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Adaptive Filtering Technique and Comparison of PS25015A Dry Electrodes and Two Different Ag/AgCl Wet Electrodes for Wearable ECG Applications

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Abstract: The electrocardiogram (ECG) is one of the most important signals acquired from the body, as it serves as the immediate source of information relating to heart performance. Hence, a lot of research has gone into various types of ECG acquisition methods and systems. With the numerous methods and systems available at hand, it is important to compare, contrast, and evaluate the existing techniques. Not only does this help distinguish between the different techniques, it also helps build on the existing methods to create successful acquisition systems that can surpass the effect of unwanted factors, such as movement and other noise artifacts. This paper builds on a previous study that compared two different ECG acquisition systems, one of which uses PS25015A dry electrodes and the other, which uses two different silver/silver chloride (Ag/AgCl) wet electrodes. The adaptive filtering technique was implemented in order to test its effectiveness when applied to a wearable ECG medical device, intended to monitor the user's ECG throughout daily activities, such as walking. According to statistical analysis, the dry electrodes may have a better SNR. However, the dry electrodes provided a lower wave amplitude, compared to the wet electrodes. Overall, the least mean squares (LMS) adaptive filtering, along with bandpass filtering, helped reduce motion artifacts in ECG signals acquired during walking. *Copyright © 2015 IFSA Publishing, S. L.*

Keywords: Electrocardiogram (ECG), Wet electrode, Dry electrode, Cross correlation, Peak detection, Adaptive filtering, Least mean square.

1. Introduction

The electrocardiogram (ECG) has arguably become one of the most recognized and used biomedical signals. ECG is the electrical interpretation of the activity of the heart, and can easily be recorded with the use of surface electrodes either on the chest or limbs [1]. As the heart is one of the most important organs in the body, its contraction activity and performance is vital to monitoring health. The most important attribute of the ECG is that its shape is altered by abnormalities and cardiovascular diseases, such as arrhythmia, myocardial ischemia, premature ventricular contraction (PVC), infarction and many more [1].

In terms of its signal acquisition, there are various methods of electrode placement. ECG is traditionally recorded using 12-channels for clinical use. In this 12 lead configuration, electrodes are placed on the right leg, and both wrists. The three augmented leads are (aVR, aVL, aVF) and six leads are placed on the chest [1]. Additionally, the left and right arm, and the left leg are used for leads I, II and III, which together form Wilson's central terminal (reference for chest leads) [1]. However, ECG can also be recorded using 6, 5 or 3 leads [1]. Recently, the advancement in technology has made it possible to record ECG from only 1 lead, either on the chest or on a limb. Furthermore, various reputable sources, such as the American Heart Association (AHA), recommend that a minimum sampling rate of 500 Hz be used for ECG data acquisition, but that a sampling rate twice that of the theoretical minimum would be ideal, i.e., 1000 Hz [1-3].

ECG is traditionally used in clinical settings, such as in the operating room, to monitor the heart rate of the patient, or to analyze a patient for various cardiovascular diseases or abnormalities. However, as technology progresses and as we become more and more aware of our health and the proper functioning of our body, this important biomedical signal is being slowly introduced in our daily life as a way of continuously monitoring one of our most important organs. New electronics and hardware, with their high efficiency and small size, have created an opportunity for the design of wearable and wireless ECG recording devices and real-time monitoring systems.

Like other biomedical signals, raw ECG signals contain various sources of interference. These noise interferences are comprised of high and low frequencies from the power line, muscle movement, breathing, and other near-by electromagnetic sources and/or cables [4]. Since in many cases real-time monitoring of ECG is important, the ECG needs to be filtered and processed in such a way that there is nearly no delay between the acquisition and representation of the signal. Different processing techniques and algorithms have been suggested by researchers and used by manufacturers, however, when we look into implementing such processing techniques in a wearable wireless ECG device, extra caution needs to be employed with the algorithm design due to processing times and data transfer speeds.

