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Real Time Adaptive Filter based EMG Signal Processing and Instrumentation Scheme for Robust Signal Acquisition Using Dry EMG Electrodes

Muhammad Zahak Jamal, Dong-Hyun Lee, and Dong Jin Hyun

Abstract— **Bio signals provide us with information which gives us valuable insight into the natural processes occurring inside the human body. This makes it absolutely imperative for the signal to be free of noise so that it provides a worthy estimate of the information provided by the bio signals. This paper focuses on the signal processing aspect of electromyography. We propose an adaptive filter based signal processing scheme in real time to remove noise from the EMG signal taking into account the unpredictable nature and changing dynamics of noise picked up from the surrounding environment while using dry EMG electrodes. In addition, we also propose an instrumentation scheme which not only cancels noise using analogue filters and Driven Right Leg circuit, but also provides a signal offset without the use of adder circuits to enable an ADC to acquire the signal. In order to validate the performance of the proposed signal processing and instrumentation scheme, we perform an analysis of the filtered EMG signal in time and frequency domains in terms of signal to noise ratio, discrete Fourier transform, and cross spectral density. In the end, we will come to a conclusion that the signal acquisition scheme proposed provides an EMG signal which sufficiently reduces noise and can be useful for various EMG applications.**

Keywords— Bio signals, electromyography, instrumentation, adaptive filter, signal processing, dry EMG electrodes

I. INTRODUCTION

The advent of bio signals has provided us great insight into the natural processes of the human body. The commonly used bio signals are namely electrocardiography (ECG), electromyography (EMG), and electroencephalography (EEG). These signals provide valuable information regarding the functioning of the heart, muscles, and brain [1]. In this paper, we focus on surface electromyography, which is a method to acquire the EMG signals by placing sensing materials called electrodes over the skin of the human body [2]. The EMG signal gives information regarding activation of the muscles when they are provided efferent signals from the central nervous system down to the individual muscle fibers [3]. EMG serves as a valuable bio signal as it arguably provides the most natural translation of muscle force to an electrical signal [4].

Since the discovery of EMG signals, it has found great applications in clinical studies for motor unit recruitment, motor unit disorders, identifying neuromuscular diseases, and kinesiology. Since the amplitude of the EMG signal provides a roughly linear relationship with the force produced by muscles of the human body, it has been used as a tool for human machine interface [5]. Interesting examples of human machine interface using EMG range from simply controlling slides of a computer presentation to control of robotic arms using intention estimation of the user [6]. It is for these reasons that the EMG signal needs to be properly filtered so that it may be used for its more intricate applications as the EMG signal is susceptible to contamination by noise [7].

There have been many studies regarding the means to acquire the EMG signal and much research has already been done regarding instrumentation design for EMG signal acquisition. The most common way to acquire EMG signals is the bipolar technique where two electrodes are used to acquire the EMG signal in a differential scheme [8]. In most EMG applications, wet or gelled EMG electrodes are used which have low electrode skin impedance, reduced impedance mismatch at the analogue front end, and allow for a stable electrode skin contact [9]. However, wet EMG electrodes have disadvantages of limitations in long term use which hinder their application in certain applications e.g. robotic prosthesis. Thus, dry EMG electrodes are used to substitute wet electrodes. Dry EMG electrodes, however, show high electrode skin impedance, high impedance mismatch at analogue front, and consequently a high noise input to the electrode front end [10]. It is for these reasons that it becomes important to remove noise in order to have the most accurate estimate of the EMG signal for its intricate applications such as intention estimation of individual fingers where the signal can be very small in amplitude [11].

In this paper, we propose a method for application of adaptive noise cancellation from the EMG signals using an external noise source which is roughly correlated to the noise mixed with the EMG signals. We suggest a signal processing scheme which uses the adaptive filter to cancel the noise from the EMG signal in real time. The adaptive filter automatically adjusts filter weights according to the changing nature of noise with time [12]. Hence, the filter can be used in high noise environments, instances where noise dynamics are unknown, and where it is unsure whether the power line interference is at 50 Hz or 60 Hz. Thus, the adaptive filter provides an advantage over ordinary fixed coefficient filters which are only designed to remove a fixed frequency of noise from the signal [13]. The adaptive filter statistically cancels the noise which contaminates the EMG signal using an additional noise channel whose signal is correlated with the noise observed with the EMG signal. Thus, the filter allows us to remove noise contaminations which may be distributed in the frequency domain [14].

