Advancing Cardiac Care: The Future of Portable ECG Technology

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***Abstract*—This paper explores the challenges and advancements in portable Electrocardiogram (ECG) technology, particularly focusing on the limitations of current portable ECG systems in diagnostic capabilities compared to standard 12-lead ECGs. Despite their convenience and mobility, portable ECG systems typically offer fewer leads, hindering their diagnostic effectiveness. The paper proposes a hybrid device, combining the comprehensive diagnostic features of the standard 12-lead ECG with the portability and ease of modern portable systems. This aims to bridge the gap in cardiac care, especially in non-clinical settings where traditional ECG systems are impractical. The paper delves into the technological, clinical, and logistical aspects of creating a 12-lead portable ECG system, addressing potential challenges and strategies for overcoming them. The development of this hybrid technology marks a significant stride in cardiac diagnostics, promoting a more patient-centric approach and expanding quality cardiac monitoring to a broader population.**

***Index Terms*—ECG Labeling, ECG Synchronization, ECG Denoising, Cross-correlation, Correctness measure Portable ECG, 12 Lead ECG.**

I. Introduction

THE human heart generates a characteristic electrical waveform during each cardiac cycle, detectable through Electrocardiograph (ECG) devices. The ECG graph produced is crucial for identifying cardiac rhythm disorders, conduction abnormalities, and morphological changes, making the understanding and interpretation of these graphs critical for managing cardiovascular diseases. Recent technological strides have led to the development of ECG recorders, enhancing cardiac diagnostics.

At the forefront of cardiac diagnostics is the 12-lead ECG device, which provides an in-depth view of the heart's electrical dynamics. By utilizing twelve electrodes placed on the patient, this device captures detailed electrophysiological data from various vectors, effectively mapping the heart's electrical activity in three dimensions. The standard ECG comprises 12 leads, consisting of six limb leads (Lead I, II, III, aVR, aVL, aVF) and six chest leads (Lead V1, V2, V3, V4, V5, V6). The limb leads are recorded using electrodes placed on the arms and legs, while the chest leads are obtained by positioning electrodes at six different spots on the chest. Each of the 12 leads represents a specific spatial orientation, providing comprehensive information about the heart's electrical activity. However, the use of the 12-lead ECG device is not without its challenges. A significant issue is the need for a substantial power supply, which can be a logistical hurdle in some clinical settings or during mobile use. Additionally, the system can present tripping hazards in busy healthcare environments and during cardiac stress tests due to the numerous wires and electrodes involved. This not only complicates the setup process but also increases the risk of accidents Furthermore, the effectiveness of the ECG can be compromised by electrode misplacement, a common issue that can lead to inaccurate readings or misinterpretations, potentially affecting the diagnosis and management of cardiac diseases. These limitations underscore the need for continuous refinement and innovation in ECG technology. In addition to the traditional method of measuring ECGs, portable ECG devices have been developed to offer an alternative approach. These compact, handheld tools are designed to facilitate cardiac monitoring during routine activities, making them invaluable for ambulatory or long-term cardiac assessments. They provide essential insights into conditions such as arrhythmias and other cardiac irregularities. However, these portable ECGs have their own unique set of challenges, including issues with signal quality and lead synchronization. Both traditional and portable EKG devices are prone to motion artifacts, particularly when patients are physically active, which can disrupt the EKG signal. Furthermore, portable EKGs, used outside of the controlled clinical setting, are more susceptible to environmental noise sources. This includes electromagnetic interference from various electronic devices and radio frequency interference from wireless networks. These challenges are often more pronounced in portable EKGs due to their intended use in a variety of settings, unlike the more controlled environment suitable for traditional EKG tests. To address these challenges and maximize the effectiveness of portable ECGs, ongoing research is directed towards integrating advanced techniques. These include denoising methods, adaptive signal processing, and hardware improvements, all aimed at enhancing the quality of data captured by these devices. The goal is to align the performance of portable ECG readings more closely with those from traditional, stationary ECG machines. However, a significant limitation of portable ECGs is their inability to provide the full 12-lead functionality that is standard in traditional ECGs. Most portable devices offer only a limited number of leads, restricting their diagnostic scope compared to their traditional counterparts. Given these constraints, there is an imperative need for a hybrid 12-lead portable ECG device that combines the best of both worlds: the comprehensive diagnostic capabilities of the standard 12-lead ECG and the convenience and mobility of portable ECG systems. Such an innovation would represent a significant leap forward in cardiac care, allowing for more detailed and accurate cardiac monitoring in various settings outside of traditional clinical environments.

