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Research paper

Muscle Contraction Sensor Filtering and Calibration for Virtual Manufacturing Development

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Abstract

In terms of its software development, virtual manufacturing continues to be developed and updated following the manufacturing technology development. To develop the input aspect of virtual manufacturing and improve virtual interactivity, a muscle sensor is used to convert a user muscle contraction value into software inputs. This study aims to filter and calibrate the digital signal from a muscle sensor input device designed for virtual manufacturing environment interaction. Common type of digital filters are designed, tested, and compared using MATLAB to find the optimum filter types and parameters. Furthermore, the signal is calibrated to each individual user. The filtered and calibrated input allows the user to interact with objects virtually in a virtual manufacturing environment.

Keywords: *Computer-Aided Design; Muscle Contraction; Signal; Virtual Manufacturing.*

1. Introduction

As a way to minimalize error and maximize efficiency and resources in production in this rapid era, industrialist commonly design, tested, and simulate the production process in a virtual manufacturing environment. This includes the use of computer-aided design (CAD) and virtual assembly. The virtual manufacturing system allows early optimization of costs, quality and time [1]. Common virtual manufacturing practice is done with the help of CAD program utilizing a standard computer mouse and keyboard as its input method. To enhance user interactivity with virtual object, it is necessary to develop an input device that can simulate human force acting on an object.

The level of interactivity between the subject and the virtual environment is closely related to the perception of the presence of virtual objects [2]. To improve the interactivity and immersion of a virtual environment, one way is to develop a wearable device to detect human physical force provided in real time. By detecting inputs in the form of user muscle contraction, the resulting force can be virtually interacted with a weight-specified object in a virtual environment. For practical use, the said device needs to be easy to set and use. A wearable and compact device would be suitable for the application. This wearable device must be able to detect muscle contraction accurately and maintain a stable signal.

Signal readings from the muscle sensor are not completely clean of the disturbance that affects the accuracy of signal readings, which is commonly called a noise. In electronics, noise is an unwanted interruption in electrical signals [3]. To extract a desired stable signal reading, noise from the device output needs to be minimized as small as possible. In order to achieve this, a digital filter is applied to the signal.

In addition, to allow user interact with virtual manufacturing environment smoothly and in accordance with real state conditions, it is necessary to calibrate the muscle sensor device to each individual. Muscle contraction sensor readings are individually unique [4]. Furthermore, slightly different muscle sensor position yields different input. The output from the muscle sensor needs to be calibrated so that its value can be adjusted to the virtual human muscle force in the CAD program.

2. Surface Electromyography (Semg) Sensor, Filtering and Calibration

2.1. Surface Electromyography (sEMG)

There are two general types of EMG, intramuscular EMG and surface EMG. Intramuscular EMG, or commonly called invasive electrode, use various types of electrodes. The most commonly used intramuscular EMG electrode is a needle electrode that is penetrated into the skin. The tip of the needle acts as an active electrode. On the other hand, surface EMG, or often also called non-invasive electrode, measures muscle activity from the surface of the skin. It takes more than 2 electrodes with this EMG surface because the recorded difference is the potential (voltage difference) between two separate electrodes. When EMG signals are obtained from electrodes mounted directly on the skin, the signal is a composite of all muscle fiber action potentials that occur in the underlying muscle of the skin. The potential of this action occurs randomly. So at some point, EMG signal can be either positive or negative voltage. This study uses SEMG type because it provides safe, easy and non-invasive muscle contraction recording compared to Intramuscular Electrode. The recording is sufficient to obtain muscle-related information and integrate it with CAD applications for Virtual Manufacturing purposes.8. References

2.2. Semg Sensor Noise

Signals recorded by the muscle sensor are not entirely clear from disturbance that affect the accuracy of signal readings or commonly called noise. In electronics, noise or noise is an undesired interference in electrical signals [3]. The noise generated by electronic devices varies greatly because it is produced by several different effects. The two major source of noise in an SEMG sensor are caused by inherent noise and motion artifacts. All types of electronic equipment generate inherent noise [5]. This could be from the sensor electrodes, leads along the wire, amplifier, and transceiver. Movement of the cable connecting the electrode to the amplifier and the interface between the detection surface of the electrode and the skin creates motion artifacts. Muscle fibers generate electric activity whenever muscles are active [6].