Muhammad Zahak Jamal, Dong-Hyun Lee, and Dong Jin Hyun are presently working as part of the Articulated Robotics Group, Robotics Team at the Hyundai Motor Company, Uiwang Research Center, Uiwang-Si, Gyeonggi-Do, 16082, Republic of Korea (Author e-mails: 6830018@ hyundai.com, lee.dh@hyundai.com, mecjin@hyundai.com).

The concept of the adaptive filter has been studied in detail in contemporary literature [15]. The application of the adaptive filter has already been applied in the case of ECG signals, and the removal of noise artifact from ECG signals [16]. In this paper, we expand the application of the adaptive filter to EMG, where noise values can be unpredictable i.e. high or low depending on the environment surrounding the subject. In addition, we also propose a signal acquisition instrumentation scheme which uses a modified Driven Right Leg circuit to not only reduce noise, but also provide a signal offset so that it may be used with the ADC of a microcontroller.

II. Electrodes

The material of the dry EMG electrodes selected for this study is silver. The reason why the material silver was selected is that it shows good compatibility in EMG recordings [3]. It also shows better values of electrode skin impedance as compared to its counterparts [3]. An apparatus was designed to place three electrode surfaces. Two electrodes were used to acquire the EMG signal in a bipolar differential signal acquisition technique, and the third electrode was used as a reference electrode placed in between the two surfaces. Two armbands were used to place the electrodes on the target muscle location which was the flexor digitorum profundus muscle in the forearm. The reference electrode was positioned in the middle of the signal electrodes. The center to center distance of the reference electrode to the electrode on its either side is 11 mm, and the inter-electrode distance of the signal pick-up electrodes is 23 mm. The length and width of the contraption are 36 mm and 18 mm. The apparatus carrying the electrodes is shown in Fig. 1.

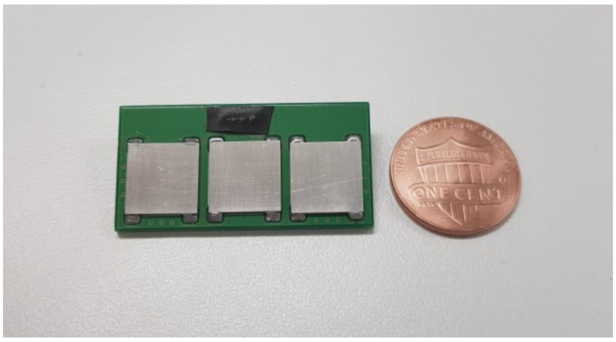

Figure 1. Apparatus containing 99.9 % silver electrodes used for EMG detection compared with a one cent coin

III. Instrumentation Design Methodology

The acquisition of the EMG signal is achieved using a hardware circuit. The instrumentation design can vary depending upon the designer's requirement for the engineering problem. However, almost every circuit design consists of a pre-amplification circuit which consists of an instrumentation amplifier [9]. We used the bipolar signal acquisition method, i.e. two electrodes are used to acquire the EMG signal. The instrumentation amplifier for our application is the INA333. However, unlike most circuits, the designed instrumentation circuit consists of a modified driven right leg (DRL), which drives the skin to an offset level of 1.65 V. Thus, the signal's reference was set to 1.65 V rather than 0 V. Furthermore, since the signal was at a 1.65 V reference; therefore, the reference electrode was also at a 1.65 V reference [17]. This was done so that the signal acquired from the circuit could be directly input to a microcontroller with a positive supply input. In addition, the DRL circuit is known for its role in the effective removal of common mode noise from the EMG signal [18]. The circuit was also equipped with a third order band pass filter. The bandwidth of the signal was set between 16.3 Hz and 613 Hz, and the complete system gain was set at 2000. The circuit was designed to function using a +3.3 V supply voltage.

For proper understanding of the instrumentation design, a block diagram of the schematic is shown in Fig. 2, and the instrumentation circuit is shown in Fig. 3.