One of the most predominant problems with ECG acquisition starts once the subject leaves the resting position and starts to move. This marks the time when the signal begins to pick up on various unwanted artifacts and noise. Adaptive filters are able to amend the frequency and impulse response based on the input signal and noise. This approach, for example, can be used to distinguish between the mother and fetus' ECG [1]. The main input to the adaptive filter includes both the signal and noise. The noise, e(n), is estimated and removed from the primary input using a reference input (in this case accelerometer data) [1]. The reference input, r(n), should be related to the noise interfering with the primary signal. The output, y(n), of the adaptive filter can be represented using (1) [1]:

$$y(n) = \sum_{k=0}^{N-1} \omega_k r(n-k), \tag{1}$$

where ω_k represents the tapped weights, N is the filter order, $r(n)$ is the input, and k is the tap number [1]. The weight vectors for this filter can then be computed using (2) [1]:

$$w(n+1) = w(n) + 2\mu e(n) r(n), \tag{2}$$

where μ is the convergence parameter and $e(n)$ is the error estimation.

Another way in which ECG data acquisition differs is in the choice of electrode. The two most common categories of surface electrodes are wet and dry electrodes. Wet electrodes, specifically Ag/AgCl, are among the most commonly used electrodes for bioelectric applications. They certainly have their advantages, such as their simplicity, ease of use, low weight, and that they are disposable [5]. However, they are not without their disadvantages. Electrolytic gel should be applied between the skin and the electrode in order to improve conductivity. This gel could cause allergic reactions or skin irritation [5]. These electrodes also have a limited shelf life due to dehydration, which affects impedance, generating noise [6]. The dehydration issues make these electrodes unsuitable for long-term continuous measurement [7]. Finally, the spacing between electrodes may be so small that the gel may smear and lead to short circuiting [8]. On the contrary, dry electrodes, generally metal plates, do not encounter any of these problems, and are easier to set up, however, they have their own drawbacks as well. Since there is no secure adhesion between the electrode and the skin, they can shift during motion [6]. Furthermore, these electrodes have relatively large contact impedance with the skin [6, 9].

A previous pilot study used two wet Ag/AgCl electrodes (3M Red Dot™ Monitoring Electrodes, and Bio-Protech Telectrodes) and a PS25015A dry electrode to simultaneously record ECG signals from the chest using one lead for 60 seconds while the subjects were seated [10]. The resulting signals were then analyzed and compared in order to draw conclusions based on their performance. This study built on the mentioned pilot study by gathering ECG data from the dry wearable ECG system, while the subjects were walking. The purpose of this project was to process the ECG data in order to remove any artifacts and/or distortions caused by physical motion, muscle movements, as well as respiration. Successful techniques can be used in the future to help achieve clean signals from wearable devices which are intended for daily monitoring.

This paper will proceed by looking at previous studies which have been done in relation to the comparison of dry and wet electrodes, in Section II. Section III will move on to outlining the proposed procedure regarding how the study was extended to process signals with motion artifacts. The results will be presented in Section IV, and finally Section V will wrap up with the concluding remarks.

2. Previous Studies

A paper by Chi M.Y., *et al.* [11] compared dry electrodes by analyzing the data acquired, as well as their performance limits. As mentioned in this paper, the circuit designs of electrodes seem to be described well in literature; however a detailed comparison between electrodes are yet to be found. A standard testing procedure that compares noise and errors between the electrodes does not exist.

Furthermore, Gandhi N., *et al.* [12] compared Ag/AgCl wet electrodes to dry and non-contact electrodes. The comparisons were made by analyzing noise processes, as well as the physiological measurements. The non-contact electrodes had a higher resistance compared to the conductive electrodes. ECG data acquired from various materials were all compared to data acquired Ag/AgCl electrodes. Simple comparisons were made between the graphs, by analyzed different amplitudes, noise artifacts and frequency drifts. Results showed that the best dry electrodes that can potentially replace wet electrode are ones with a PCB finish. Many dry non-contact electrodes were found to have low frequency noise, which restricts their use for clinical purposes.

Additionally, another study performed by Chi M. Y., *et al.* [13] compared wet and dry electrodes for EEG purposes. The electrodes were compared using EEG data acquired from 10 subjects as they gazed at a target stimulus, and amplitude sizes and steady state visual evoked potential (SSVEP) were used to compare the signals. The signals were compared using PSD values, signal-to-noise ratios, and cross correlation. The correlation between the wet and dry electrodes was nearly perfect. However, the correlation between the wet and non-contact were lower. However, a lot of the comparisons made between electrodes seem to be based on just the graphs or a few parameters, such as amplitude, SNR, and correlation. Table 1 compares the existing techniques used to compare electrodes, and shows how this paper further builds on these techniques to compare wet and dry electrodes.