2.3. Filtering

In Digital Signal Processing (DSP), the input and output signal inputs are within the time domain [7]. This is because it is usually made by sampling at regular intervals of time. The most common way of sampling is at the same space interval, or sample. Many other types of domain can represent a signal; however, time and space domains are the most common.

Filtering can be done in a time and frequency domains. For example, a type of filter which only process a signal in a time domain is a Moving Average filter. This is because it's simple algorithm process of finding the average on a number of points or window size and continue to shift along the data. Moving Average is the most common filter in DSP because of its simplicity. However, Moving Average is a poor filter for frequency domain signals because of its poor ability to separate one frequency band from other frequencies [8]. As for common example of filters which are performed on frequency domains are Chebyshev, Butterworth, and Elliptic filters. The process remove noise by allowing a desired frequency to be passed in the filter, and forbidding or attenuating other undesirable frequencies to pass on to some extent.

Chebyshev's response is a mathematical strategy to achieve faster roll-off by allowing ripple in frequency response. Chebyshev response is the optimal balancing between these two parameters. There are two types of Chebyshev filters, the first one being a type 1 filter, meaning that the ripple is only allowed in the passband. While the type 2 filter Chebyshev only has a ripple in stopband.

When the ripple is set to 0%, this filter is called the maximum flat or Butterworth filter. Ripple of 0.5% is often a good choice for digital filters. This corresponds to the precision and accuracy typical of the analogue electronics passed by the signal [8]. Aside of these two filters, is another filter called the Elliptic filter, which has a ripple both in passband and stopband. However, Elliptic filters provide faster roll-off advantages than Chebyshev and Butterworth for certain poles.

2.4. EMG System Calibration for Virtual Environment

EMG signals are directly related to the physiology of each individual. These measurements are influenced by physiological factors including muscle fiber patterns, motor vehicle discharges, changes in blood flow in the muscles, the forces that produce the capacity of each muscle, nerve activity, and neurotransmitter activity in different areas of the muscle, skin conductivity, position. shape and size of muscle. The EMG signal has different characteristics depending on age, muscle development, motorway unit, bone density, heat distribution of muscle, skin fat layer, and gesture style. The external appearance of a two-person movement may look the same, but the characteristics of the EMG signal are different [4]. Because each individual can have different EMG signal values and range, system calibration is performed to calibrate each individual unique signal. This way, a large group of user can have a similar interactive experience in a virtual environment.

3. System Modelling, Semg Sensor Filtering, and Calibration Development

3.1. System Modelling

SEMG sensor used in this study is a Myoware muscle sensor producer by Advancer Technologies. This sensor is used because it's one of the simple and practical EMG sensor in the market. The size is relatively small and the module is designed to be directly attached to the electrode. As it eliminates more cable use, it also minimize the potential motion artifacts noise. Furthermore, this device is compatible with common microcontrollers such as Arduino which makes it easy to tweak the signal. Output signal from this sensor is amplified, rectified, and integrated or commonly called EMG envelope. But this EMG envelope signal still needs further calibration for virtual manufacturing purposes as the signal still frequently fluctuate along the time. To integrate the sensor signal in a virtual environment, a minimum ripple signal is needed. Arduino nano is used in this study to receive data through one of its analog-to-digital converter (ADC) port. The data is converted into voltage value by Arduino nano and then transmitted by the NRF24. The NRF24 module serves to transmit or receive data streams wirelessly between the same modules over a 2.4GHz radio frequency. The other NRF24 connected to Arduino and the computer is set to receive data transmitted from the SEMG sensor.