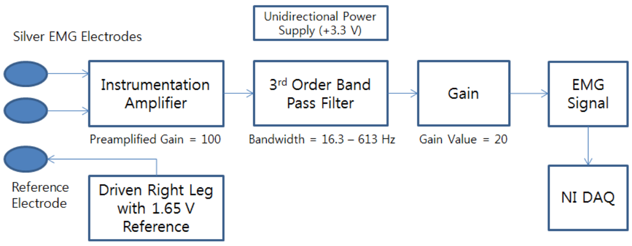

Figure 2. A block diagram of the instrumentation scheme designed for EMG acquisition

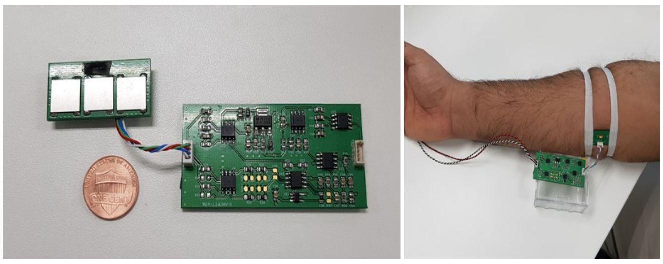

Figure 3. (Left) The instrumentation circuit designed for EMG signal acquisition. (Right) An image depicting electrode location for measurements

IV. Adaptive Filter Design and Implementation

In this study, our intention is to extend the application of adaptive filters to the EMG signal. The adaptive filter is a recursive filter whose weights change according to the surrounding noise. Therefore, this filter can be used to delete noise which can have changing dynamics in the frequency domain or remove noise components which are spread in the frequency domain and mixed with the target signal [14].

The adaptive filter is an FIR filter which works on the principle of the mean square error approximation, where the weights or coefficients of the filter act as features in a linear regression problem [19]. A general representation of the filter can be shown as in Fig. 4.

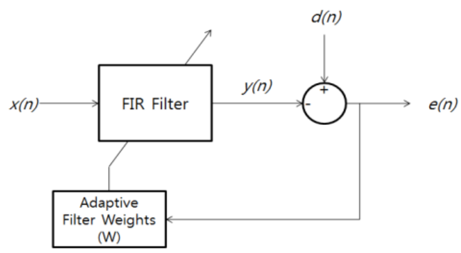

Figure 4. A block diagram representation of the adaptive filter

In our application, *d(n)* is the raw EMG signal acquired from the instrumentation scheme explained in the previous section. This signal may contain noise elements of 50 or 60 Hz, their harmonics, or other noise components distributed in the frequency spectrum [7]. The signal *x(n)* is the input signal which is roughly correlated with the noise carried by the EMG signal, and *e(n)* is the error signal which can not only be considered as our filtered EMG signal, but it also forms the cost function to evaluate the mean square error [19]. In other words, the adaptive filter is used to find *y(n)*, which cancels the noise carried by the signal *d(n)* to give a filtered signal *e(n)*. *y(n)* can be found by passing the signal *x(n)* through the FIR filter with adaptive weights *'W'* with *l* elements or weights which can be represented as in Eq. (1).

$$W(n) = [w_0(n) \;\; w_1(n) \;...\; w_{(l-1)}(n)] \tag{1}$$

The signal *y(n)* shown in Fig. 4 can be found as:

$$y(n) = W^T X(n) \tag{2}$$

Consequently, the error signal *e(n)* or the filtered EMG signal in our case can be found out by the following equation [19].

$$e(n) = d(n) - y(n) \tag{3}$$

The filter weights are updated every step according to gradient descent algorithm:

$$W(n+1) = W(n) + \mu[P_{dX}(n) - R_{XX}(n)W(n)] \tag{4}$$

'μ' is called the learning rate in Eq. (4). The vector $P_{dX}(n)$ and the correlation matrix $R_{XX}(n)$ are given as:

$$P_{dX}(n) = d(n)X(n) \tag{5}$$

$$R_{XX}(n) = X(n)X^T(n) \tag{6}$$

In this way, by using the adaptive filter, the filter weights are automatically updated with each computational iteration [19].

