EMG Instrumentation Modeling and Feature Processing Based on Discrete Wavelet Transform

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Abstract. Electromyography (EMG) instrumentation is essential in generating electrical signals from skeletal muscles. EMG sensors are helpful in various cases requiring the detection of human muscle contractions, neuromuscular disorders, and rehabilitation. EMG instrumentation is divided into two parts, namely, the analogue part and the digital part. The EMG instrumentation design comprises a digital-to-analog converter (DAC), instrumentation amplifier, filter, and analog-to-digital converter (ADC). Meanwhile, in digital signal processing adopting the Discrete Wavelet Transform (DWT) method, frequency analysis using DWT has proven superior. It is used in various research and has exceptionally detailed coefficient features for classifying neuromuscular disease signals. Therefore, this research aims to design analogue and digital EMG instrumentation and identify features in the form of detailed coefficients. The data used are two Physionet signals from the anterior tibialis body with myopathy and neuropathy disorders. The results obtained for EMG analogue instrumentation provide the expected results until they reach the filter component stage. The resulting signal forms a block in the filter component, different from the initial EMG signal. Meanwhile, the DWT decomposition results are of the Daubechies4 wavelet type with the highest level 17, which has a high detail coefficient at low frequencies, high dilation and the result of a mixture of neuropathy and myopathy EMG signals, or in other words, at low energies, this result is by the DWT theorem. Determining the efficiency of the DWT detailed coefficient feature requires further study with the same signal subject. The DWT features obtained can then be developed for various needs in EMG signal recognition.

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INTRODUCTION

Electromyography (EMG) instrumentation aims to obtain electrical signals generated from skeletal muscles and detected on the skin's surface. Generally, this EMG has a type of surface electrode (Merletti et al., 2009). EMG sensors have several vital functions, including detecting human muscle contractions, diagnosing peripheral nervous system diseases, detecting neuromuscular diseases, assessing low back pain, kinesiology, motor control disorders, and reviewing rehabilitation results. One rehabilitation that can be observed using EMG is asthma rehabilitation, especially in the respiratory muscles, with the help of a spirometer (Zukro Aini et al., 2020).

EMG instrumentation has a standard preparation, with several components consisting of amplifiers and filters. The amplitude of the signal obtained from Surface EMG is 0-10 mV (peak-peak) and the filter used also has a range of 1 Hz-1 kHz with a sampling frequency of 5 kHz. These two components are the basis of the electrodiagnostic system (Tankisi et al., 2020). In addition to these two components, EMG is also integrated into digital instrumentation. Digital instrumentation converts the EMG analogue signal generated from the amplifier into a digital signal using an analogue-to-digital (AD) converter.

The result of EMG instrumentation is an EMG signal. Just like ECG signals (Shabihah et al., 2023) and other bioelectrical signals, digital signal processing is performed to simplify the interpretation of EMG signals. Frequency analysis, usually obtained from the Fourier transform, is essential but has the disadvantage of frequency variation over time. The wavelet transform simultaneously analyses signals in both the time and frequency domains. In some EMG studies, DWT plays a role in evaluating muscle fatigue (Chowdhury et al., 2013), classification features for signals for neuromuscular diseases (Achmamad & Jbari, 2020), signal denoising of both signals and images (Zhang et al., 2005), (Rasyida Shabihah Zukro Aini & Ira Puspasari, 2023). DWT is a reliable solution for multi-resolution/multi-frequency representation.

Therefore, this research aims to design the best EMG instrumentation modelling and its parameters with signal analysis in discrete wavelet transform. In the future, the features in the form of detailed coefficient energy generated from signal decomposition can be developed to implement EMG signal analysis in various fields.

RESEARCH METHODOLOGY

EMG Signal

Generally, EMG consists of 2 input electrode leads processed in the differential amplifier section. So, due to the limited signal database available, it is assumed that the first signal is an EMG signal for myopathy disorder, and the second signal is an EMG signal for neuropathy disorder. The electromyography (EMG) signals used are in the form of the Physionet database as "Example of electromyography" measured from the Tibialis Anterior body part in different subjects for each disorder. The signals were stored in a file extension (.txt) with a recording length of 60 seconds using a sampling frequency of 4000 Hz and a 16-bit ADC.

Analog Circuit

In the analogue part, EMG instrumentation is designed in several stages: digital-to-analogue converter (DAC), instrumentation amplifier, filter, and analogue-to-digital converter (ADC). This section will explain the design of some of these stages.

