

ECG Dry-electrode 3D Printing and Signal Quality Considerations

Abdelrahman Abdou, *Member, IEEE* and Sridhar Krishnan, *Senior Member, IEEE*

Abstract— A single-lead electrocardiographic (ECG) sensor with 3D printed dry electrodes is developed and tested for short-term wireless ECG monitoring. In a first of its kind approach, a 3D printer and available cost-effective conductive plastics are used to manufacture dry electrodes that can detect an ECG when placed on the chest. The electrodes could be produced in less than 10 minutes and with minimal material resources. To demonstrate the utility of the newly developed sensor, 30-second, 1 and 5-minute recordings are captured and statistically analyzed using established Signal Quality Indices (SQIs) for consumer and medical-grade ECG applications. Heart rate (HR) algorithmic considerations for dry electrode ECG is also explored. The performance of the proposed dry electrode ECG is reliable for HR estimations similar to wet-electrode ECG measurements. The obtained ECG signals demonstrated acceptable quality with Signal to Noise Ratios (SNRs) ranging around 13 dB and Kurtosis Signal Quality Index (kSQI) from approximately 18 to 21. Also, visually, the QRS complexes and T-wave features of an ECG were easily identifiable. These dry electrodes are feasible low-cost rapid manufacturing solutions for single-lead ECG monitoring that takes into consideration the added benefit of better patient comfortability, good quality ECG content and minimum cost for electrode development.

I. INTRODUCTION

Many wellness and medical wearables start relying on ECG and photoplethysmography (PPG) based biosignal acquisition in determining the heart health of individuals [1]. Some prominent wearables such as the Apple Watch Series 4 solely rely on single-lead ECG technology to determine HR in Beats per Minute (BPM), and also monitor the presence of Atrial Fibrillation (AF) in its users [2]. Many wearable companies developed their own approaches in obtaining single-lead ECG information using different types of sensors and acquisition techniques. One of the most important research segments in this field is in the development of dry electrodes to replace wet electrodes for medical and wellness applications alike. The goal of dry electrode research is to achieve better comfortability for wearable users, producing higher quality ECG while also maintaining a high standard of clinical relevance for medical diagnosis. Dry electrodes can be used for longer periods of time for long-term monitoring applications without compromising patient comfortability [3]. Dry electrode development is suitable for mass production and low-cost applications.

There are many ways that researchers partook in to achieve the above-mentioned goals. Chlaihawi et. al developed flexible dry ECG electrodes by printing silver (Ag) ink on a substrate that was later coated using Polydimethylsiloxane (PDMS), a popular conductive hydrophobic polymer chosen

by researchers in the field [4]. Three different sizes of the electrode were developed and compared to standard wet electrodes. Chlaihawi concluded that their developed dry electrode is highly reproducible and was able to identify key ECG characteristics during motion and rest due to the electrode's high conformal contact with the skin [4]. While Meziane et. al reviewed most dry electrodes for ECG applications. The authors produced 3 different categories: stiff material, soft/flexible material and fabric dry electrodes [5]. Stiff material dry electrodes constitute stainless steel, aluminum, brass, ceramic and other types of hard metals that were used in detecting ECG signals. Soft material dry electrodes include conductive foam, polyesters, conductive polymer paste, polymer coated metals, thermoplastics, and other soft-based materials. Lastly, fabric dry electrodes include silver-coated yarns, and any material that can be developed as conductive threads such as polyester and other metal coated yarns [5]. Meziane et. al also explored the use of amplifiers and microcontrollers for dry-electrode ECG systems and recommend using single-chip instrumentation amplifiers for patient safety, low bias current and high Common Mode Rejection Ratio (CMRR) [5]. Also, they discuss certain practical design considerations that consider skin-electrode interface and wirelessly transmitting ECG data to a server [5].

