Analysis of Surface Electromyography Signals of the Arm in Adults

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Abstract

In human history, medicine has always sought to improve the quality of life of patients with disabilities by designing what is now known as either an assistive device or prosthesis. For a person who has an amputated arm, rehabilitation engineers have taken the approach of a myoelectric-controlled prosthesis. The use the surface electromyography (sEMG) technique, to measure the muscle response or electrical activity in response to nerves, is necessary to gather data for this approach. Over the years, it has been proven that older patients exhibit a lot of muscle fatigue and, due to this, their sEMG signals will be less stable and show greater burst. The signals from the muscles of these patients behave as a dynamic system when activities are performed. Nowadays, rehabilitation engineers select motors that are over designed so they can work with a big range number of signals, but this might lead in future problems such as excessive weight in lower and upper limbs. The main objective of this research is to learn if a correlation between the deteriorating EMG signal and the age can be found. To find this correlation, data analysis of arm aputated adults with similar characteristics was done using Minitab. Boxplots, probability plots, Kruskal-Wallis test, and Mood's median test were used to analyze the sets of data. The significance level for these test (denoted as α or alpha) is 0.05. This indicates a 5% risk of concluding that a difference exists when there is no actual difference. In both tests, Kruskal-Wallis test and Mood's median test, the P-value is less than alpha, meaning that the null hypothesis is rejected and is concluded that not all the group medians are equal. Because of these results, the correlation to determine how much is deterioration couldn't be calculated. This means that to avoid selecting motors that are over designed another approach must be taken.

Introduction

A person who has an amputated arm gets a severe reduction in their quality of life and can no longer do some of the normal activities of daily living (ADL). To solve these types of problems, rehabilitation engineers use engineering principles to develop technological solutions and devices to assist individuals with disabilities and aid the recovery of physical and cognitive functions lost. For amputated patients, assistive device or prosthesis are design to give them a better quality of life. An assistive device is an external device that is designed to assist a person in performing a particular task. Many patients that have disabilities depend on assistive devices for daily activities and tasks.

Since the 1940s the idea of a myoelectric approach control was proposed for prosthesis, but it was not until the 1960s that this idea was able to be develop. (Li, 2011) Myoelectric is the term used to refer to the electric properties of muscles. A myoelectric-controlled prosthesis offers the ultimate combination of function and natural appearance by using the electrical signals given by the muscle. A myoelectric approach is a great option for this advances prosthesis this why, nowadays, some companies have been focusing in the creation of myoelectric-controlled prosthesis.

In order to provide a feasible solution, rehabilitation engineers shall evaluate the affected area of the patient. As part of the gathering data, rehabilitation engineers us the technique used to measure the muscle response or electrical activity in response to a nerve's stimulation of the muscle, called electromyography (EMG).

Recordings use for myoelectric prosthetics are normally done with surface electromyography (sEMG). Like any other signal, EMG signals recording can be contaminated with different kind of noises.

Over the years, it has been proven that older patients exhibit a lot of muscle fatigue and, due to this, their EMG signals will be less stable and show greater burst. Nowadays rehabilitation engineers select motors that are over designed to make sure range of signals are within acceptable parameters can work with big range of number of signals, but this might lead in future problems such as excessive weight in lower and upper limbs.

Another approach that can be taken to work this issue is creating a mathematical model to optimize the electrical signals recorded and get the best output signal possible.

Objectives

1. Learn if there is a correlation between the deteriorating EMG signal and the age of the patient.
2. Conclude if mathematical models dedicated to analyze stable EMG signals can recognize in a fractional period the demand needed.

Methodology

As part of the data analysis methodology, the raw data had to be filtered, rectified, smooth and normalize using MATLAB.

I. Data Filtering and Rectification

The Fast Fourier Transform (FFT) from MATLAB was used to filter the data and switch from the time domain to the frequency domain. After applying the FFT to the data, the rectification was performed by using the MATLAB absolute (abs) function.