The question is to how to find the noise input signal which may be correlated to the noise in the EMG signal. We used the NI USB-6212 DAQ for our study to acquire both noise and preamplified EMG signal inputs. The preamplified or prefiltered EMG signal is acquired by hooking the instrumentation scheme explained earlier to the input channel of the DAQ in differential mode. Noise input can be obtained using two methods: placing an additional EMG electrode on the skin and hooking it onto the DAQ board, or hooking a wire on the DAQ with its other end open to act as an antenna in RSE mode. A floating signal input can be used for both these methods. We recommend using the antenna method to avoid placing an extra electrode on the skin. By using any of these methods, we can receive a stream of noise having many peaks in the frequency domain. While showing results in this paper, we will mostly focus on the frequency spectrum of the time signals as it is difficult to analyze random signals in the time domain. The signals are sampled at 1000 Hz. The FFT of the noise signal is shown in Fig. 5.

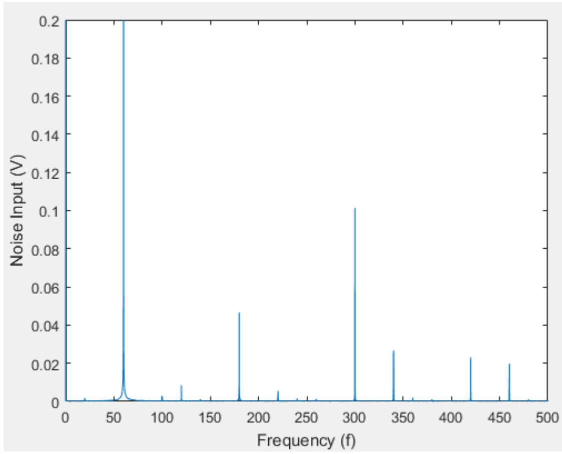

Figure 5. Frequency spectrum of the noise signal *x(n)*

We see from the above figure that the noise signal has peaks at 60 Hz and its harmonics. Thus, we can come to a conclusion that this signal can be effectively used to remove the noise in the EMG signal as it is correlated with the noise mixed with the EMG signal (*d(n)*) when the muscle is not flexed as shown cross spectral density graph in Fig. 6.

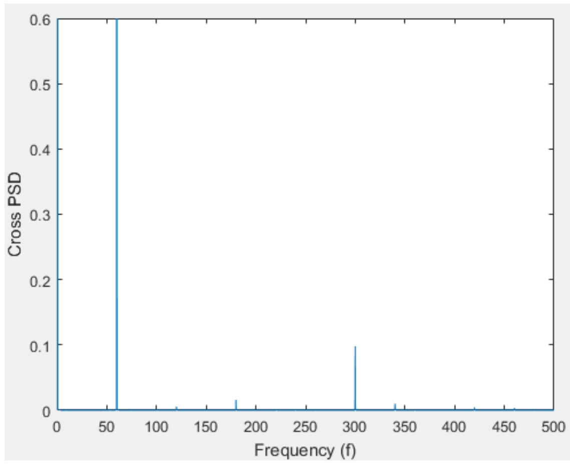

Figure 6. Cross Spectrum of noise in EMG signal and noise from Fig. 5

V. Results and Discussions

The adaptive filter explained from equations 1 – 6, was implemented using a Labview Program. Once that we have established that the noise mixed with the EMG signal and noise received from the open ended wire which acts as an antenna are correlated, we then proceeded to designing our signal processing scheme which centers around the adaptive filter. It is a common observation that there is a significant increase in noise in the EMG signal once the human body comes in contact with a power supply, battery, or a metal surface which may be connected to an electromagnetic source. In such cases, the 60 Hz electromagnetic noise component and its harmonics become even more significant [20]. The adaptive filter is especially useful in the removal of such noise which is unpredictable in nature. After properly observing the signal resulting from the adaptive filter, other filters were also added to further delete remnants of unwanted noise in the signal to complete the signal conditioning scheme. The digital signal conditioning scheme is shown in the Fig. 7.