1. DAC

A digital-to-analog converter (DAC) is used because the Physionet data has undergone an ADC process. Hence, it must be returned to the analogue domain to assume it as a body signal from the electrodes. According to the information from the Physionet, the ADC used was 16-bit, so a 16-bit DAC was also used. The type of DAC used is AD5766. AD5766 has a voltage output. In Figure 1, the input data in a file is contained in Vdac. At the same time, the output (Vout) is given an additional 100 pF capacitor as decoupling, AVdd, and AVss are positive and negative power supply voltages of 12 V, respectively. In the NO section, a sine signal of 0.5 mV amplitude with a frequency of 1000 Hz is input, this is done to act as a "dither" to the 5V offset. Dither is a signal added and summed with digital data before being sent to the DAC. Dither helps increase the resolution of the DAC.

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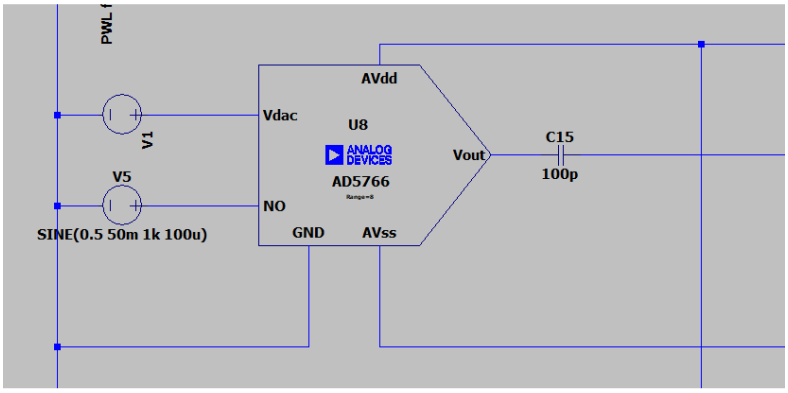

FIGURE 1. DAC 16 bit

2. Amplifier

Because the amplitude of the myopathy signal (V_1) that has been input to the DAC has a Vpp of 4.75 mV and the amplitude of the neuropathy signal (V_2) that has been input to the DAC has a Vpp of 10.5 mV and if the two are added together it will produce a Vpp of 5.75 mV, so there is no need for excessive gain, so an instrumentation amplifier is designed in Figure 2. Then, the gain of the result of Equation (1) should be around 0.83.

$$V_0 = \left(1 + 2\frac{49.9K}{100\ K}\right)\left(\frac{49.9K}{100\ K}\right)(10.5 - 4.75) = 4.78\ mV \quad (1)$$

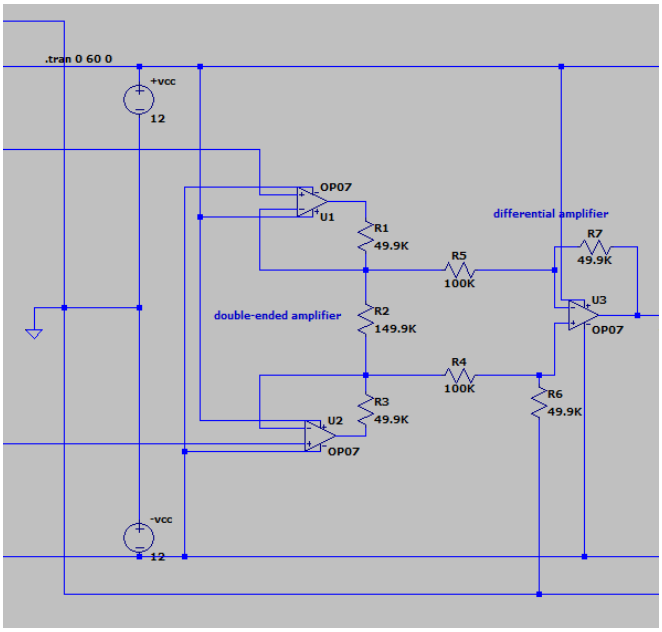

FIGURE 2. Instrumentation amplifier

3. Filter

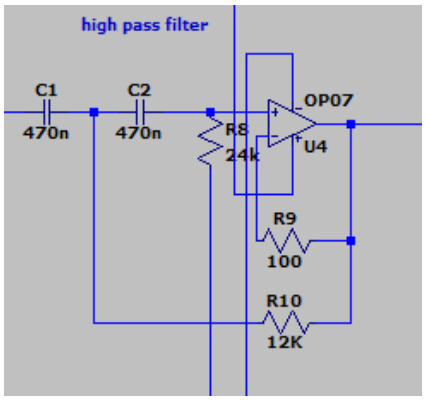

FIGURE 3. High Pass Filter -40 dB/dec

The filter has three stages: high pass filter, low pass filter and band pass filter. The high pass filter (HPF) design has a cut-off frequency of 20 Hz because the minimum frequency of normal EMG is 20 Hz. The HPF has a Sallen-Key topology Butterworth filter type of order 2 (Yuliansyah, 2017). This HPF circuit is used to reduce the signal below the frequency of 20 Hz.