Moreover, the previous studies have been limited in the parameters used for comparison. This paper builds on a study that proposed an in-depth statistical analysis method with numerous parameters to compare wet and dry electrode systems. Once a comparison of the signals at rest was completed, an adaptive filter was implemented to reduce motion artifacts seen in signals acquired by a wearable acquisition system.

There have been many studies that test the effect of adaptive filtering on noisy ECG signals. However, this study applies this signal processing technique to a wearable device that is intended to provide continuous monitoring, while the user carries on with his/her daily activities.

Table 1. Comparison of Existing Techniques.

Comparison of Existing Techniques	
Chi M.Y., *et al.*	✓ Circuit designs ✓ Performance limits
Gandhi N., *et al.*	✓ Amplitudes ✓ Noise artifacts ✓ Frequency drifts
Chi M. Y. *et al.*	✓ Amplitudes ✓ SNR
Currently Presented Method	In-depth Statistical Analysis: ✓ Amplitudes ✓ Noise artifacts ✓ SNR ✓ Cross correlation ✓ DC off-set ✓ Mean ✓ Variance ✓ Std deviation ✓ Std error

A study by Tong D. A., *et al*. tested the ability of adaptive filtering to reduce ECG motion artifacts [14]. Their study showed that the adaptive filter did indeed reduce noise in the signal. Accelerometer data was used as the reference, and it was found that a reference signal with 3-axis' of motion worked better than 2-axis' of motion.

A similar study performed by Hamilton P. S. and Curley M. G. showed that adaptive filtering was able to reduce motion artifacts by 12.5 dB [15]. These studies both induced motion during acquisition by pressing on the electrode or pulling on the electrode wires. Not many experiments have focused on applying this technique towards a wearable ECG device.

Other studies compared different types of adaptive filtering techniques. A study by Chan K. W. and Zhang Y. T., for example, compared the variable step-size Least Mean Square (LMS) filter to the fixed step-size [16]. The varying step-size was found to produce better results than the fixed step-size. A study by Raya M. D. and Sison L. G. discussed the differences between the two most popular types of adaptive filtering: LMS and Recursive Least Squares (RLS) [17]. The LMS approach is a simple one which uses less computational time. All these factors were considered when designing an adaptive filter for the Plessey system in this study.

3. Methods

3.1. Subjects

The comparison method was tested on data acquired from the first three authors of this paper, which included one 32 year old male, and two females, 23 and 22 years old. These subjects were also used to gather data for the reduction of motion artifacts. The subjects were healthy and had no history of heart conditions.

3.2. Experimental Setup

Initial testing was performed on two ECG acquisition systems. The systems as well as different electrode types were compared by acquiring ECG signals from the chest at 1000 Hz. The Plessey ECG system was used to acquire dry electrode data, while the wet electrode system used was the CleveMed BioCapture. The skin was cleaned with alcohol wipes before positioning the wet electrodes.

The dry and wet electrodes can be seen in Fig. 1 and Fig. 2 respectively. As prescribed in the user manuals of the systems, the PS25015A dry electrodes, 3M Red Dot™ Ag/AgCl electrodes, and the Bio-Protech Ag/AgCl Telectrodes were placed near the subclavius muscles (3 cm beneath the left and right clavicles), as seen in Fig. 3 [18].

Fig. 1. PS25015A Dry Electrodes.

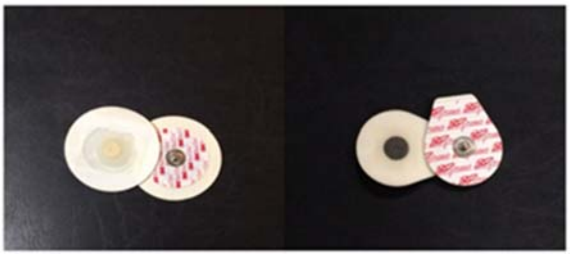

Fig. 2. Wet Ag/AgCl Electrodes: 3MTM Red DotTM Monitoring Electrodes (left) and Bio-Protech Telectrodes (right)

Standard chest electrode positions can also be referred to in a paper authored by P. M. Rautaharju, *et al.* [19]. Both elbows were used as ground (not shown in Fig. 3).

Once the electrodes were placed on the body, the dry electrodes were fed into the Plessey system, which was connected to a computer, and an offset of 0.1 V was implemented.