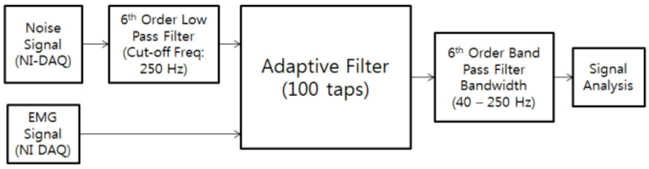

Figure 7. The final signal filter scheme for the EMG signal

The adaptive filter was designed with 100 coefficients or weights or taps which are found to be sufficient for our adaptive filter application [19]. Additional filters were added to further filter the EMG signal of remnant unprocessed noise from the adaptive filter. Since there were significant noise components of the 60 Hz electromagnetic harmonics at 300 Hz, it was deemed that the target EMG signal's frequency bandwidth be limited from 40 Hz to 250 Hz. This bandwidth is depicted by the 6th order band pass filter in Fig. 7. In addition, we also limited the noise signal to 250 Hz so that only the harmonic noise components less than 250 Hz have a role to play in the removal of noise from the EMG signal. Thus, a 6th order low pass filter was added to filter the noise signal as shown in Fig. 7.

There are two engineering design aspects of the adaptive filter: the selection of learning rate μ in Eq. 4 and selection of the number of coefficients. The response of the adaptive filter depends upon the value of learning rate μ. If the learning rate is small, the filter coefficients can be more accurate; however, the filter response can be slow and vice versa. There is one drawback of selecting a high learning rate as it can render the filter unstable [14]. Similarly, the selection of the filter coefficients is an important factor as well. The higher the filter coefficients, the better the response; however, higher number of filter coefficients can result in higher code complexity [15]. It is, thus, very important to select the optimum possible parameters for an acceptable response of the adaptive filter. We selected the number of taps as 100 and set the learning rate μ as 0.005. To see the effectiveness of the filter, first we show the frequency response of EMG signal along with noise which is mixed with it. In Fig. 8 it is shown that how noise affects the acquired EMG signal. Since EMG is a random signal, we focus our results more in the frequency domain rather than time domain.

We see in Fig. 8 that the dominant noise frequencies are located at 60 Hz and 300 Hz, and there is a DC error as well. The frequency spectrum of the result using the adaptive filter is shown in the Fig. 9.

In Fig. 9, we can see that the noise components in the frequency spectrum seen in Fig. 8 have been almost removed. For the interest of readers, a filtered time sample of the EMG signal is shown in Fig. 10.

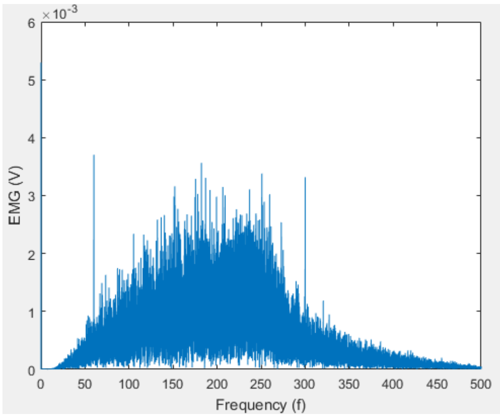

Figure 8. The frequency spectrum of the EMG signal mixed with noise. Two noise peaks are observed at 60 Hz and 300 Hz along with a DC error

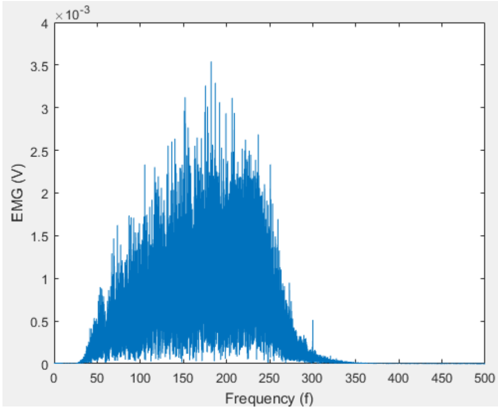

Figure 9. The frequency spectrum of the EMG signal after adaptive filter implementation