II. Data Smoothing

By using a smoothing function in MATLAB (smoothdata), the data smoothing was performed. This function has a reliable algorithm to remove noise from a data set.

III. Data Normalization

Data normalization was performed by using a MATLAB function (normalize). This is done because is necessary to be able to find relations between the data.

IV. Data Analysis

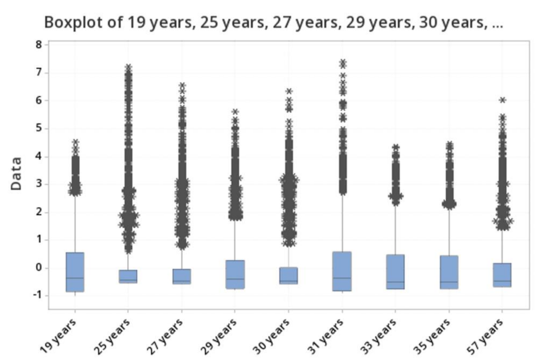
Data analysis was done using Minitab. Boxplots, probability plots, Kruskal-Wallis test, and Mood's median test were used to analyze the two sets of data.

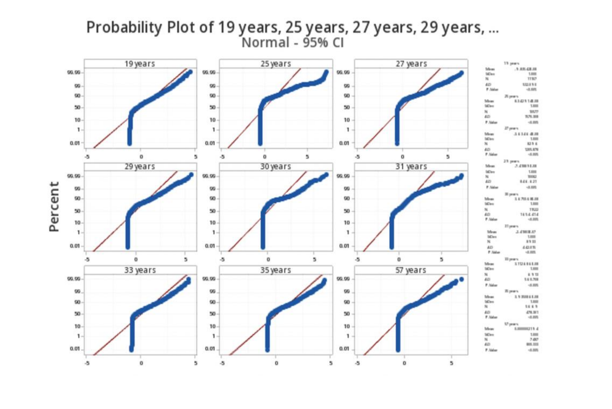
Example of Data Processing

```
clear, close all, clc
% Subject 1, 32 Years Old
load('S1_E1_A1.mat');
t1 = emg;
L1 = length(t1);
% Sampling Time
Ts1 = mean(diff(t1));
% Sampling Frequency
Fs1 = 2000;
% Nyquist Frequency
Fn1 = Fs1/2;
% Fourier Transform (Normalised) and rectification
FEMG1 = abs(fft(t1)*2/L1);
% Frequency Vector
Fv1 = linspace(0, 1, fix(L1/2)+1)*Fn1;
% Index Vector
Iv1 = 1:length(Fv1);
% Plot
figure(1)
plot(Fv1,(FEMG1(Iv1)))
title('S1 32 Years Old Patient FFT and Rectification');
xlabel('Frequency (Hz)');
ylabel('milliVolts');
grid
```

```
% Data Smoothing
smooth1 = smoothdata(FEMG1(Iv1));
figure(2)
plot(Fv1,smooth1)
title('S1 32 Years Old Patient Data Smoothing');
xlabel('Frequency (Hz)');
ylabel('milliVolts');
grid
% Data normalization
normal1 = normalize(smooth1);
figure(3)
plot(Fv1,normal1)
title('S1 32 Years Old Patient Data Normalization');
xlabel('Frequency (Hz)');
ylabel('milliVolts');
grid
```

Results





Kruskal-Wallis Test: Value versus Age

Descriptive Statistics

Age	N	Median	Mean Rank	Z-Value
19 years	11107	-0.346360	37210.3	-15.04
25 years	10577	-0.430970	45721.9	25.75
27 years	8296	-0.448835	43563.5	13.52
29 years	10082	-0.405645	38973.3	-6.09
30 years	11522	-0.457370	42900.3	12.99
31 years	8933	-0.366010	37215.7	-13.26
33 years	6913	-0.504100	37019.7	-12.24
35 years	5669	-0.493450	37736.1	-8.58
57 years	7487	-0.472830	39972.7	-1.25
Overall	80586		40293.5	