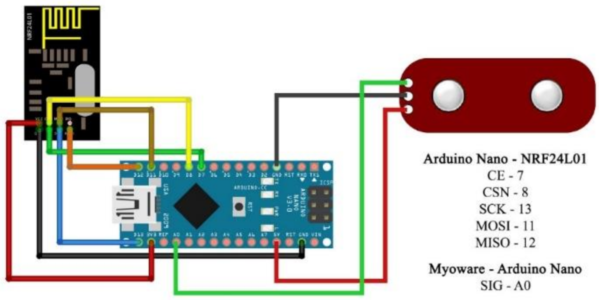

Fig. 1: EMG Sensor Transmitter System Model

3.2. sEMG sensor Filtering

Types of filter tested and compared in the paper are moving average, Chebyshev, Butterworth, and Elliptical filter. For moving average filter, filter results will be displayed by varying the number of points. To get an overview of the filter effect on the data, the number of points varied is 10 points, 25 points, 50 points, and 100 points. Because the only changeable parameters is the number of points, then to obtain the optimal number of points, a moving average filter is tested using 2 to 200 points with each 1 point increment. Then, the filter result of the various points is compared to the sum absolute difference (SAD) value to find the value where the filter results will be more or less the same at a certain point.

As for the frequency domain filters that includes Chebyshev Filters, Butterworth, and Elliptic, the first step is to display graph signal in the frequency domain. This process is done using FFT available in MATLAB. By analyzing the graph in the frequency domain, cut-off and filter are determined (low-pass, high-pass, band-pass, or band-stop). The process is followed by determining the optimal order. It will be determined through a trial and error method from the smallest value of order, which is 1. The order will be incrementally increased by 1 until it is analyzed that the filter have the same effect up to a smallest value of order. The order of a filter has the same effect on all three Chebyshev, Butterworth, and Elliptic filters.

When the filter cut-off frequency and optimal order are obtained, the types of filters are compared to find the the most ideal filter for Virtual Manufacturing purpose.

3.3. Semg Sensor System Calibration

EMG sensors are calibrated in order to measure biceps brachii muscle contraction force so that their force values can be used as inputs to interact with objects in a virtual CAD application. The relationship between filtered EMG signal amplitudes with dumbbell loads that varied in weight in the real world are examined. Then, the R squared value of each user will be compared to determine the linearity of the muscle sensor reading. To implement it in a virtual manufacturing system, each user line function calculated from the sample weights will be used to modify the Arduino code. It will allow the Arduino to modify and calibrate its reading depending on the user.

4. Results

4.1. Filtering

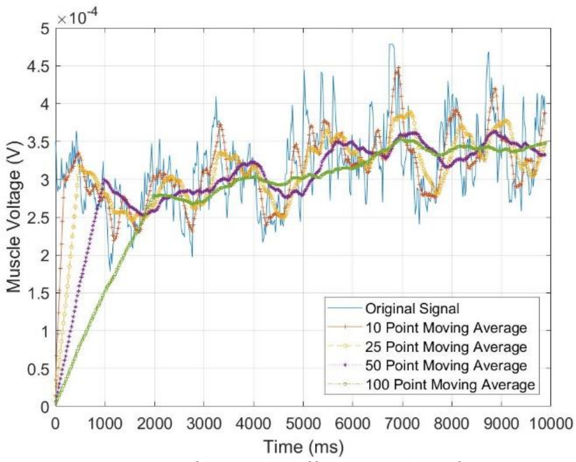

Fig. 2: Moving average filter with different number of points / window sizes

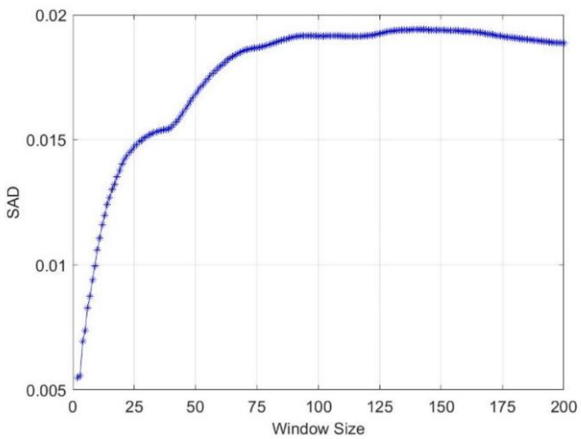

Fig. 3: SAD to window size graph

In accordance with the Moving Average function theory, the graph will have less ripple as the number of points is increased. As the number of points increased, the filter took longer time to display the calibrated data because it needs more data.