II. Literature review

The history of the electrocardiogram (ECG) begins with the first recording from an intact human heart by Augustus Waller in May 1887 using a mercury capillary electrometer. Waller's initial tracings were rudimentary, showing only two distorted deflections [1]. The significant advancement in ECG technology came from Willem Einthoven (1860-1927), a professor of physiology who initially used the mercury capillary electrometer for his ECG studies and later mathematically improved its distortion, enabling a more accurate representation of the ECG before the twentieth century. His major contribution was the development of a string galvanometer [2], which significantly enhanced ECG recordings. Einthoven's first publication on the string galvanometer appeared in 1901, with a more comprehensive description following in 1903, including ECGs taken with this new instrument [3].

The foundation of the modern 12-lead ECG system was significantly advanced by the pioneering work of Augustus D. Waller and Willem Einthoven. Waller was among the first to record the electrical activity of the human heart. However, it was Einthoven who made groundbreaking contributions that shaped the 12-lead ECG system as we know it today.

Einthoven's pivotal role in electrocardiography is marked by his innovative clinical implementation of ECG technology and foundational research. His work, especially evident in his seminal papers "Le Telecardiogramme" (1906) [4] and "Weiteres uber das Elektrokardiogramm" (1908) [5], revolutionized the understanding and application of ECG in cardiac disease research. These publications not only presented various ECG patterns and arrhythmias but also set the stage for the standardization of electrocardiographic techniques. His invention of a triaxial bipolar system, which consisted of three limb leads, brought a much-needed standardization to the recording of the heart's electrical activity. By conceptualizing the leads as vertices of an equilateral triangle—later known as the Einthoven triangle—he provided a method to visualize the heart's electrical axis in the frontal plane as a single vector. This was a significant leap forward, as it allowed for the calculation of the heart's electrical axis and thereby improved the interpretation of cardiac rhythms and pathologies.

The standard limb leads I, II, and III, as defined by Einthoven, represent the frontal plane lead vectors of the heart, effectively mapping the electrical field of the heart in a two-dimensional plane. This innovative approach not only facilitated the interpretation of ECG results but also laid the groundwork for the subsequent development of additional leads. Einthoven's recognition of the ECG's diagnostic and investigative potential earned him the Nobel Prize in Physiology or Medicine in 1924, "for the discovery of the mechanism of the electrocardiogram," cementing his legacy as the founder of modern electrocardiography. After 1920, Frank N. Wilson and his associates became key figures in advancing electrocardiography. Burch and DePasquale [6] highlighted that among many contributors, Frank N. Wilson was especially influential in enhancing electrocardiographic knowledge. During this time, the focus of the field shifted from arrhythmias to more in-depth studies of ECG theory, the intricacies of electrocardiographic leads, and the nuances in waveform abnormalities.

One of the most notable contributions from this era was Wilson and his team's 1944 work, "The Precordial Electrocardiogram," [7]. This publication played a critical role in demonstrating the significance and practical application of unipolar precordial leads in the realm of clinical cardiology. This groundbreaking work marked a crucial turning point, paving the way for the modern era of clinical electrocardiography. Wilson's work during this period significantly molded the contemporary approach to and understanding of ECG in medical practice [8]. In the late 1940s, the advent of direct writing equipment marked a significant milestone in the evolution of electrocardiography. This technological advancement transformed the ECG into what it remains today: the most frequently utilized procedure in cardiovascular laboratory diagnostics. This innovation greatly enhanced the accessibility and efficiency of ECG, solidifying its role as a fundamental tool in cardiac assessment and care [1].

Building upon Einthoven's initial work, additional leads were developed to provide a more comprehensive view of the heart's electrical activity from different angles, particularly the precordial or chest leads V1 through V6. These leads give a horizontal plane perspective, complementing the limb leads and providing the detailed 12-lead perspective that is used universally in clinical practice today.

The traditional 12-lead ECG, known for its non-invasive approach, provides an extensive analysis of cardiac activities through its twelve leads. This extensive coverage enables it to diagnose a broad spectrum of heart conditions with high accuracy. However, this method necessitates that patients remain stationary, often in a quiet, controlled environment. This setup can be inconvenient and time-consuming. Additionally, the substantial size of the 12-lead ECG equipment demands specific space and a power source, hindering its suitability for ongoing monitoring. Its lack of portability, as a result, restricts patient mobility and adds to its cost.