Test

Null hypothesis H_0: All medians are equal

Alternative hypothesis H_1: At least one median is different

Method	DF	H-Value	P-Value
Not adjusted for ties	8	1475.28	0.000
Adjusted for ties	8	1475.28	0.000

Mood's Median Test: Value versus Age

Descriptive Statistics

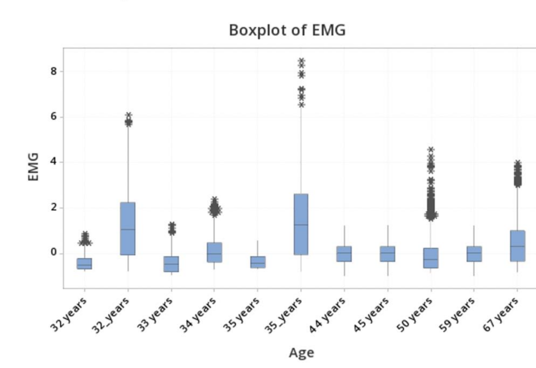
Age	Median	N <= Overall Median	N > Overall Median	Q3 – Q1	95% Median CI
19 years	-0.346360	5221	5886	1.40188	(-0.373615, -0.319264)
25 years	-0.430970	5204	5373	0.46025	(-0.437523, -0.423658)
27 years	-0.448835	4270	4026	0.52487	(-0.456720, -0.440317)
29 years	-0.405645	4899	5183	1.01528	(-0.426094, -0.382580)
30 years	-0.457370	5942	5580	0.57357	(-0.466601, -0.444684)
31 years	-0.366010	4285	4648	1.41187	(-0.409905, -0.328272)
33 years	-0.504100	3633	3280	1.23880	(-0.534110, -0.472484)
35 years	-0.493450	2962	2707	1.17325	(-0.528536, -0.461988)
57 years	-0.472830	3877	3610	0.83961	(-0.495937, -0.448139)
Overall	-0.436630				

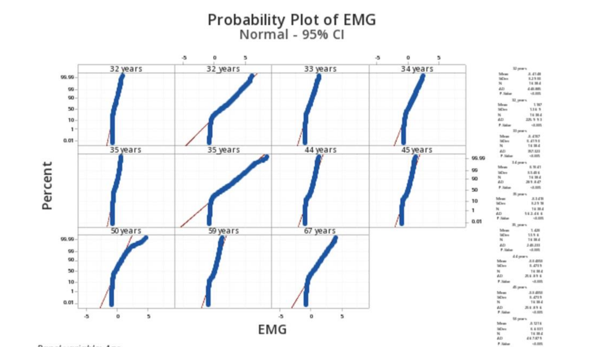
Test

Null hypothesis H_0: The population medians are all equal

Alternative hypothesis H_1: The population medians are not all equal

DF	Chi-Square	P-Value
8	122.83	0.000





Mood's Median Test: EMG versus Age

Descriptive Statistics

Age	Median	N <= Overall Median	N > Overall Median	Q3 – Q1	95% Median CI
32 years	-0.48791	13831	2553	0.46321	(-0.494714, -0.481145)
32_years	1.04355	4019	12365	2.30413	(1.01072, 1.07928)
33 years	-0.47317	12670	3714	0.69392	(-0.483896, -0.461315)
34 years	-0.00272	7526	8858	0.83063	(-0.0175525, 0.0122891)
35 years	-0.42085	12794	3590	0.49428	(-0.428866, -0.412715)
35_years	1.24610	3953	12431	2.64026	(1.20261, 1.29355)
44 years	0.05232	6530	9854	0.65402	(0.0423634, 0.0617015)
45 years	0.05232	6530	9854	0.65402	(0.0423634, 0.0617015)
50 years	-0.27183	9754	6630	0.87034	(-0.288124, -0.255364)
59 years	0.05232	6530	9854	0.65402	(0.0423634, 0.0617015)
67 years	0.31655	5975	10409	1.33845	(0.294411, 0.337202)
Overall	-0.07966				