From the condition of $\omega = \omega_c$ if the value of $C_1 = C_2 = C$ is made and the value of $R_{10} = 0.5R_8$, the calculation for connecting the cutoff frequency is shown in Equation (2)

$$f_c = \frac{1}{2\pi\sqrt{CCR_8 0.5R_8}} = \frac{1.414}{2\pi CR_8} \tag{2}$$

If the value of C = 470nF is set, the value of R_8 is 24K and R_{10} is 12K, resulting in the HPF design in Figure 3

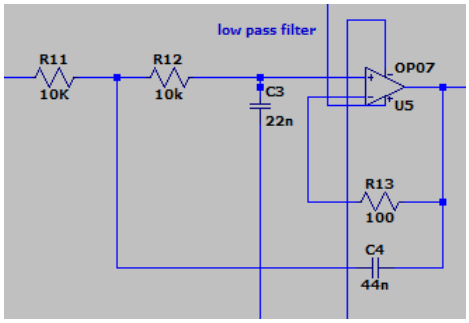

FIGURE 4. Low Pass Filter -40 dB/dec

Furthermore, the designed low pass filter (LPF) has a cut-off frequency of 500 Hz because the maximum frequency of normal EMG is 500 Hz. The LPF has a second-order Sallen-Key topology Butterworth filter type. This LPF circuit is used to avoid anti-aliasing when sampling.

From the condition $\omega = \omega_c$ if the value of $R_{11} = R_{12} = R$ and the value of $C_4 = 2C_2$ are made, the calculation for connecting the cutoff frequency is shown in Equation (3)

$$f_c = \frac{1}{2\pi\sqrt{C_3 2C_3 RR}} = \frac{0.707}{2\pi C_3 R} \tag{3}$$

If the value of R = 10K is set, then the value of C_3 is 22 nF and C_4 is 47 nF (with the tolerance of components on the market), resulting in a design like Figure 4.

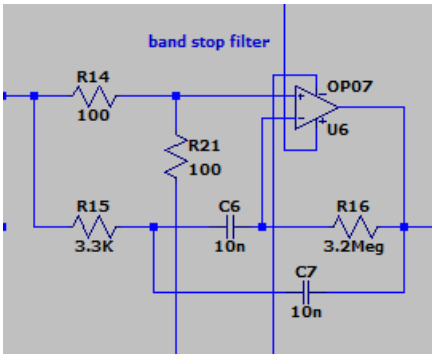

FIGURE 5. Band Stop Filter +40 dB/dec

The last stage in the analogue filter process is the Band stop filter (BSF), designed to have a cut-off frequency of 50 Hz, where there is interference from the mesh signal. In this design, the Q value is determined to be 5 to have a bandwidth that is not too narrow. Bandwidth can be found using Equation (4)

$$, B = \frac{\omega_c}{Q} = \frac{2\pi f_c}{Q} = \frac{2\pi 50}{5} = 62.8 \approx 63 \quad (4)$$

From the condition that ω=ωr and the BSF gain drops to 0.707, the bandwidth is calculated according to Equation (5)

$$B = \frac{2}{R_2 C} \quad (5)$$

$$\omega_c = \frac{1}{C\sqrt{R_{15}R_{16}}} \quad (6)$$

If the value of $C_6 = C_7 = 10\ nF$ is set, then the value of R_{16} if tolerated is 3.3M, then based on Equation (6) the value of R_{15} is 3.3k, resulting in a design like Figure 5.

4. ADC

The Analog Digital Converter (ADC) is an LTC 6360 Opamp. This component was chosen because it has low noise, high accuracy, and high speed. The power supply used is 5V (SHDN). The SAR ADC is designed with a non-inverting gain configuration. The input bias current induced DC voltage signal can be minimised using the parallel form of R_{17} and R_{18} to R_{20}. The relationship is calculated in Equations (7) and (8) resulting in the SAR ADC design in Figure 6.

$$\frac{R_{17}}{R_{18}} = \frac{V_{out}(\max) - V_{out}(\min)}{V_{out}(\max) - V_{out}(\min)} \quad (7)$$

$$V_3 = \frac{\left[\left(V_{out} + \frac{R_{17}}{R_{18}}\right) 2V_{in}\right]}{\left[1 + \frac{R_{17}}{R_{18}}\right]} \quad (8)$$