On the other side of the spectrum are portable ECG devices, exemplified by the Holter monitor. These too are non-invasive and are engineered for mobility. Generally equipped with 5-7 leads, they offer valuable insights into heart function, albeit less extensively than their 12-lead counterparts. These medium-sized devices can be worn continuously for periods ranging from 24 to 48 hours, or even longer. This feature is particularly advantageous for long-term heart monitoring and for detecting heart events that occur sporadically. However, the extended wear of a Holter monitor may lead to discomfort over time.

The primary distinctions between these two types of ECGs lie in their mobility, user-friendliness, and the depth of cardiac data they gather. The conventional 12-lead ECG excels in providing detailed, short-term cardiac analysis in clinical environments, thanks to its thorough data acquisition and precision. Conversely, the Holter monitor shines in its adaptability for long-duration monitoring, proving invaluable in identifying occasional heart anomalies. The decision to use one over the other hinges on the specific requirements of heart monitoring, the granularity of data needed, patient mobility and comfort, and the monitoring duration.

In light of these considerations, there is a growing interest in developing a hybrid device that merges the detailed diagnostic capabilities of the conventional 12-lead ECG with the portability and user-friendliness of modern portable systems. Such a device aims to fill a critical void in cardiac care, particularly in non-clinical settings where traditional ECG systems are not feasible, offering a versatile solution that accommodates both detailed assessments and the need for mobility and continuous monitoring.

III. Project Assignment and Approach: Enhancing a Prototype Portable ECG Device

I was assigned to work on a project focused on addressing the challenges associated with a prototype ECG device developed by an ESE Lab at Washington University in St. Louis: a portable electrocardiogram (ECG) board. This promising device represents a significant step forward in revolutionizing cardiac patient care.

My approach to this project began with an in-depth investigation into the various challenges that were impeding its optimal functionality. This process was crucial, as identifying and understanding these challenges would be the first step in devising effective solutions.

The research commenced with a detailed analysis to identify the primary issues. My approach entailed a multi-faceted exploration, beginning with the identification and formulation of the research problem. This step was crucial in pinpointing the specific obstacles that needed to be overcome. Subsequently, I embarked on a meticulous search for effective methodologies to address these challenges.

A key component of this phase was the development of a mathematical proof of concept. This theoretical framework involved the intricate crafting of equations and formulas, serving as a foundational proof of concept for the proposed solutions.

In addition, the selection of appropriate tools and techniques to tackle these problems was an essential part of the process. This strategic choice of resources was instrumental in ensuring a practical and efficient approach to problem-solving.

Upon thorough analysis, I identified three primary challenges that needed addressing to maximize the utility of the ECG device. These included synchronizing the ECG readings, ensuring the accuracy of ECG labeling, and ensuring the mapping with the state-of-the-art 12-lead ECG systems. A summary of these challenges is presented in Figure 1.

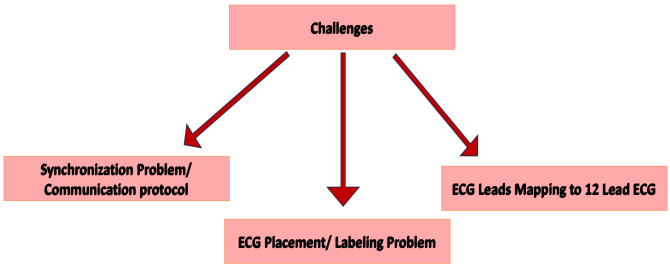

Fig. 1: Challenges Summary.

As part of my project requirements for future research involving patient studies, I swiftly completed CITI Training Human Research Stage 1 and GCP – Social and Behavioral Research Best Practices for Clinical Research. Completing these trainings was vital in preparing for the ethical, legal, and practical aspects of conducting research with human subjects, thereby ensuring that the research is conducted responsibly, legally, and effectively, upholding the highest standards of research integrity.

Another vital aspect of my research involved engaging with medical professionals, including cardiologists, where I met Dr. Peterson and other nurse practitioners at Barnes Hospital-Downtown and at Barnes West Hospital. Through a series of collaborative meetings, we delved into the practical needs and urgency for such a system. I attended two cardiac stress tests where I directly observed the challenges and the trip hazards posed by the conventional 12-lead ECG during these tests. These interactions were invaluable, as they infused the research with real-world relevance and applicability, ensuring that the outcomes were not only theoretically sound but also pragmatically valuable.