To the best of our knowledge, there has been no attempt in 3D printing dry electrodes using already available conductive Polylactic Acid (PLA) filaments. After 3D printing, the electrodes are ready for use, and they do not undergo further structural processing. The used conductive PLA is a conductive carbon polymer that is semi-flexible [6]. This material is mainly used in tactile sensors, robotics, and low conductivity applications, and its potential candidacy for ECG dry electrode fabrication will be explored. This approach is chosen because it is cost-effective, can be mass produced in a rapid fashion, uses available production techniques such as 3D printing, and can detect low-current based signals such as ECG.

To ensure that electrode signal quality is maintained and is of a high clinical standard, many methods and SQIs are developed. Common SQIs in the literature include kurtosis, skewness, histograms, Signal to Noise Ratio (SNR), HR estimation, standard deviation (SD), activity, mobility, complexity, zero crossing rate, turn counts and signal frequency content [7]. This work will utilize kSQI, skewness signal quality index (sSQI), histograms, SNR, activity, and mobility to determine the overall signal quality. These SQIs are chosen because they could reflect ECG morphology and rhythm, and are reliable indicators of ECG signal quality. In

addition to visually inspecting and labelling of QRS complexes, the signals will undergo known HR detection algorithms to examine its feasibility of producing a reliable HR estimation for consumer and medical applications. To the best of our knowledge, the above mentioned SQIs have not been used with 3D printed dry electrodes and an examination of its use with available HR algorithms such as Pan-Tompkins QRS detection technique have not been explored.

Kurtosis is used to determine the Gaussianity of a signal distribution. ECG signals are known to be hyper-Gaussian which exemplifies that higher kSQI values represent lower quality ECG [7]. On the other hand, skewness is defined as the examination of the symmetry behavior of a distribution. sSQI can be used in ECG to determine whether the signals are heavily tailed, values above -1 or 1, or moderately tailed values range between -0.5 and -1 or 0.5 and 1. sSQI with values below 0.5 or above -0.5 identify the distribution as approximately symmetrical. Tail behavior is associated with noise context in the signal where heavily tailed ECG signals show more noise than moderately tailed signals. Histograms assist in visualizing the distribution of the signal, and they are valuable in examining the skewness visually. Activity and mobility of the signal can be used to see the randomness of the signal where activity is defined as the variance of the signal and mobility the square root of ratio of the first derivative variance to original signal variance [7]. As both values increase for an ECG, the higher the noise presence of different noise sources is detected. Lastly, SNR is defined as the measure of the desired signal power to the noise power of the signal [8]. This ratio determines the overall quality of the ECG signal in comparison to its noise in the form of decibels (dB).

II. METHODS

For the development of the dry electrodes, a 3D printing filament with electrically conductive properties is used; Proto-pasta Conductive PLA 1.75 mm filament. An ANYCUBIC i3 S 3D printer is used to print the dry electrode design as shown in Figure 1 using printing settings that are appropriate for the above-mentioned material; Nozzle Temperature: 215 °C; Heated Bed Temperature: 60°C; Print Speed: 35 mm/s, Fill Ratio: 100%. The 3D printing material and printer are chosen because they are easily accessible which helps in examining the feasibility of printing dry electrodes using available materials and technology. The electrical conductivity and resistivity of the electrodes are examined using a multi-meter to ensure the 3D printed

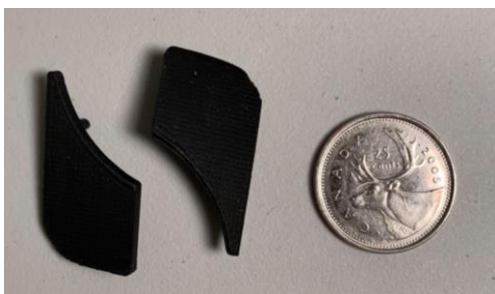


Figure 1: 3D Printed Dry Electrodes

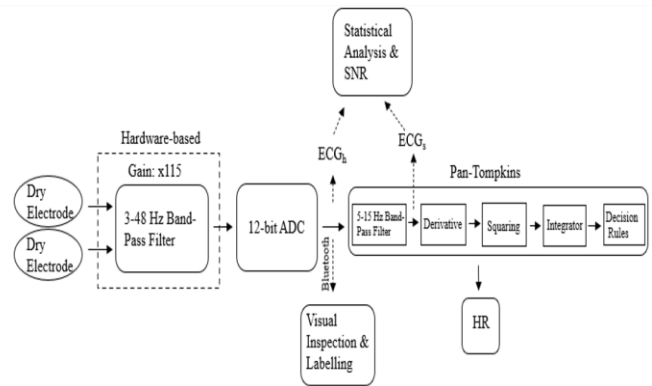


Figure 2: Experimental Single-lead ECG Device Setup

electrode material properties did not change with heating, cooling, and reshaping.