As shown in Figure 2, the time it took to display a calibrated data for 10 point Moving Average is under 1 second, compared to 100 point Moving Average at above 2 seconds. The result would be better achieved with the lowest number of points or window size possible. With short window size, the minimum amount of data required to calibrate the data becomes smaller. On the other hand, window size must not be too small because the filter result will not be optimal.

To find the optimal number of points, the Sum Absolute Difference (SAD) is calculated for each data range, from 2 data points up to 200 data points for each 1 point increment, which then displayed in graphical form. From Figure 3 it can be concluded that starting at 100 points, the graph starts to become linear. This means the number of dots or data ranges above 100 points will have roughly the same filter response to the data.

To design the frequency domain filter, the signal is displayed in a frequency domain graph using MATLAB FFT function.

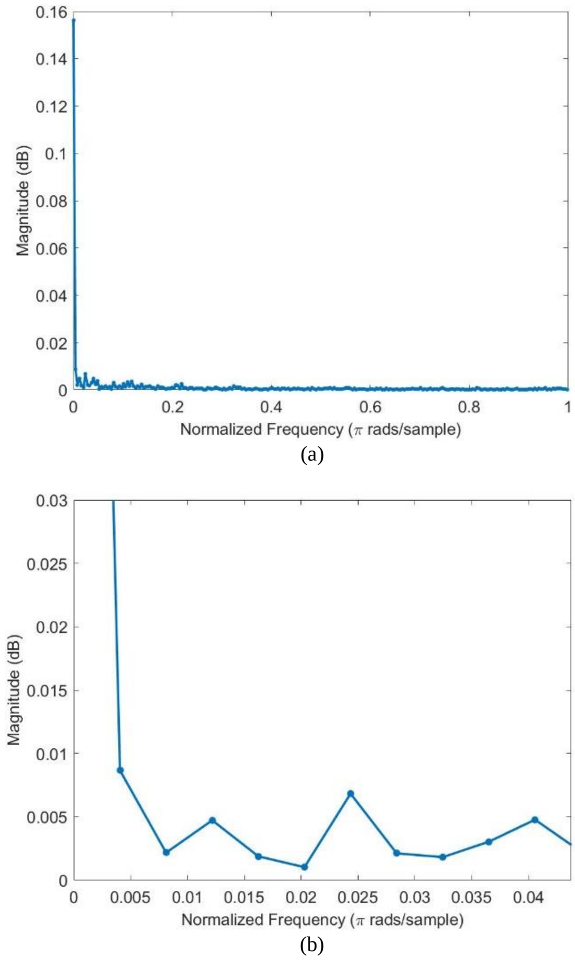

Fig. 4: (a) Normalized frequency data of Myoware sensor, (b) Magnification of normalized frequency data

The FFT function yields a figure with an extreme graph hike in the frequency close to 0. This is likely due to the overall noise sources being minimized in addition to the rectified and filtered output data from the EMG Myoware sensor to some extent from the beginning. Figure 4b shows that the lower end of the extreme slope shows the value 0.005π. If traced to its peak, this line will end at a frequency value of 0. This line indicates that the suitable type of filter is low-pass filter with a 0.005 π cut-off frequency.

To determine the optimum order of the filter, a low-pass Chebyshev filter with 0.005 π cut-off frequency and 50dB passband ripple is designed, and then compared with increasing value of order.

Figure 5 shows that the 2nd order is adequate to filter the signal with minimum result. The order above 2nd order has roughly the same result which indicates that the rest order are redundant.