Given that the project focused on an ECG system and my academic background was primarily in Computer Science and Electrical Engineering, I enrolled in Bioelectric Phenomena course to acquire a solid understanding of cardiac electrophysiology. This course was pivotal in comprehending how the heart's action potentials propagate through cardiac muscle and how these signals correlate with the readings captured on our ECG boards. The course provided an in-depth exploration of bioelectrical activities, including the chemistry of ion channels and the pathophysiology of related diseases. This knowledge was crucial for me to understand the biophysical basis of the signals we were measuring and interpreting through the ECG system. Though the content was outside my original field of expertise, the course proved to be an enriching and enlightening experience.

To this end, and with the aim of thoroughly revisiting and addressing the original three main challenges, the remaining of this report outlines my rotation work on the three main challenges identified, highlighting significant progress in each area. The report is structured for clarity and comprehensiveness. In Section IV, we define each research problem, ensuring clarity for the reader. This sets the context for the challenges addressed. Section V details the methods used in approaching and solving these challenges, describing the strategies and tools employed.

In Section V, we present the outcomes of the project, highlighting the results and their impact on enhancing the functionality of the ECG prototype. In Section VI, we highlight the various factors affecting the accuracy of EKG signals. These factors include signal noise, patient movement, electrode placement, and environmental interference. In Section VII, we delve into the preprocessing and denoising techniques applied to ECG leads to enhance signal quality. Preprocessing involves steps such as signal normalization, baseline wander removal, and filtering out high-frequency noise. The report culminates in Section VIII, where we draw conclusions, reflecting on our findings and their broader implications in the

field of cardiac care. Following this, in Section IX, we propose future research directions to further advance ECG technology and cardiac care.

IV. ECG BOARD MAIN CHALLENGES

In this Section we discuss and outline and formulate the research problem for the main three challenges facing any portable ECG device.

A. Synchronization Problem

In traditional 12-lead EKG systems, the synchronization of electrical signals recorded from various leads is effectively managed through integrated internal clocks. These clocks are critical for assigning accurate timestamps to the data, ensuring precise alignment of the cardiac events captured across different leads. Additionally, specific markers are employed within the EKG data to identify key cardiac events, like the QRS complex, aiding in their consistent synchronization across all leads, which is essential for a unified and accurate depiction of the heart's electrical activity. Moreover, sophisticated software algorithms are a key component in these traditional systems. They are adept at identifying and rectifying any slight discrepancies between the leads. This process enhances the synchronization, ensuring that the final EKG output is a true and synchronized representation of the cardiac activity. The standardized positioning of EKG leads also plays a vital role in achieving synchronization in traditional systems. By consistently placing leads at specific, standardized points on the body, it is ensured that each lead is capturing the electrical activity of the heart from a consistent and expected angle, contributing significantly to the overall synchronization.

The devices that lack the internal clocks synchronized across distributed devices and are typically found in portable ECG systems are generally referred to as asynchronous devices. In the context of ECG systems, these devices do not rely on a central clock to maintain synchronization, unlike traditional EKG systems that ensure effective synchronization through such mechanisms.

Portable ECG devices also encounter additional challenges, such as delays in transmission or other factors that might alter the signal timing. This issue becomes more complex when multiple portable devices are used simultaneously, as each may introduce its own timing variations. As a result, a key challenge for portable ECG technology is to overcome these synchronization issues. Innovating new synchronization techniques that are adapted to the unique limitations of portable devices is imperative.

Upon investigating the portable ECG board, it has been noted that the device transmits data using the RF capabilities of Texas Instruments technology. This opened a promising direction for addressing the synchronization challenges. By leveraging these RF capabilities, a specialized communication protocol can be devised.

I present a protocol that integrates a central controller within a network of portable ECG devices, serving a critical role in harmonizing the data collection process across the network. The protocol's innovative approach involves coordinating serially labeled data packets from multiple devices and employing a round-robin acknowledgment transmission protocol to ensure efficient and orderly data communication.

This protocol operates on two key principles: serial labeling of ECG data packets and round-robin acknowledgment transmission. Each ECG reading transmitted from the portable devices is serially labeled, ensuring the preservation of the chronological order and integrity of the data. The central controller orchestrates the transmission cycle using a round-robin method, whereby each device in the network is given an equal and sequential opportunity to transmit its data, thus minimizing data collision and ensuring a smooth flow of information.