In Figure 2, the experimental design setup of a signal lead-ECG device is shown. The hardware-based 3-48 Hz Band-Pass filter is used to eliminate power line interference and high frequency (HF) noise before signal digitization and transmitting it in real-time through Bluetooth to a graphical web-interface. The hardware filter is deployed using the Analog Front-End (AFE) AD8232 Chip. The signal is later digitized and wirelessly transmitted using a STM32WB55 microcontroller. The signal is analyzed visually on the PC to ensure that we are collecting ECG signals. The main ECG signal characteristic waves are identified, P, Q, R, S and T waves. The QRS complexes are labelled through visual inspection.

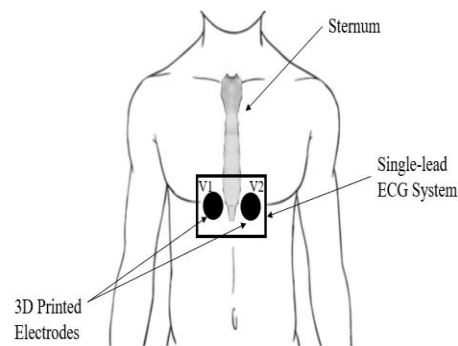


Figure 3: Dry Electrode Positioning on the Chest

Dry electrodes are positioned at V1 and V2 chest locations, as shown in Figure 3. These positions are chosen because they show the best quality of ECG visually through trial and error and reasoned by mimicking approximate locations of wet electrode positions for the V4 channel in a 12-lead ECG system. The electrodes are placed in those positions because the ECG signal has the highest amplitude and is the closest to the apex of the heart. 30 seconds, 1 minute and 5-minute ECG recordings are obtained to examine the short-term signal acquisition repeatability of the dry electrodes. The device is placed on the body for 10 seconds before signal acquisition to consider ECG settling time. Also, ECG acquisition is performed in a relaxed sitting position without any previous electrode skin preparation. It is important to note that the single-lead ECG device can operate for a maximum of 6 hours

of continuous operation and have a recording potential of that time length. Such a long-term recording provides opportunities for robust ECG signal analysis needed in many health and wellness applications.

The 12-bit digitized ECG signal is recorded and analyzed offline. Frequency-domain analysis is performed, and the spectral plot is obtained to examine the most prominent frequencies in the ECG. The Pan-Tompkins algorithm is used to determine average HR from the recordings. The algorithm performs a 5-15 Hz band-pass filter to ensure that any hardware-based noise is removed such as Bluetooth and random radio wave interferences. This step is performed because the single-lead ECG system is not shielded.

Performance metrics-based analysis such as statistical analysis and SNR calculations are performed. These performance metrics are chosen because they are easy to obtain from the signal, contain highly relevant information about signal quality and are used extensively in literature as a feature selection tool. Statistical analysis is also used to examine the ECG signal's features that can act as a validation step for future researchers in 3D printing dry electrodes. The statistical analysis involved; histogram, kSQI, sSQI, SD, activity, mobility, and standard deviation error computations of the ECG_h, the ECG signal obtained after hardware filtering. The ECG_s is the signal obtained after the software filtering portion of Pan-Tompkins. SNR is calculated by taking the ECG_s signal as the signal of interest and ECG_h as the noise power signal because it is the raw ECG obtained that contains motion artifact and other noises. SNR is calculated to examine ECG quality empirically and determine what kind of role that simple hardware-based filtering for dry electrode ECG can perform. While HR is estimated using Pan-Tompkins to see if whether 3D printed dry electrodes are reliable enough to operate with already available HR detection algorithms.