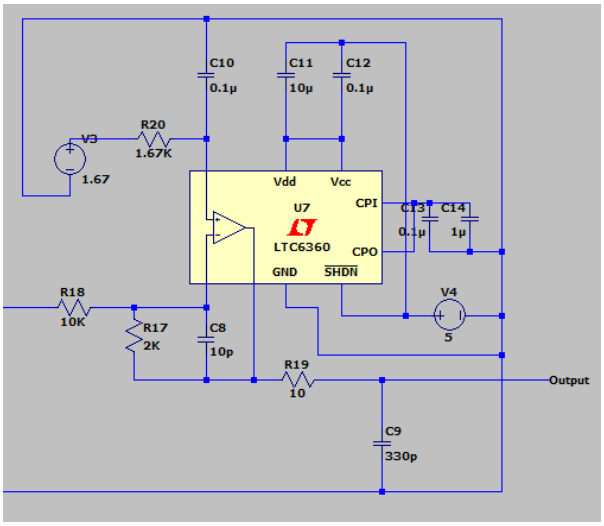

FIGURE 6. ADC 16 bit

Digital Signal Processing

In the digital part, EMG signal processing is divided into several stages: fast Fourier transform (FFT), Butterworth bandpass filter, and feature extraction in the form of detailed coefficient energy from discrete wavelet transform (DWT) decomposition. This section will explain the design of the EMG signal processing.

1. *FFT*

The FFT converts signals from the time domain to the frequency domain. The FFT is computed from the discrete Fourier transform (DFT). The FFT calculation is represented in Equation (9) where $x[n]$ is the EMG signal, n is the sample, and L is the amount of EMG signal data.

$$X[k] = \sum_{n=0}^{L-1} x[n] e^{-j2\pi/L}, \quad 0 \leq k \leq L-1 \tag{9}$$

2. *Butterworth Bandpass Filter*

After observing the frequency domain, since the frequency interval of an average EMG signal is between 20-500 Hz, a Butterworth bandpass filter was chosen because the signal from the EMG instrumentation is very different from the initial signal from the Physionet data.

3. *Energy Coefficient Details*

The steps in extracting detail coefficient energy features using DWT start by defining the wavelet parameters, namely the wavelet type and maximum level. The type of wavelet used is Daubechies4, while to determine the maximum level of decomposition, a calculation involving Equation (10) is used with the logic of thinking for the maximum level where at least one coefficient in the output is not disturbed by edge effects caused by signal extension. In other words, the decomposition stops when the signal becomes shorter than the length of the FIR filter for the given wavelet type.

$$\max level = \left| log_2 \left(\frac{data\ length}{filter\ length-1} \right) \right| \tag{10}$$

Next is the step of decomposing the signal into approximation and detail coefficients. The calculation for the decomposition process is presented in Equation (11).

$$W(l,s) = 2^{\frac{s}{2}} \sum_n x(n) \psi(2^s n - l) \tag{11}$$

$$A(k) = \sum_n x(n)h(2k-n) \tag{12}$$

$$D(k) = \sum_n x(n)g(2k-n) \tag{13}$$

where l is shifting, s is scale, $x(n)$ is a discrete signal with signal sample parameters, and $\psi(n)$ is the mother wavelet. The decomposition result is the detail coefficient ($D(k)$) of the high pass filter and the approximation coefficient ($A(k)$) of the low pass filter. Meanwhile, $h(n)$ and $g(n)$ represent the half bands of the low and high pass, respectively. The last step is to determine the coefficient energy of each level with Equation (14) where N_1 is the length of the data.

$$E(D_k) = \sqrt{\frac{1}{N_1}\sum_{i=1}^{N_1}(D_k)^2[i]} \tag{14}$$

RESULT AND DISCUSSION

1. *Analog*

The errors of analogue instrumentation can be examined by comparing theoretical calculations and simulation results presented in this section; in addition, the EMG instrumentation will be tested to determine whether it is appropriate for the EMG signal. In addition, the EMG instrumentation will be tested to determine whether it is appropriate for the EMG signal.

2. *DAC*

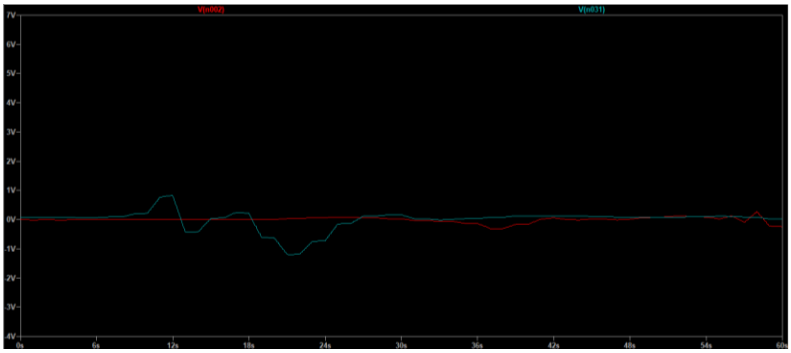

FIGURE 7. Raw signal 1 (red) and signal 2 (dark green)