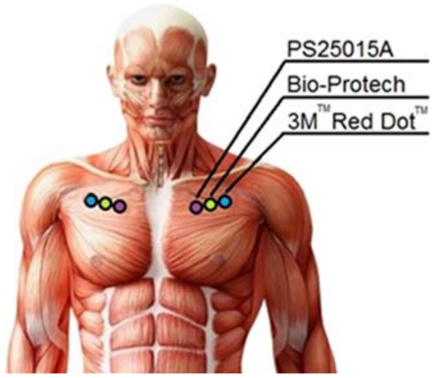

Fig. 3. Electrode Placement on the Chest [adapted from 20].

Snap leads were attached to each of the wet electrodes. The snap leads were fed into the input channels 1 and 2 and ground on the CleveMed Bioradio 150 system. The Bioradio was then connected to another computer via a wireless receiver. Moreover, data was acquired from both systems simultaneously; providing the same input to both systems, allowed for the quality and variations in the ECG signals to be analyzed.

In the first part of the study the ECG was measured from each subject for 60 seconds, in the sitting position, and three trials were performed on each subject. In order to compare the differences in dry sensor acquisition patterns between rest and during motion, the second part of the study consisted of recordings with resting ECG for the first 30 seconds followed by ECG during walking motion. The entire recording lasted for 87 seconds per trial. An accelerometer was used simultaneously, to gather motion data as noise reference to the ECG signal. A 3-axial accelerometer was used, to determine whether an adaptive filter can effectively reduce motion artifacts produced by a wearable ECG acquisition system. The data files were then converted into CSV files, in order to perform signal processing in MATLAB.

3.3. Signal Processing

The ECG signals acquired from both systems were sampled at 1000 Hz. Furthermore, the raw ECG data was filtered using low-pass, high-pass, and notch filters.

First, an 8 th order low-pass Butterworth filter was used with a cutoff frequency of 180 Hz. The filter was designed based on (3) [1].

$$|H(\Omega)|^2 = \frac{1}{1+(\frac{\Omega}{\Omega_c})^{2N}} = \frac{1}{1+\varepsilon^2(\frac{\Omega}{\Omega_p})^{2N}}, \quad (3)$$

where N is the order of the filter, Ω_c is the corner frequency, Ω_p is the pass-band edge frequency, and $1/(1+\varepsilon^2)$ is the band edge value.

Next a stop-band filter was used for a notch filter at 55-65 Hz, followed by a high-pass FIR filter with a cutoff frequency of 0.002 Hz. In order to detect heart rate, the R waves were made prominent by squaring the entire ECG signal. Peak detection was performed using the thresholding technique, similar to the R-wave detection performed by H. Kew and D. Jeong [21]. A threshold value was used to detect the R-wave peak, as seen in a study by P. Verdecchia, *et al.* [22].

Statistical analysis was performed on the R-wave peak values detected in order to compare the ECG signals obtained through the wet and dry electrode systems. The parameters computed include mean (4), standard deviation (5), variance (6), and standard error (7). The signals were also compared by computing the signal-to-noise ratios (SNR) and the cross-correlation. Cross-correlation (8) was performed on the outputs from each electrode to evaluate the similarity between the signals by obtaining the correlation coefficient [1, 23-24].

$$\bar{x} = \frac{\sum x}{n}, \tag{4}$$

where $\bar{x}$ is the mean, n is the number of samples and x are the data values.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}, \tag{5}$$

where σ is the standard deviation x_i are the data values and $\bar{x}$ is the mean of x_i.

$$\sigma^2 = \frac{\sum (x_i - \bar{x})^2}{n-1}, \tag{6}$$

where σ^2 is the variance.

$$SE = \frac{\sigma}{\sqrt{n}}, \tag{7}$$

where *SE* is the standard error.

$$r = \frac{\sum_i [(x(i) - mx) \times (y(i-d) - my)]}{\sqrt{\sum_i (x(i) - mx)^2} \sqrt{\sum_i (y(i) - my)^2}}, \tag{8}$$

where r is the correlation coefficient, $x(i)$ and $y(i)$ are the two signals, mx and my are their means respectively, and d is the delay.

An adaptive filter was designed in MATLAB and tested on the newly acquired data consisting of both resting ECG and ECG acquired during motion. Accelerometer data was used as noise reference for the adaptive filter.