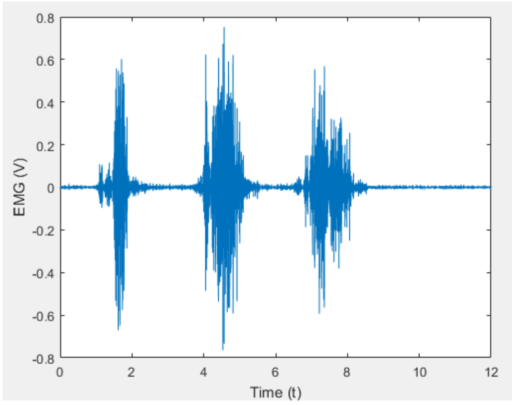

Figure 10. The frequency spectrum of the EMG signal after implementation of the adaptive filter

The adaptive filter is also very effective in high noise conditions. High noise in EMG signals is usually observed when the human body comes in contact with a power supply, surroundings with high electromagnetic interferences, or metal surfaces connected with power sources etc. Thus, noise becomes difficult to predict in these cases. The adaptive filter is particularly useful in this case as it deals with the statistical removal of noise which is correlated with the noise signal. An example of a frequency spectrum of a noisy EMG signal when the body comes in contact with a power supply is shown in Fig. 11.

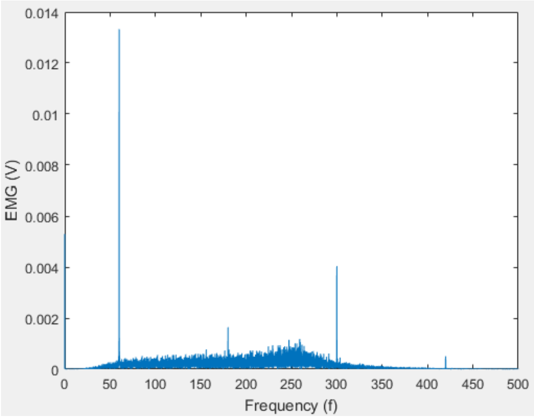

Figure 11. Frequency spectrum of a noisy EMG signal. The 60 Hz harmonic components have now become more prominent than in Fig. 8

The noise components in the EMG signal have become prominent in the frequency spectrum shown in Fig 11. We also see that additional 60 Hz harmonic components have become noticeable at 180 Hz and 420 Hz. The frequency response of the EMG signal after implementation of the adaptive filter is shown in Fig. 12.

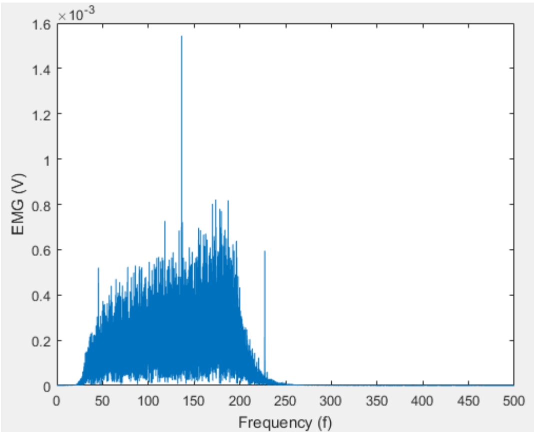

Figure 12. The frequency spectrum of the EMG signal after implementation of the adaptive filter

If we compare Fig. 11 and Fig. 12, we see that the noise in the signal has been considerably removed and the resulting EMG signal has become clean of contamination. We also observe that the major components of noise at 60 Hz, 180 Hz, and 300 Hz have been considerably deleted. For the interest of readers, a filtered time sample of the noisy EMG signal is shown in Fig. 13.

We also carried out comparisons of the filtered EMG signals with not only the unfiltered EMG signals acquired from the instrumentation circuit, but also with conventional ordinary fixed coefficient IIR filters. The comparisons were done in terms of signal to noise ratio (SNR) are shown in Table I. For the purposes of comparison, we used a 6^{th} order Butterworth band pass filter with cut off frequencies at 40 Hz and 250 Hz and used a 2^{nd} order notch filter at 60 Hz with a quality factor of 0.05. The comparisons using signal to noise ratio (SNR) were calculated by taking an average of five independent readings of noise and EMG signal, and the comparison is shown in Table I.