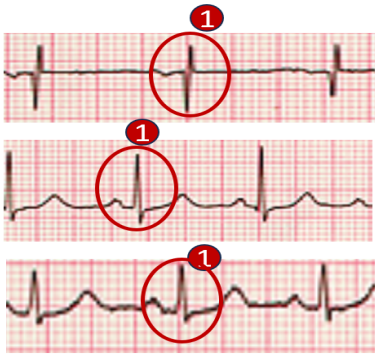

Fig. 2: ECG Readings Synchronization.

The proposed protocol for synchronizing portable ECG sensors involves a central controller that coordinates the data transmission from these sensors. The central controller operates by granting transmission permissions to the ECG sensors in a round-robin manner. This method is designed under specific constraints to ensure data synchronization. The key aspect of this protocol is that the controller completes a full round of transmission permissions before the buffer of the first sensor becomes full. This approach ensures that all data from the sensors are collected synchronously and without loss or delay. The efficacy of this protocol can be demonstrated through a mathematical proof, which is outlined below.

The nonations of the protocol is presenented below:

Num_{sen} : Number of sensors.
Sr : Sampling rate of a sensor.
DPS : Data per sample.
B_{Cap} : Buffer capacity of a sensor.
Tr : Transmission rate of a sensor.
DPR : Data per response.
Num_{pkt} : The number of packets.
T_{Cycle} : Time for the controller to complete a full communication cycl
T_{Sensor} : Time taken for each sensor to respond.
T_{Buffer} : Time taken to fill the buffer of a sensor.

To demonstrate the effectiveness of the proposed protocol, it is essential to calculate the time it takes for the device's buffer

to fill up, referred to as the Buffer Fill Time. This calculation is crucial to ensure that data transmission occurs before the buffer reaches its capacity, thereby preventing data loss and ensuring synchronization. The Buffer Fill Time (T_{Buffer}) can be calculated using the following equation:

$$T_{\text{Buffer}} = \frac{B_{\text{Cap}}}{Sr \cdot DPS} \tag{1}$$

Where:
- B_{Cap} is the buffer capacity of the Texas Instruments RF Chip, which is 8100 Bytes.
- Sr is the sampling rate of the system, which is 1000 samples per second.
- DPS is the data per sample, which is 2 bytes per sample for each of the ECG sensor boards.

Given these values, the Buffer Fill Time can be calculated as:

$$T_{\text{Buffer}} = \frac{8100 \text{ Bytes}}{1000 \text{ samples/sec} \cdot 2 \text{ Bytes/sample}} = 4.05sec \tag{2}$$

This calculation will yield the time in seconds that it takes for the buffer of the portable ECG device to become full. It's a crucial factor in ensuring that the data transmission and synchronization protocol functions as intended, by allowing the system to transmit data before the buffer overflows. This ensures the integrity and continuity of the ECG data being collected.

To calculate the Sensor Response Time (T_{Sensor}) and the time taken by the controller to complete one cycle of communication with all sensors (T_{Cycle}), we use the following formulas and data for the Texas Instruments RF chip:

The Sensor Response Time is the time taken for each sensor to transmit its data at the given transmission rate. It can be calculated as:

$$T_{\text{Sensor}} = \frac{DPR}{Tr} \tag{3}$$

Where:
- DPR is the Data Per Response, which includes the data sensed and the permit packet with the header.
- Tr is the Transmission rate, which is 50kbps for the texas instrument RF chip

Given: - Data sensed = 2000 bytes (1000 samples x 2 bytes/sample).
- Permit packet with header = 4 bytes (2 bytes for sensor number, 2 bytes for address filtering).
- Additional data = 2 bytes for sensor ID, 2 bytes for serial number, 2 bytes for address.
- Total DPR = 2000 bytes + 4 bytes + 6 bytes = 2010 bytes.

Therefore,

$$T_{\text{Sensor}} = \frac{2010 \text{ bytes}}{50 \text{ kbps}} = 0.33sec \tag{4}$$

The time taken by the controller to complete one cycle of communication with all sensors can be calculated as:

$$T_{\text{Cycle}} = Num_{\text{Sen}} \cdot T_{\text{Sensor}} \tag{5}$$

Where Num_{Sen} is the number of sensors, which is 12 for a 12-lead ECG system.