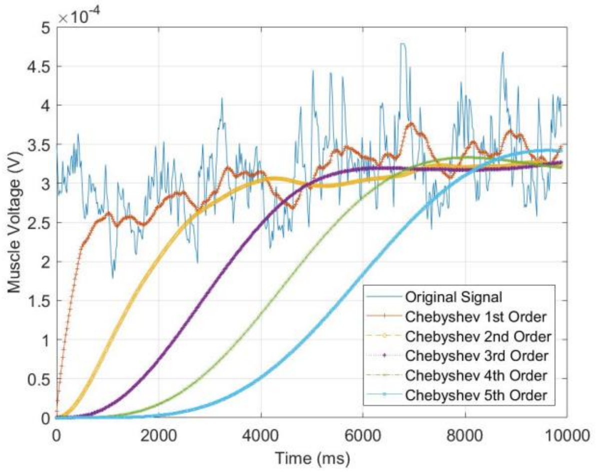

Fig. 5: Comparison of Chebyshev filters with different order

The optimum cut off frequency and order obtained from the trial is used for designing the frequency domain filter which includes Butterworth, Chebyshev, and Elliptical filter. The value of pass-band ripple is determined at 0.5 dB and the stopband attenuation for Elliptic filter is determined at 40dB. The Butterworth, Chebyshev, Elliptic filter with the same cut off frequency and order and the optimum moving average filter obtained earlier is then compared in one graph.

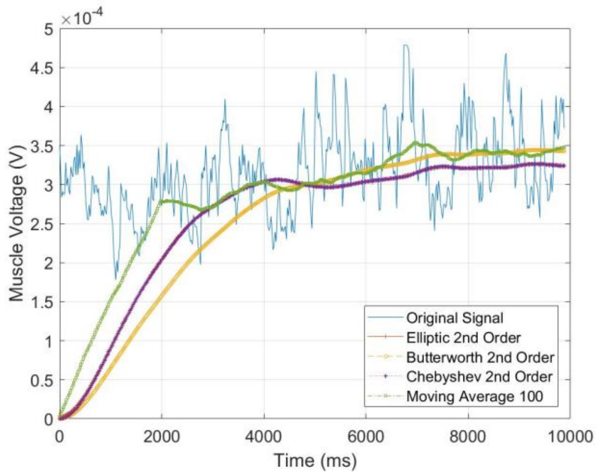

Fig. 6: Comparison of Moving average, Elliptic, Chebyshev and Butterworth filter

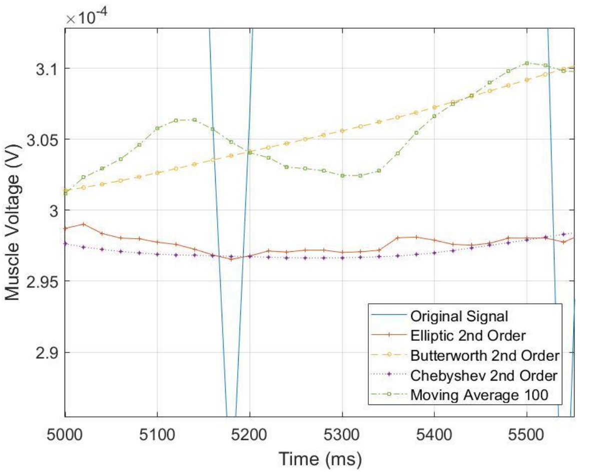

Fig. 7: Magnification comparison of Moving average, elliptic, Chebyshev and Butterworth filter around t = 5000ms

The comparison of filters indicates that the filter works better in the frequency domain. Moving average filter fluctuate more than the other three filters.

In general, elliptic and Chebyshev filters have similar curves but when examined on an enlarged scale, it appears that Elliptic filters have more ripple along their curves.