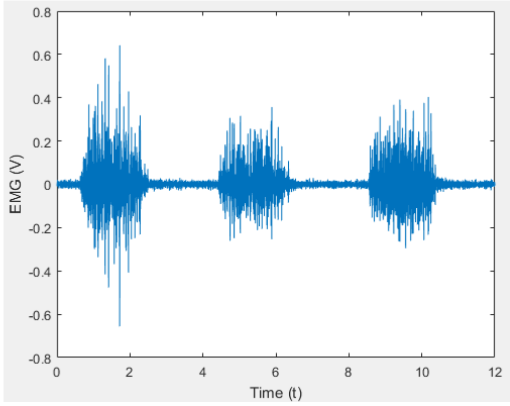

Figure 13. The adaptively filtered high noise EMG signal

Table 1. A comparison of the proposed signal filtering scheme as compared to an unprocessed EMG signal and a conventional IIR filtered signal

Noise Conditions in EMG Signal	Digitally Unprocessed EMG Signal SNR (dB)	Ordinary IIR Filtered EMG Signal SNR (dB)	Filtered Signal using Proposed Scheme SNR (dB)
Ordinary	25.1	28.8	37.6
High	5.8	24.4	25.1

Table 1 shows that the adaptive filter shows better filtering as compared to the EMG signal directly obtained from the instrumentation circuit. Furthermore, the adaptive filter has an added advantage that it filters the EMG signal with minimum loss of information, which makes it useful in its application to EMG signal.

VI. Conclusion and Future Work

We have shown how to implement the adaptive filter and have shown how it can be a useful method to remove noise from the EMG signal. We implemented the adaptive filter in real time and tested its effects in ordinary and high noise conditions. In both these conditions, we found that the adaptive filter based signal processing scheme is in fact much effective in cancelling noise from the EMG signal. For our study, we designed and developed an instrumentation scheme to acquire a preamplified and prefiltered EMG signal. We then designed a complete adaptive filter based signal filtering scheme using Labview and observed the performance of the adaptive filter in real time. We then saved the results and verified them in terms of signal to noise ratio.

An adaptive filter can be particularly useful in bio signal applications. The EMG signal finds one of its most extensive applications in intention estimation of a human being in human machine interfaces [21]. Since this signal is so susceptible to noise, it becomes exceedingly important to implement innovative means to filter the signal.

The salient advantages of the adaptive filter are that it automatically detects noise components and removes it from the signal as filter weights adapt themselves to change in noise dynamics e.g. DC noise, power line interferences (50 Hz or 60 Hz), and white noise (unpredictable noise distributed in the frequency spectrum) [14]. Hence, this system can be used easily in high noise environments, instances where noise dynamics are unknown, and where it is unsure whether the power line interference is at 50 Hz or 60 Hz. This is a particular advantage of the filter as target frequencies are specifically defined in fixed coefficient filters e.g. Butterworth filters. Therefore, it is highly recommended in complex EMG applications e.g. multichannel muscle physiological analysis and HMI intention estimation devices.

Our purpose of implementing the filtering scheme is to apply it in robotic human machine interfaces where a paraplegic or an upper limb amputee can easily control a robotic extension using the EMG signal to perform complex tasks e.g. moving individual fingers of a robotic hand [22]. However, we still feel that there is much room for improvement, as the application of the adaptive filter becomes a little more complicated in multichannel signal acquisition for specific tasks. Another area for prospective study is to find the optimum number of features or coefficients for the filter, and to find the optimal value of learning rate or μ. The selection of these engineering parameters is imperative in the robust application of the adaptive filter based design.

It is our objective to make the EMG signal more robust so that it can be useful in its various applications. With the increase of applications of bio signals in interesting and intricate fields, it is increasingly becoming essential to come up with useful ways to make the signal more beneficial in its applications. Applications in complicated human machine interfaces pose significant challenges in bio signal acquisition. Therefore, real time processing of the bio signal should be done appropriately for the control algorithms and the machine interface to work properly. We have made these problems a basis of our research to develop a practical signal acquisition mechanism for EMG signals for its various applications.

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