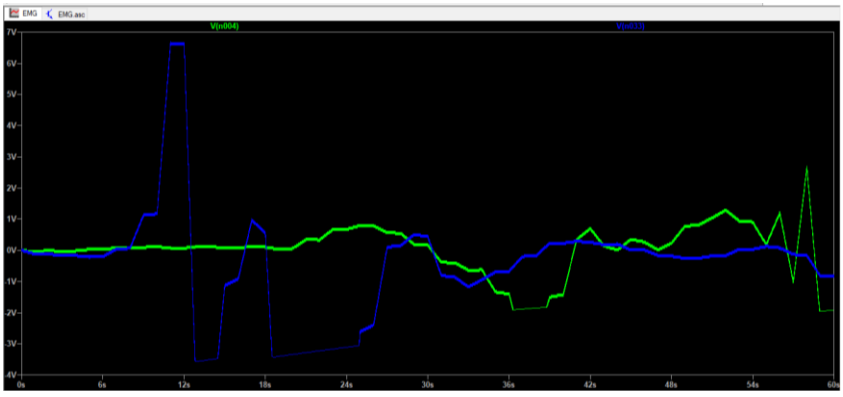

FIGURE 8. DAC signal 1 (green) and signal 2(blue)

From Figure 8, it is known that signal 1, which is the EMG signal of myopathy signal, produces a DAC with a Vpp amplitude of 4.75mV, while signal 2, which is a neuropathy EMG signal, produces a DAC with a Vpp amplitude of 10.5mV. Signal produces a DAC with a Vpp amplitude of 10.5 mV. The initial signal data (Figure 7) has experienced significant strengthening and shifting. Shifts are pretty significant. This is due to the effect of adding a sine signal as a dither that increases the signal amplitude by five mV.

a. Amplifier Instrumentation

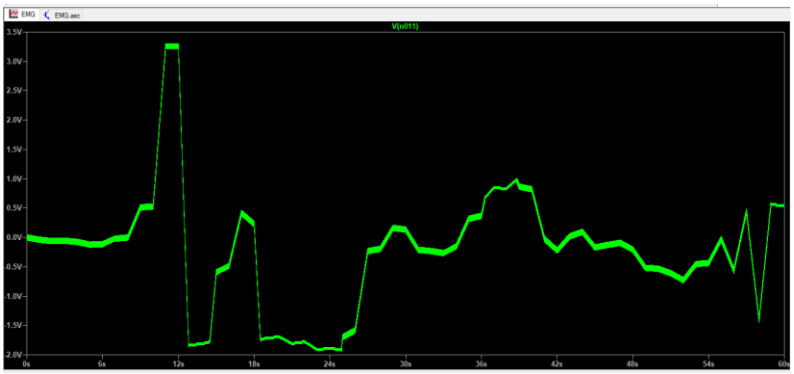

FIGURE 9. *Instrumentation amplifier* result

Figure 9 shows that the amplitude of the instrumentation amplifier results has a Vpp value of 5.35mV while Equation (1) has a Vpp value of 4.78mV. Results This result is different from the results of theoretical testing and simulation. In addition, the signal shape resembles a neuropathy signal due to its higher voltage, so the input in the differential amplifier still has a residual signal amplitude.

b. Filter

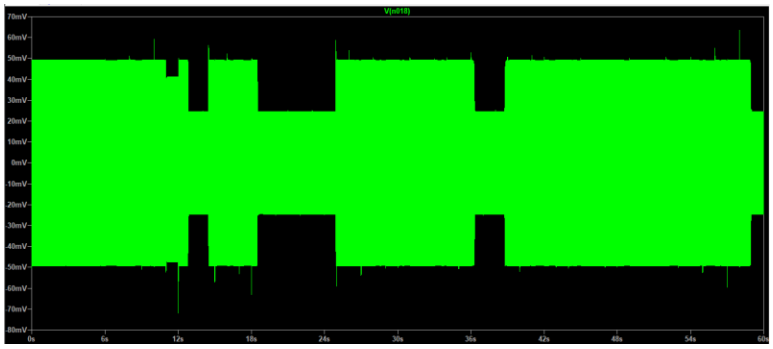

FIGURE 10. HPF -40 dB/dec with 20 Hz cutoff frequency

The result of the HPF at a cutoff frequency of 20 Hz (Figure 10) produces a signal block that is quite dense compared to the result of the instrumentation amplifier. It is pretty dense compared to the instrumentation amplifier results. The amplitude of this HPF result has a Vpp of 130 µV. The tentative hypothesis is the mismatch of the input signals that should have come from the same subject with adjacent areas and the same problem. Secondly, the HPF filter configuration does not match the signal characteristics.

