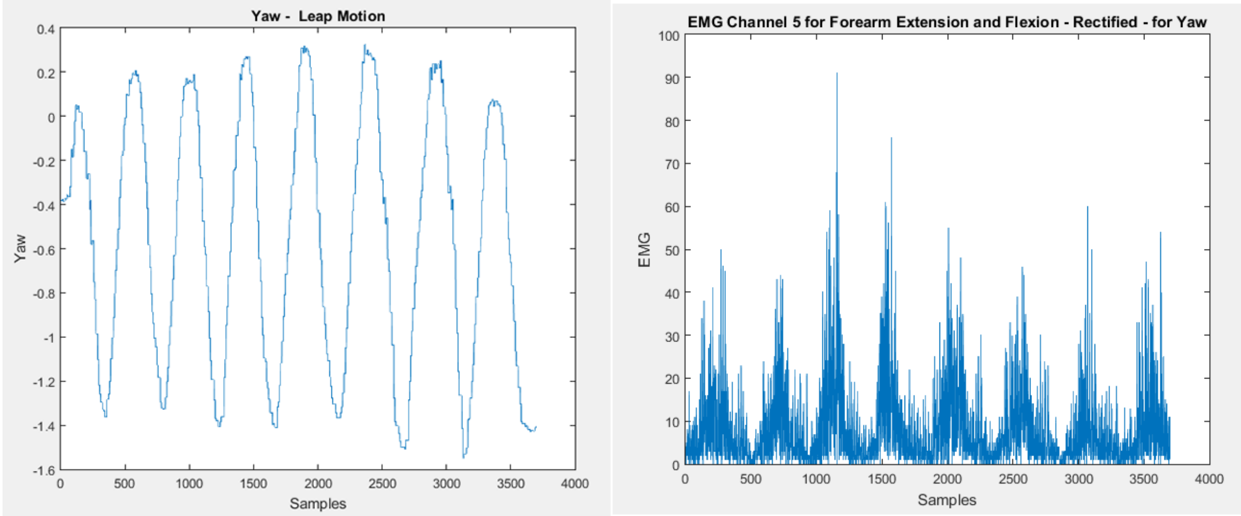

Figure 15 - Yaw and EMG 5

4.6 Leap Motion Yaw Estimation

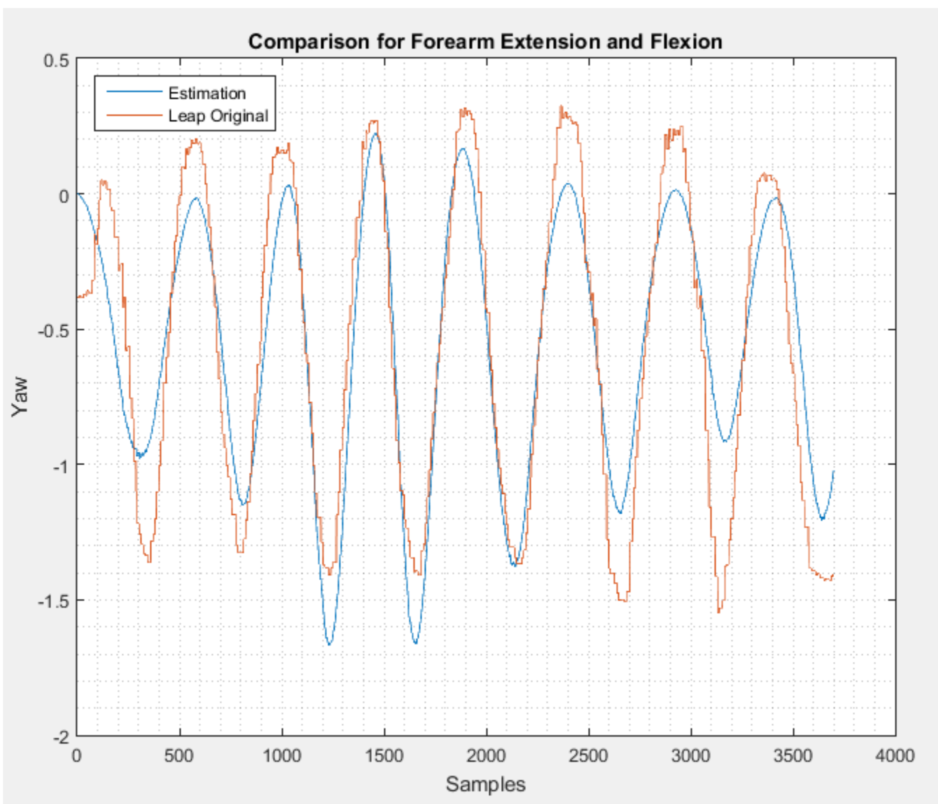

Figure 16 - Yaw Estimation, Comparison

5 Conclusion

By using RLS it was possible to find three different models to estimate from sEMG signals of the upper arm, the three different rotations of the forearm and hand. These models might be used to replace the leap motion by just using the Myo arm band, and it could be used as a new human machine interface for video games. However, it is needed to test this models on people without forearms, to verify its functionality, and complete the objective of this project. Although initially, the purpose of this project was to find a model for the finger motions using the upper arm sEMG signals, along with the already found models. There was not found any evident and strong relation between the upper arm sEMG signals and the finger motions. On the other hand, it was indeed found that the flexion and extension of the hand was detected on the upper arm, but as seen in the identification model section (Figure 13), the identification needed more than 100 coefficients for A, and B, which forces the RLS algorithm more to find a relation between any hand movement with regard to the muscle activity of the upper arm, generating in this way more delay at the output estimation. In addition, there are to many artifacts that affects indisputably the fingers detections, due to the forearm movement. Notwithstanding, this new approach, by identifying these three new models, brings closer, theoretically, the people without forearms to the virtual reality environment and it was proven that devices such as the Myo armband have the potential of replacing the Leap Motion. Lastly, there are other methods that wanted to be implemented such as a recurrent neural network using tensorflow to compare the obtained results with the RLS algorithms, nonetheless, more time was needed to implement them.

6 Reference

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