The Plessey system and the accelerometer recorded data at two different frequencies. The higher the sampling frequency used for ECG acquisition, the better the accuracy [1]. Since the built-in sampling frequency of the accelerometer was much lower, the accelerometer data was upsampled to match the ECG sampling frequency of 1000 Hz. Upsampling was necessary in order to have equal accelerometer and ECG data vectors. This would allow for mathematical operations to be performed using the vectors when computing the errors.

During initial phases of testing, it was evident that the magnitude of the accelerometer data was much larger than the ECG signal. This resulted in the adaptive filter producing an output ECG signal which had a larger magnitude than the raw ECG signal. Hence, the accelerometer data was scaled down 500 times to matched the very small magnitude of the ECG data. In order to successfully remove artifacts from the ECG signals acquired from a dry sensor device, the following steps needed to be taken:

- Loading of simultaneous ECG and accelerometer data
- Upsampling of accelerometer data
- Removal of dropped bits
- Visualization of frequency spectrum
- Adaptive filtering
- Bandpass filtering

4. Results

Fig. 4 shows a sample plot illustrating the three ECG signals obtained from the three electrodes, PS25015A dry electrodes, Bio-Protech Ag/AgCl wet electrodes, and 3M Red Dot Ag/AgCl wet electrodes respectively. It is evident from Fig. 4 that the dry electrode system shows a lower amplitude, compared to the wet electrode systems. Both of the wet electrode systems show amplitudes of approximately 1 mV.

Thresholding was used to perform R-wave detection in order to detect the heart rate, similar to the techniques used by H. Kew and D. Jeong [21]. The average instant heart rate can be seen in Fig. 5.

Table 2 compares the processed data acquired from the three electrodes. As expected, the two wet electrodes showed higher correlation with each other than with the dry electrodes. The dry electrodes were found to have a negative DC-offset, compared to the wet electrodes, and provided the best SNR. Statistical analysis was performed on the R-wave peak values for each of the three electrodes, similar to analysis performed by G. Crifaci, *et al.* [25]. The 3M Red Dot electrodes showed higher mean R-wave peak voltages. For example, subject A had a mean R-wave peak of about 0.99 mV when measured through the 3 M Red Dot electrodes and a mean of only 0.39 mV when measured through the dry electrodes.

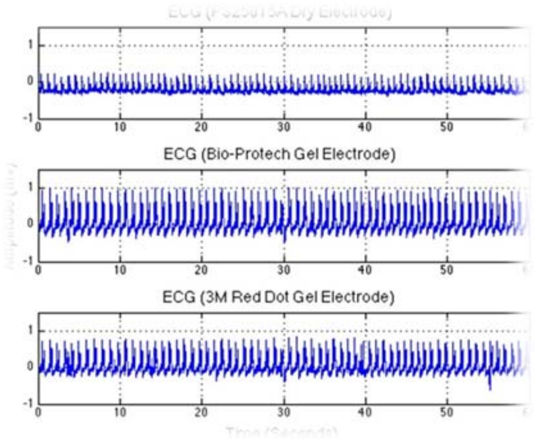

Fig. 4. ECG signals acquired from the three electrodes.

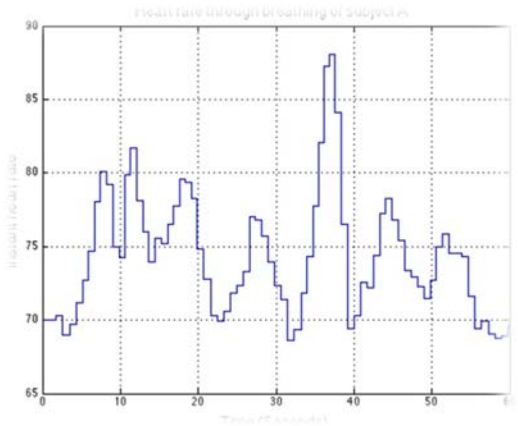

Fig. 5. Heart Rate while Breathing.