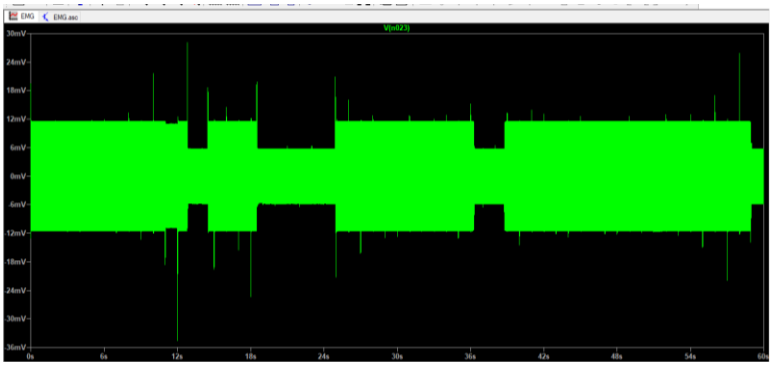

FIGURE 11. LPF -40 dB/dec with 500 Hz cutoff frequency

The result of the LPF at a cutoff frequency of 500 Hz (Figure 11) reduces the thickness of the signal block that occurs in Figure 16 but the signal's amplitude goes down to 63 µV. This explains the refutation of the second hypothesis. The EMG signal slowly starts to be visible.

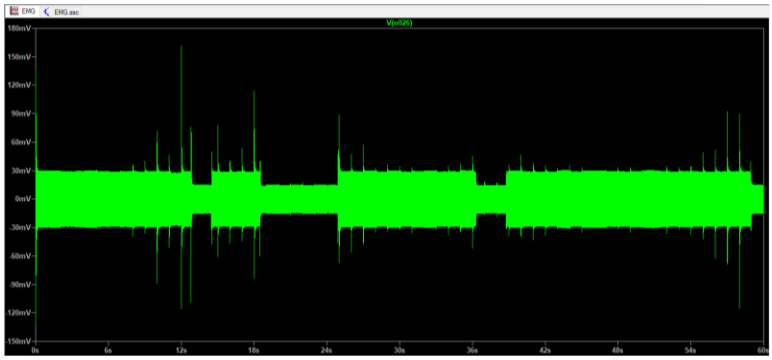

FIGURE 12. BSF +40 dB/dec with 50 Hz cutoff frequency

The result of BSF at a cutoff frequency of 50 Hz (Figure 12) to remove the mesh signal at a frequency of 50 Hz makes the EMG signal clearer. The signal at a frequency of 50 Hz further clarifies the EMG signal; this is also supported by the return of the EMG signal amplitude increase returns, whose Vpp is 285 µV. This explains the refutation of the second hypothesis. The EMG signal slowly began to be visible.

c. ADC

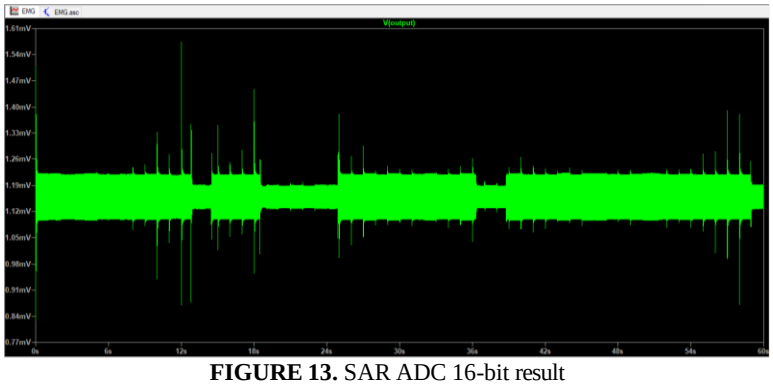

FIGURE 13. SAR ADC 16-bit result

When entering the value into Equation (7), the SAR ADC's results should produce an output signal Vpp of 57 µV, but the simulation results are much different; it only produces an output signal Vpp of 0.7 µV. The SAR ADC

results also show a noise reduction, as evidenced by the more visible EMG signals. In addition, the signals are all above 0V or by the ADC configuration on the microcontroller, generally located between 0-5V.