Test

Null hypothesis H_0: The population medians are all equal

Alternative hypothesis H_1: The population medians are not all equal

DF	Chi-Square	P-Value
10	30394.89	0.000

Kruskal-Wallis Test: EMG versus Age

Descriptive Statistics

Age	N	Median	Mean Rank	Z-Value
32 years	16384	-0.48791	53067.2	-95.59
32_years	16384	1.04355	131626.5	107.12
33 years	16384	-0.47317	53182.5	-95.29
34 years	16384	-0.00272	99407.7	23.99
35 years	16384	-0.42085	61515.2	-73.79
35_years	16384	1.24610	133653.4	112.35
44 years	16384	0.05232	90063.8	-0.13
45 years	16384	0.05232	90063.8	-0.13
50 years	16384	-0.27183	76744.9	-34.49
59 years	16384	0.05232	90063.8	-0.13
67 years	16384	0.31655	111848.6	56.09
Overall	180224		90112.5	

Test

Null hypothesis H_0: All medians are equal

Alternative hypothesis H_1: At least one median is different

Method	DF	H-Value	P-Value
Not adjusted for ties	10	47884.21	0.000
Adjusted for ties	10	47884.21	0.000

Analysis of Results

Two graphical tools, boxplots and probability plots, were used to understand the data, see their distribution, compare the shape, see their central tendency, see and compare the variability of sample distributions, estimate percentiles, and to look for outliers. In these graphs it can be observed that these data sets don't follow normal distribution. Although by looking at the graphs one can assume there are many outliers, this isn't true because the data doesn't follow a normal distribution. Therefore, these values are not yet considered to be outliers, and they are not removed.

The next step to follow is to perform non-parametric (since there is no normal distribution) tests, like the Kruskal-Wallis test and Mood's median test, to determine variation and measure centralization. With this information, it can be determined if there is any trend in the data according to the age of the patients.

The significance level for these test (denoted as α or alpha) is 0.05. This indicates a 5% risk of concluding that a difference exists when there is no actual difference. In both tests, Kruskal-Wallis test and Mood's median test, the P-value is less than alpha, meaning that the null hypothesis is rejected and is concluded that not all the group medians are equal.

In other words, the differences between some of the medians are statistically significant. Also, by observing the Z-value, which measures the difference between an observed statistic and its hypothesized population parameter in units of the standard deviation, it can be concluded that there is no tendency by ages. This means that, although the EMG signals are different between ages, there is no tendency or correlation observed between them.

Conclusions

Although the EMG signals are different between ages, there is no tendency or correlation observed between them. Due to the muscle fatigue, older patients' EMG signals will be less stable and show greater burst. The signals from the muscles of these patients behave as a dynamic system when activities are performed. Nowadays, rehabilitation engineers select motors that are over designed so that they can work with a big range number of signals, but this might lead in future problems such as excessive weight in lower and upper limbs. To avoid this, if a correlation is calculated between the deterioration of the EMG signal and the age of the patient, the use of that deteriorating signal can be maximized. To find this correlation, a series of statistical test were done. The results of these tests showed that although it is known that there is deterioration with the aging factor of the patients, the correlation to determine how much is deterioration couldn't be calculated. This means that to avoid selecting motors that are over designed another approach must be taken.

Recommendations

Another approach must be taken to avoid selecting motors that are over designed. One of the approaches that can be taken to avoid this is to eliminate the delay found in the control system of the prosthetic device. This will make the device more efficient and faster to recognize the signal. Another approach that can be taken to look for a process of optimization of the signal.

References

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