When comparing the standard errors across the three electrodes for the different subjects, the results seem to vary. Subject A had an error of 0.0011 mV for the dry electrode, and errors of 0.003 mV and 0.0054 mV for the wet electrodes, giving a slight difference of 0.0043 mV between the dry and wet electrodes, with the dry electrode having the lowest error. On the other hand, Subject B had an error of 0.0045 mV for the dry electrode, and errors of 0.0019 mV and 0.0017 mV for the wet electrodes, resulting in a difference of 0.0028 mV, with the dry electrode having the highest error. Similarly, for Subject C, there was an error of 0.01 mV for the dry electrode, and errors of 0.0072 mV and 0.0055 mV for the wet electrodes, resulting in a difference of 0.0045 mV with the dry electrode once again having the highest standard error. In summary, there is no suggestion of consistent differences in the standard errors between electrodes.

It is important to note that there were a few factors which may have affected the results. Although the data was acquired simultaneously from the three electrodes, there was an inter-electrode distance of 3.0 cm. This may have affected the results, as the electrodes were each acquiring ECG data from slightly different positions on the chest.

Table 2. Numerical Analysis.

	PS25015A	3M Red Dot	Bio-Protech
DC-Offset (mV)	-0.2099	0.0205	0.0239
Corr Coef (%)	PS25015A & 3M Red Dot = 5.05		
	3M Red Dot & Bio-Protech = 87.6		
	PS25015A & Bio-Protech = 5.71		
SNR (dB)	28.9	19.5	19.3
Subject A			
Mean (mV)	0.3897	0.9940	0.7050
Variance (mV)	0.0013	0.0094	0.0364
Std Dev (mV)	0.0355	0.0925	0.1669
Std Error (mV)	0.0011	0.0030	0.0054
Subject B			
Mean (mV)	0.172	0.7952	0.6320
Variance (mV)	0.0056	0.0066	0.0027
Std Dev (mV)	0.0697	0.0572	0.0510
Std Error (mV)	0.0045	0.0019	0.0017
Subject C			
Mean (mV)	0.0708	0.2490	0.4420
Variance (mV)	0.0010	0.0124	0.0295
Std Dev (mV)	0.0322	0.1110	0.1711
Std Error (mV)	0.0100	0.0072	0.0055

The skin was wiped with alcohol before the electrodes were positioned; however, there may not have been 100 % electrode-to-skin contact.

Furthermore, the dry electrodes were attached firmly onto the subject, but the pressure on the electrodes may not have been uniform for the entire duration of the experiment because of the elasticity of the fastening band. Moreover, two individuals were running the two systems on two different computers to start data acquisition. Hence, there may have been a slight delay in start/stop times during acquisition, but this was adjusted in the data analysis by aligning the R-waves.

For future work, the results may be more definitive if more subjects are used. Once the different sensors were tested, adaptive filtering was performed on data acquired from the Plessey system. Fig. 6 shows an example of an ECG signal acquired from the device. The graph begins with resting ECG followed by ECG acquired during walking motion. It is evident that the raw data is affected by artifacts and distortions. Fig. 7 shows a close up view of the signal both at rest and during motion, while Fig. 8 shows both the accelerometer data and the ECG signal on the same chart, after the magnitude of the accelerometer data was adjusted.

Once adaptive filtering was performed, the input and output ECG signals were analyzed. Parts of the raw ECG signal acquired from the Plessey system showed flat horizontal lines during motion.