Therefore,

$$T_{\text{Cycle}} = 12 \cdot 0.33 = 3.96Sec \tag{6}$$

System Constraint: - It is crucial that the controller finishes its communication cycle before the buffer of the first sensor reaches its capacity. This is expressed as $T_{\text{Cycle}} < T_{\text{Buffer}}$.

Operational Requirement: - To ensure the system operates effectively within its constraints, it is imperative to adhere to the following:

$$\frac{(Num\_sen \cdot DPR)}{Tr} < \frac{B_{Cap}}{(Sr \cdot DPS)}$$

In the proposed communication protocol for the network of 12 portable ECG sensors, our calculations reveal that the time taken for the protocol to complete a full loop (cycle time) is 3.96 seconds. This timing is particularly significant when considering the buffer capacity of each sensor, which is set to fill at the 4.05-second mark. This synchronization of the communication loop and buffer capacity ensures that data transmission from each sensor is completed efficiently and effectively, just before the buffer reaches its full capacity. Thus, the protocol successfully prevents data overflow and loss, ensuring the integrity and continuity of ECG data across the network. These findings affirm the viability and robustness of the communication protocol in managing data transmission in a synchronized manner across a network of 12 portable ECG sensors, hence 12 leads.

B. ECG Placement/Labeling Problem

ECG electrodes, used in electrocardiograms, have specific roles in capturing the heart's electrical activity and are generally not reversible. Their placement on the body follows a stringent guideline known as the 12-lead ECG. Each "lead" in this system provides a unique perspective of the heart's electrical activity, essential for accurate diagnosis and monitoring.

The polarity of ECG electrodes plays a crucial role. When electrodes are placed in their designated locations, they capture the electrical activity of the heart from specific angles. This standardized placement is critical because reversing or incorrectly positioning these electrodes can lead to misinterpretations of the ECG tracings. For example, if limb leads are swapped, the ECG might falsely suggest conditions like dextrocardia, where the heart is located on the right side of the chest. It could also inaccurately indicate signs of a heart attack.

Stepping back to provide a broader perspective, it is essential to acknowledge that the challenge of lead misplacement is not unique to our portable ECG device; it similarly affects the conventional state-of-the-art 12-lead ECG systems.

The implications of incorrect ECG (electrocardiogram) lead placement are extensive and critical, especially when considering the data and statistics reported by authoritative bodies like The Centers for Medicare and Medicaid Services (CMS). In the context of 12-lead ECG devices, CMS has provided substantial data, revealing that a total of 30,646,824 ECGs

have been recorded[9]. This figure underscores the widespread use and significance of ECGs in medical diagnostics.

However, the accuracy of these ECG readings is paramount. Mispositioning of ECG leads, a seemingly minor error, can have far-reaching consequences. When leads are not placed correctly, the ECG can display significantly abnormal patterns. These aberrations are not just trivial inconsistencies; they can lead healthcare professionals down a path of false diagnoses [10]. An incorrect reading on an ECG can suggest the presence of cardiac anomalies that do not actually exist, prompting unnecessary and potentially invasive cardiovascular testing. This not only places undue stress and risk on patients but also contributes to inefficient use of medical resources.

Moreover, the economic impact of ECG lead mispositioning is staggering. The estimated cost associated with this issue is approximately 3,201,069,077 dollers per year [11], translating to about 3.2 billion dollars. This figure represents a substantial financial burden on the healthcare system. It encompasses not just the costs of the additional tests and procedures that result from incorrect diagnoses but also the broader implications of misallocated medical resources and the potential for increased insurance premiums and healthcare costs for patients.[12]

The American Heart Association (AHA) and the International Electrotechnical Commission (IEC) have established standardized color coding for 12-lead ECG (electrocardiogram) systems to aid in the correct placement of leads. This color coding is intended to reduce errors and improve consistency in ECG recordings. However, the contribution of this color coding to mislabeling is somewhat paradoxical. While it's designed to minimize errors, reliance on color alone without adequate training and awareness can still lead to mistakes, underscoring the need for comprehensive training and adherence to standard procedures in ECG lead placement.

Regarding our portable ECG board, a significant challenge lies in determining the correct orientation and placement of the ECG leads, as illustrated in Figure 6. This challenge directly impacts the accuracy and efficiency of the measurements obtained from our portable ECG device. The primary goal is to develop a method that ensures each ECG reading is assigned a unique, correct position and orientation

ECG Placement: is constraint satisfaction problem (CSP) where the objective is to assign values (in this case, the orientation and placement of ECG boards) according to specific constraints.