III. RESULTS

The experimental setup described above is used to obtain 3D printed dry electrode-based ECG signals and analyze its feasibility and use in HR detection for consumer and medical applications alike. ECG signals of different recording length are statistically analyzed and examined visually. In Figure 4,

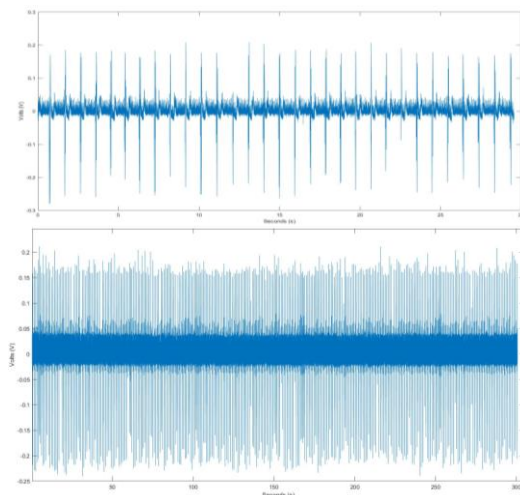


Figure 4: 30 second- and 5-minute ECG Signals

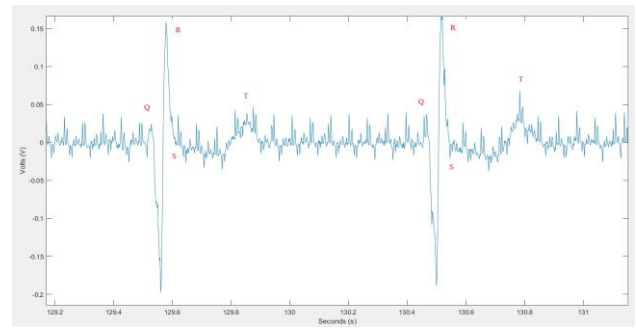


Figure 5: Snapshot of 2 ECG cycles from 5-minute signal with labelled QRS Complex and T-wave

30 seconds and 5-minute signals are presented for visual inspection. The QRS complex and T-waves are easily identifiable in all signals recorded however the P-wave is not evident, as shown in Figure 5.

Spectral diagrams are obtained to determine the significant presence of different frequency bands in the collected signals. Although hardware filtering is implemented to eliminate power line and HF noise above 48 Hz, significant HF noise is present, as can be seen in Figure 5, and this is due to the lack of proper device shielding. This noise is what lead to the inability to identify the P-wave of the ECG.

In Figure 6, 30 seconds and 5-minute recordings have histograms that are slightly skewed to the right. The 30-second recording showed a sSQI of -1.24, representing heavy skewness while the 5-minute recording showed a skewness of -0.62 representing moderate skewness.

All SQIs improve with longer duration of dry electrode ECG signals, as shown in Table 1. kSQI, sSQI decrease with increased recording length. Both values are related to the presence of randomness in a signal. Normal ECG signals are periodic in nature, which means that with longer signal length, the presence of a repeating rhythm is more evident than the noise/randomness present. As for SD, activity, mobility, the values are relatively stable across all signals. These in fact occur because the morphology of the ECG does not change over time which indicate that the person's ECG is normal. It is important to note that SD, activity, and mobility SQIs are

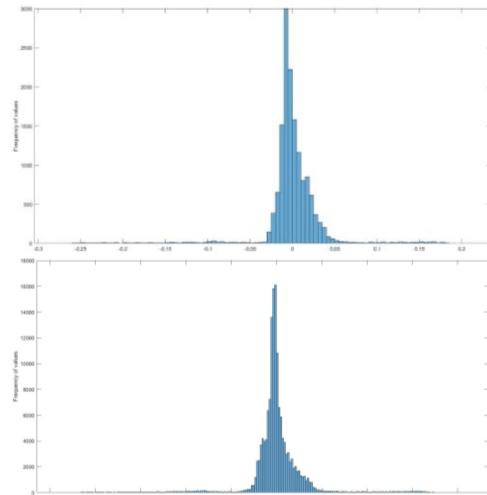


Figure 6: Histograms for 30 second- and 5-minute Signals

used in feature selection algorithms to determine abnormalities in ECG. The 5 minutes signal showed the highest SNR of, 13.05 dB. HR increased with an increase in recording time where 30 seconds, 1 minute, and 5-minute signals showed 63, 65, and 66 BPM respectively.