To determine the optimal filter, the fluctuation or variation in a steady state of the signals are compared. This can be represented by the standard deviation. If the deviation standard is large, it means a lot of ripples in the signal, and vice versa. The standard deviation will be measured from the point when the signal across the filter is stable: the data range between seconds 9 and 10. This value is compared for all test filter filters.

Table 1: Different Filters Standard Deviation in a Steady State Condition (9s – 10s)

Filter	Standard Deviation
Butterworth	5.243×10^{-7}
MA100	36.03×10^{-7}
Chebyshev	8.619×10^{-7}
Elliptical	6.219×10^{-7}

4.2. Calibration

The calibration is done by involving 5 people with a diverse body mass index as sample. This diversity aims to test and know the difference in reading of analog values for each individual. Data from 5 respondent is taken for 20 seconds with variation of load 1 kg, 2 kg, 3 kg, 4 kg, 5 kg. The weights are lifted at a 90 degrees angle between the arm and the elbow.

Table 2: Muscle Contraction Value on Different Weight

User No.	Average Muscle Contraction Value (x 10-4 V)					
	0 kg	1 kg	2 kg	3 kg	4 kg	5 kg
1	0.25	0.58	0.75	0.99	1.56	2.33
2	0.49	0.80	1.10	1.44	1.97	2.52
3	0.38	0.64	0.93	1.59	2.67	2.56
4	0.20	0.52	0.87	1.05	1.50	1.38
5	0.15	0.29	1.17	1.11	1.29	1.47
Total Average	0.29	0.56	0.96	1.23	1.80	2.05

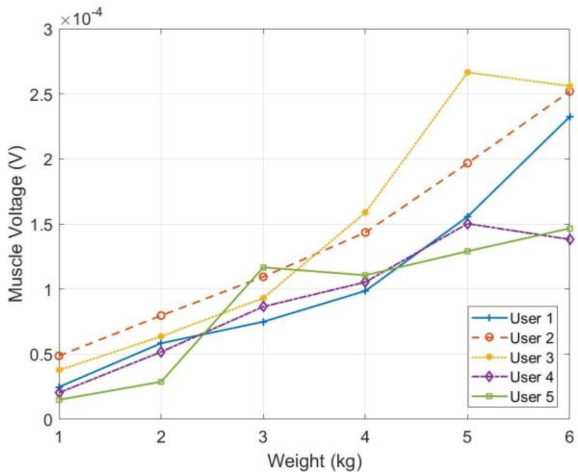

Fig. 8: Average muscle contraction on different weight

Displayed in a graphical form, it can be seen that all the graphs of each respondent have a curve close to exponential. To check the exponential trend further, the exponential R squared value of each respondent are calculated.

The R squared value table shows that the sensor readings of all respondents with load variations have a linear relationship close to 1 or 100%.

Respondent No.	Standard Deviation
1	0,96
2	0,99

3	0,96
4	0,85
5	0,79
Total Average	0.91

5. Conclusion

For Virtual Manufacturing purpose, the importance of obtaining a stable signal (minimum ripple) from EMG sensor as generated by the Butterworth filter exceeds the urgency of obtaining a fast roll-off frequency at the expense of signal fluctuations such as Chebyshev and Elliptic filters. With other approaches, Moving Average filters that process filters in time domain are not very well suited for EMG Sensor filters because after testing, the results are not as optimal as other filters that do so on the frequency domain.
Therefore, after testing for all four filters, it can be concluded that, although the difference between three frequency domain filter are not significant, the optimal filter for Myoware EMG sensors for the use of Virtual Manufacturing is a low-pass Butterworth filter with a 2nd order parameter and a cut-off frequency of 0.005π. The Butterworth filter has the smallest standard deviation value in a steady state muscle condition.
The calibration results show that the value of the filtered EMG Myoware sensor with the Butterworth filter has a exponentially approximated output for all respondents with a minimum R squared value = 0.79 and a maximum R squared of 0.99. With a high R squared number close to 1, it is probable that the ADC output value of the varied load can be predicted as an exponential approximation.

Acknowledgement

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