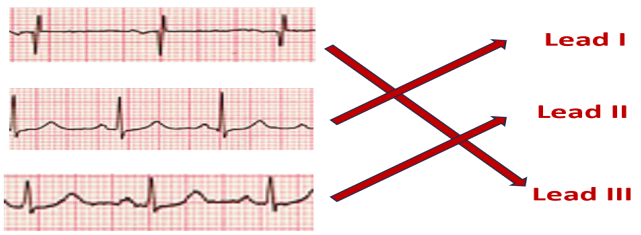

Fig. 3: Labeling ECG Readings.

Our goal is to determine the correct orientation and the correct labeling for each ECG board reading such that:

- Each ECG board is in one of the n locations.
- Each location contains exactly one ECG board.
- Each ECG board is in the correct orientation.

Traditional ECG limb leads consist of both positive (+) and negative (-) poles, which are essential for capturing the heart's electrical activity from different perspectives. The standard limb leads include Lead I, Lead II, and Lead III, each with specific electrode placements:

Lead I: The positive electrode is placed on the left arm, and the negative electrode is on the right arm. This lead measures the electrical potential difference between the left and right arms. Lead II: The positive electrode is placed on the left leg, and the negative electrode is on the right arm. This lead views the heart's electrical activity primarily from the inferior aspect. Lead III: The positive electrode is on the left leg, while the negative electrode is on the left arm. This lead also focuses on the heart's inferior aspect but from a different angle compared to Lead II. For portable ECG devices, adhering to these standard electrode orientations is vital for maintaining the integrity of the ECG readings. The correct placement of electrodes in accordance with the positive and negative poles is crucial, as any deviation can lead to inaccurate readings and potential misinterpretation of cardiac activity. In portable ECGs, ensuring adherence to these standards can be more challenging due to the device's mobility and the need for self-application in some cases.

As illustrated in Figure 4, the precise orientation and placement of electrodes for limb leads in portable ECG devices should mimic the standard configurations used in conventional ECGs. This adherence is necessary to maintain consistency in ECG readings across different platforms and to ensure that the data collected is clinically reliable and comparable to traditional ECG measurements.

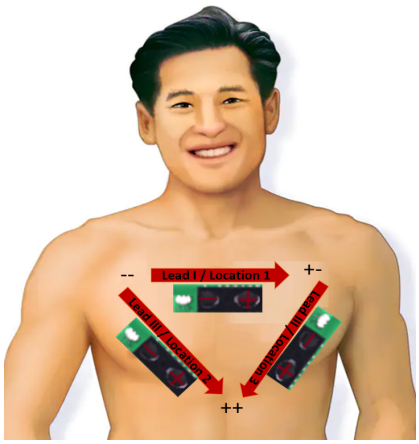

Fig. 4: The Placement of Portable ECG Boards

Modeling the placement/Labeling problem :

- Notations
  - There are n distinct ECG boards $ECG_1, ECG_2, \ldots, ECG_n$.

  - There are n distinct locations $x_1, x_2, \ldots, x_n$.
  - Each ECG board ECG_i has an orientation y_i, where y_i can be C for correct or R for reversed orientation.
- Constraints for the ECG boards placement:
  - Each ECG_i must be in a unique location, such that for all pairs of ECGs (i, j), $x_i \neq x_j$ for all $i \neq j$, where $i, j \in \{1, 2, \ldots, n\}$.
  - Each ECG must be in the correct orientation: $y_i = C$ for all i, where $i \in \{1, 2, \ldots, n\}$.
- Objective:
  Find a mapping of ECG_i to (x_i, y_i) for all i such that all constraints are satisfied.

To ensure the accuracy of lead labeling in the ECG readings, we introduce a 'Correctness Measure' that is based on the correlation of the leads. The Correctness Measure is defined as follows:

$$\text{Correctness Measure} = \begin{cases} 1 - \text{Deviation Factor}, & \text{if correlation is close to ideal} \\ 0.5 \times (1 - \text{Deviation Factor}), & \text{if mislabeling is suspected} \end{cases} \quad (7)$$

Where:

- The *Deviation Factor* quantifies the deviation of the current lead arrangement from the ideal correlation pattern.
- The measure yields a value closer to 1 when the correlation is nearly ideal, indicating correct labeling.
- A lower value (adjusted by the factor 0.5) is assigned if the system suspects mislabeling based on the correlations.