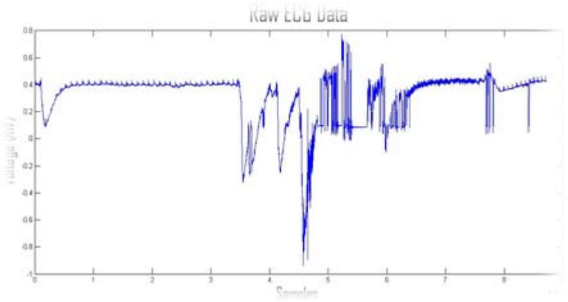

Fig. 6. Raw ECG acquired during rest and walking motion

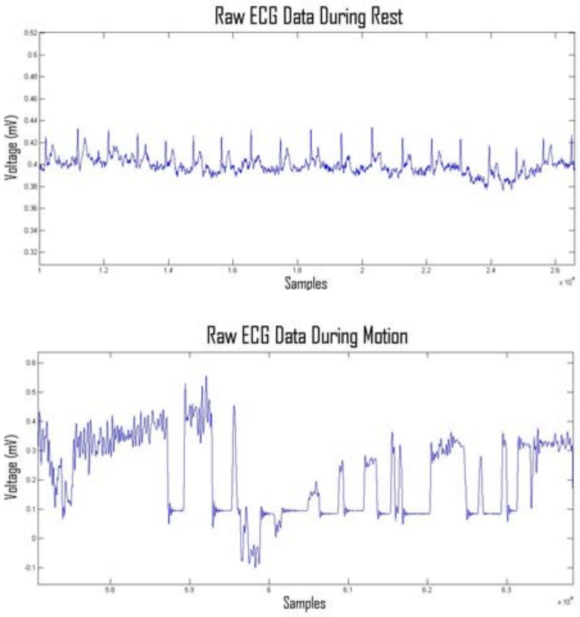

Fig. 7. Close up of ECG signal during rest and walking motion.

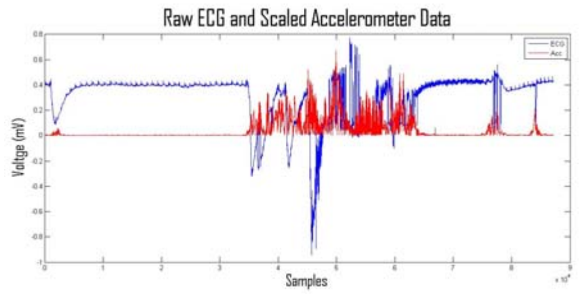

Fig. 8. Comparison of accelerometer data and ECG.

These dropped data bits were influenced by the accelerometer data which contained zero dropped bits. In order to increase the accuracy of the results produced by the adaptive filter, the algorithm was coded to only take into consideration parts of the ECG and relative accelerometer data that contained no dropped data bits.

Although the noise reference and the adaptive filter had an effect on the ECG signals, many of the large artifacts still remained in the output. Thus, the algorithm was further developed to test the effect of lowpass and bandpass filters. Once a lowpass filter was implemented at a frequency of 10 Hz it was evident that a bandpass filter was needed from a range of 10 to 15 Hz. A second order bandpass filter was designed by implementing a lowpass and highpass filter. The difference between implementing the bandpass filter before rather than after the adaptive filter was negligible. As seen in Fig. 9, there is a significant difference before and after the adaptive and bandpass filters were implemented. ECG peaks can be seen in parts of the signal that were superseded by the motion artifacts.

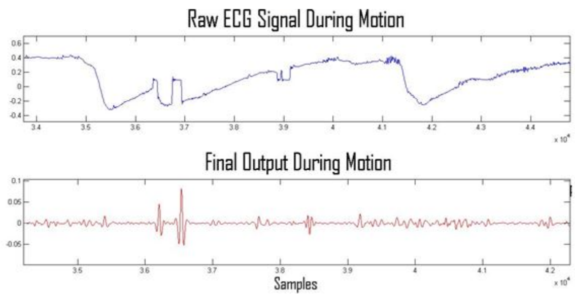

Fig. 9. ECG signal before and after filtering.

Hence, adaptive filtering is a valuable technique that can be used along with other signal processing methods to help clean up signals acquired from new wearable devices that aim to measure medical signals during activity.

5. Conclusions

The results showed fairly high signal-to-noise ratios and varying mean and variance ranges for each electrode type. However, there were suggestions of differences between the electrodes, such as the SNR, where the dry electrodes seemed to have a better SNR in our subjects, compared to the wet electrodes even though they recorded at lower amplitude. Although both types of electrodes have their own advantages and disadvantages, the determination of the most advantageous option is dependent on the individual user's applications and needs. For example, if the user desires a higher SNR value, dry electrodes should be used. However, if a lower standard error is desired, then wet electrodes should be used. The advantage of this approach consists of clearly defined pros and cons for each system so that the user can make a more informed decision. The LMS adaptive filtering technique, used with a 3-axial accelerometer noise reference, significantly reduced motion artifacts in the signals acquired from the Plessey system. For future work, these values can be compared to a wider range of dry and wet electrodes and ECG acquisition systems, and can be tested on a larger population for more accurate results. The adaptive filtering can also be tested while subjects perform other daily activities. It can be tested in addition to other signal processing techniques, to see if cleaner results can be obtained from wearable medical devices. Most importantly, the methods discussed in this paper can be used as a platform for the comparison of electrodes and the evaluation of signal processing techniques for wearable ECG devices.

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