3. Digital

The results of processing EMG signals in the digital domain will be discussed individually in this section to evaluate whether these results can be validated. Section to evaluate whether these results can be validated or not.

a. FFT

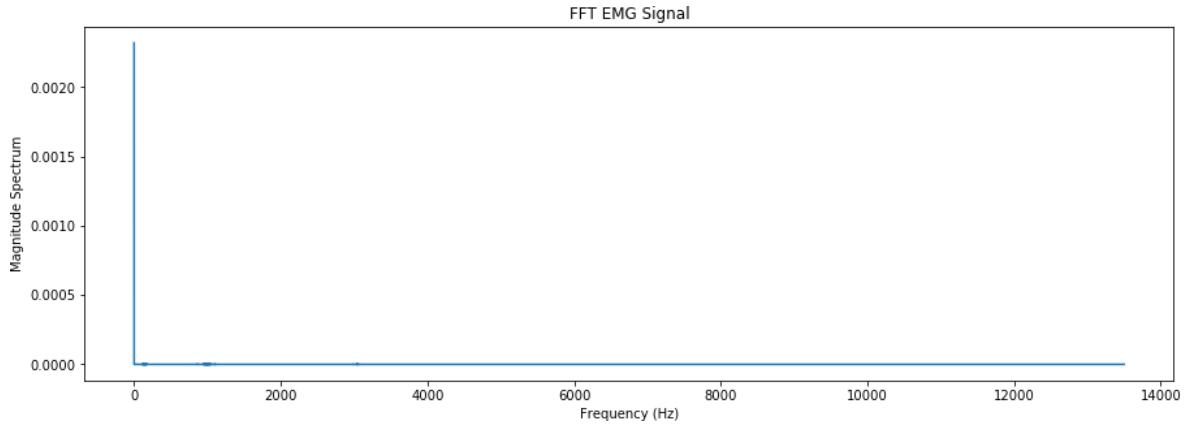

FIGURE 14. EMG signal FFT result

Based on the amount of data from analogue instrumentation results in 60 seconds, which reached 1.700.000 samples, it was decided to use a sampling frequency of 27.000, obtained by the number of samples divided by the length of the sampling time and obtained by the number of samples divided by the length of time sampling. Figure 14 shows several points at frequencies around 10 Hz, 1000 Hz, and 3000 Hz with a minimal magnitude spectrum. The magnitude spectrum is minimal.

b. Butterworth Bandpass Filter

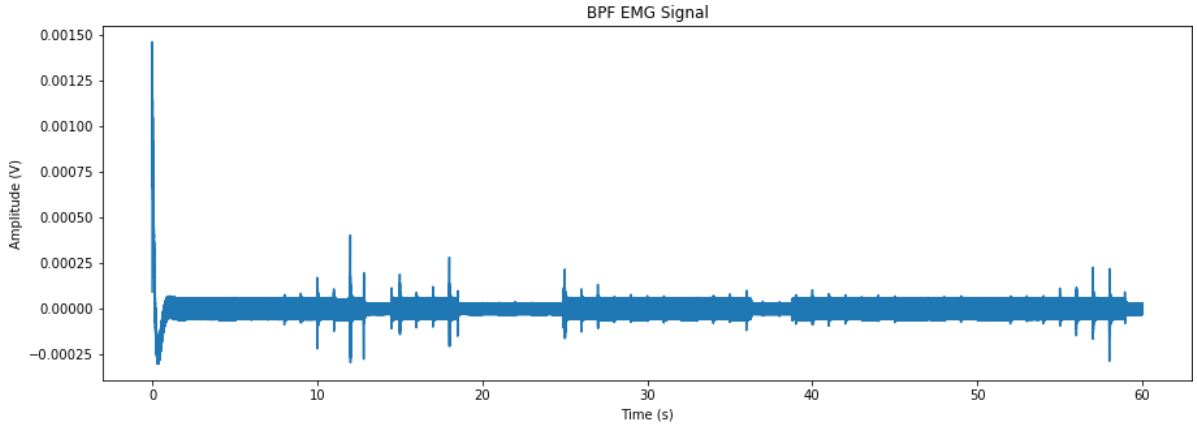

FIGURE 15. EMG signal BPF result

The FFT results are then applied to BPF signals with cutoff frequencies of 1 and 3001 Hz, obtained results as in Figure 15 with a signal amplitude of 0.5 µV.