TABLE I. SQIS FOR DRY ELECTRODE ECG

	30 seconds	1 minute	5 minutes
kSQI	21.56	19.45	18.90
sSQI	-1.24	-0.75	-0.62
SD	0.0344	0.0335	0.0317
Activity	0.0012	0.0011	0.0010
Mobility	3.18	3.26	3.15
Standard Deviation Error	2.83×10^{-4}	1.94×10^{-4}	8.18×10^{-5}
SNR in dB	12.33	12.77	13.05
HR in bpm	63	65	66

IV. DISCUSSION

The proposed dry electrode and single-lead ECG system design are used to determine the feasibility of 3D printing conductive plastics in reliably acquiring ECG and estimating HR. Also, the proposed system design examines the potential of using hardware filtering instead of software to decrease the computational complexity for real-time applications. ECG signal integrity, obtained by dry electrodes, is explored through studying some statistical features that are important SQIs. SNR is examined to see the role the impact of noise on the signal. Spectral plots are also offered to show how dry electrodes impact the frequency range of acquired signals.

Through visual inspection, the QRS, and T-wave features of an ECG are observed. However, the P-wave cannot be seen. HF noise is evidently a main contributor for the lack of P-wave where the noise is superimposed on the ECG's P-wave, as shown in Figure 5. This issue arises due to multiple factors that were later considered in the design. There is a lack of proper shielding for the hardware components of the device. Noise could be picked up from surrounding electronic devices including the laptop used to visually inspect the ECG signals and cellular devices. Although noise is still obvious in the signals, HR calculations and R-peak detection were not impacted.

Statistical analysis is performed and SQIs are determined. kSQI values for all signals are produced. The degree of kurtosis and skewness represent the randomness in a signal that impacts its quality. In Table 1, 30 seconds signal showed the highest kSQI and sSQI which shows it's the lowest quality compared to the other two longer duration signals implying that noise is more present in the 30 second signal. SNR is another metric that shows the presence of noise. With an SNR of 12.33 dB, the 30-second signal show a lower quality than the 5 minutes signal. Although all signals show some degree of difference in their quality, the signals produce HR estimations that are reasonable whereas the 1 minute and 5-minute signals have approximate HR with a difference of a single beat. This in turn is due to the Pan-Tompkins known

robustness to some degree of HF noise. It is evident that Pan-Tompkins performs well using dry electrodes for short-term ECG signals. This concept can be used in the design of low-cost single-lead ECG system for HR estimations based on available dry electrode materials and 3D printing. It is important to note out that longer ECG recordings should offer better quality signals, especially for dry electrode-based ECG because skin perspiration from longer electrode contact lead to lower electrode-skin impedance like wet electrodes. This aspect is not the case in this work because the short period comparison between 30 seconds up to 5 minutes do not allow for skin perspiration to occur.

V. CONCLUSION

3D printed dry electrodes for HR estimation is feasible for short term single-lead ECG. 3D printed electrodes are easier to make and develop for simple ECG acquisition on the chest without any previous skin preparation. The dry electrodes are developed using a 3D printer and PLA conductive filaments. Significant motion artifact and radio interferences can be picked through dry electrodes and the proposed single-lead ECG system. However, the algorithmic perspective of using Pan-Tompkins and inferencing the signal quality based on some statistical metrics show that existing HR estimation algorithms that are used with wet electrodes can work on 3D printed dry electrodes. Further work is required to examine the role of dry electrode design and electrode surface area on ECG signal acquisition. Also, the feasibility of single-lead ECG systems that are power and cost constraint should be examined in detail to determine its use in health wellness and connected healthcare applications [9].

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