c. Energy Coefficient Details

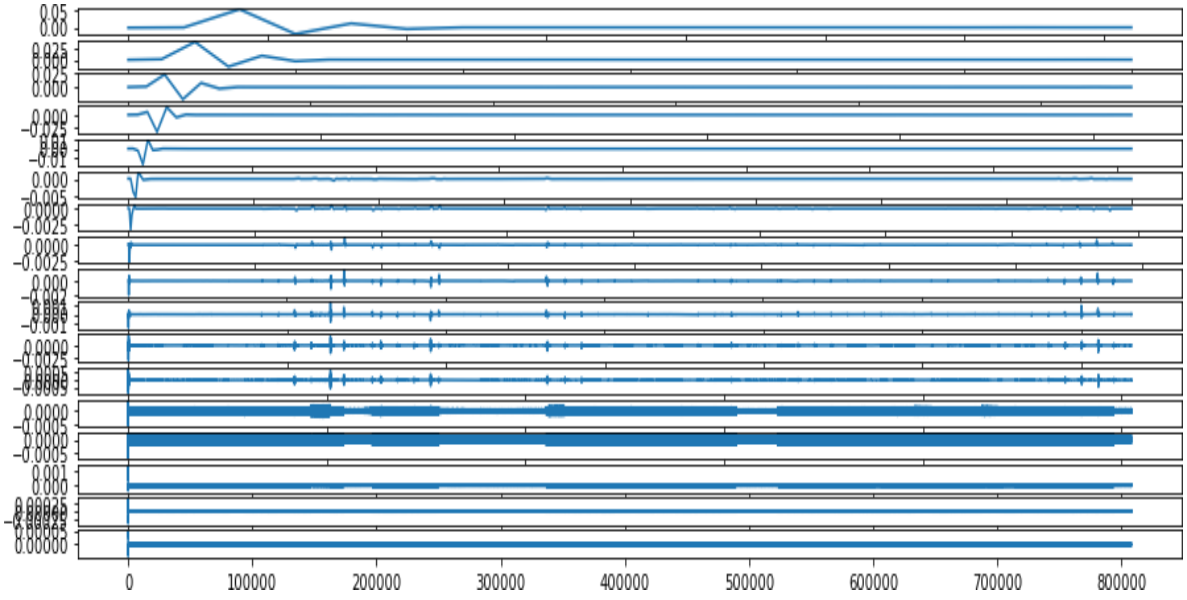

FIGURE 16. DWT Decomposition Result Coefficient

```
Energi  cD1 : 0.003175583166243954
Energi  cD2 : 0.0013979503981470767
Energi  cD3 : 0.0005965515914078321
Energi  cD4 : 0.00036055226156874224
Energi  cD5 : 9.947038978689109e-05
Energi  cD6 : 1.6997778928685936e-05
Energi  cD7 : 4.812742693448237e-06
Energi  cD8 : 2.2461244856390196e-06
Energi  cD9 : 1.2538211311289176e-06
Energi  cD10 :4.993712272649108e-07
Energi  cD11 :6.436510521814901e-07
Energi  cD12 :1.3388320258131966e-07
Energi  cD13 :3.81391435876562e-07
Energi  cD14 :3.714449366068671e-07
Energi  cD15 :4.5220322556479524e-08
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Energi  cD16 :7.273974850304083e-09

Energi  cD17 :4.5578972735573506e-10

Energi  cA17 :0.03181798188927217
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The results of DWT decomposition using the Daubechies4 wavelet type at a maximum level of 17 show that the detail coefficients at higher levels are only found at low frequencies, and high dilation, and the results of mixing EMG neuropathy and myopathy signals produce energy in the cD1 to cD17 coefficients where the higher the level, the energy produced is also smaller. Smaller. For further research, this feature can be used to classify several signals into normal and abnormal data (Mustiadi et al., 2012).

CONCLUSION

The myopathy and neuropathy signals obtained from the anterior tibial body were from different subjects. The electromyography (EMG) instrumentation designed to process these two signals consists of a digital-to-analog converter (DAC), instrumentation amplifier, filter, and analog-to-digital converter (ADC). The DAC is adapted to the ADC originating from the database, namely 16-bit. As a result, both myopathy and neuropathy signals experienced a shift and strengthening of four times and three times the initial signal, respectively. There is no need to design excessive amplification because the amplitude of the myopathy signal is 4.75 mV, and the neuropathy signal is 10.5 mV, so a differential amplifier was designed. The differential amplifier output resembles a neuropathy signal and becomes input to three filters, namely the high pass filter (HPF), low pass filter (LPF), and band stop filter (BSF). The cut-off parameters given to HPF are 20 Hz, LPF is 500 Hz, and BPF is 50 Hz. These parameters are formed based on the minimum normal EMG frequency of 20 Hz and the maximum EMG frequency of 500 Hz. The overall combination of filters provides an overview of the EMG signal, but it is still in the form of blocks that do not match the initial signal; this is possible due to poor design in the filter instrumentation. Next, the ADC results follow the ADC configuration on the microcontroller. In digital signal processing, the DWT decomposition results are of the Daubechies4 wavelet type with the highest level 17, which has a high detail coefficient at low frequencies, high dilation and the result of a mixture of neuropathy and myopathy EMG signals, or in other words at low energies.

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