Method for Lead Correlations

To effectively utilize the Correctness Measure, a method for assessing lead correlations is required. This method involves:

1) **Establishing Ideal Correlation Patterns**: Define the expected correlation patterns for correctly labeled leads based on standard ECG characteristics.
2) **Comparing with Actual Data**: For each permutation of lead labels, compare the observed correlations with the established ideal patterns.
3) **Calculating Deviation**: Quantify the deviation of each permutation from the ideal patterns to determine the Deviation Factor.
4) **Applying Correctness Measure**: Utilize the Correctness Measure to evaluate each permutation, selecting the permutation with the highest measure as the correct labeling.

C. ECG Leads Mapping to 12 Lead ECG

The challenge involves correlating the readings from our portable ECG device with the standard 12-lead system. Although the portable ECG measures different vectors for the leads, we preserve the integrity of the information during this mapping process.

V. Results

A. Synchronization Problem

In the development of a robust communication protocol for the portable ECG system utilizing the Texas Instruments RF

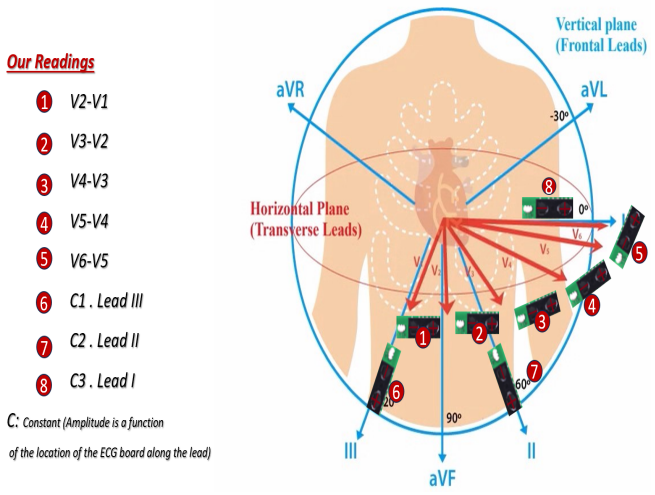

Fig. 5: ECG Leads Mapping to 12 Lead ECGl.

Chip, we have employed Code Composer Studio to program the RF core. The current iteration of the protocol effectively operates in Debug mode, supporting up to four ECG sensor boards. A significant enhancement in our approach is the incorporation of the Advanced Packet mode. This feature allows us to manage payload lengths exceeding the basic mode's limitation of 250 bytes, a necessary adaptation allows our system's of data per response from the ECG sensors to the controller is 2006 bytes. This extended payload capacity ensures that comprehensive ECG data can be transmitted without fragmentation, thereby maintaining the integrity of the cardiac information.

To enhance the security and specificity of the communication within the system, Address Filtering has been implemented. This ensures that each sensor receives packets exclusively from its assigned controller, mitigating the risk of data crossover or interference from extraneous sources. Furthermore, the controller's permit signal is uniquely tailored for each sensor, identified by its ECG sensor ID, ensuring that sensors transmit their data only upon verification of their specific permit signal coupled with the correct packet address. As Illustrated in Figure 9.

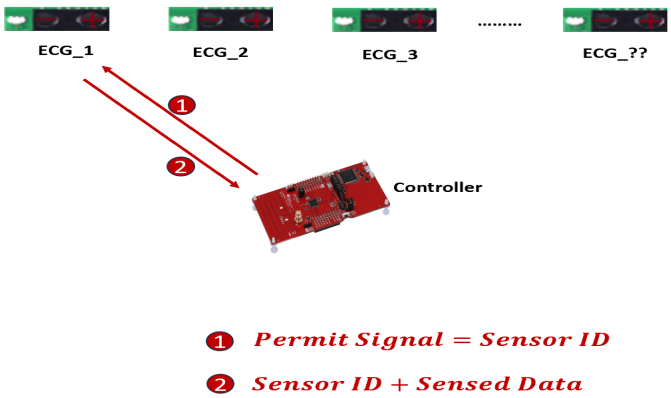

Fig. 6: Proposed Communication protocol.

Power optimization is a critical aspect of our system design,

especially considering the portable nature of the ECG sensors. The controller is configured with a Rx Timeout set at 30 milliseconds, a feature designed to enhance reliability and prevent single points of failure. If no data is received within this period, the controller transitions to the next sensor, thereby maintaining an efficient communication cycle. Additionally, the controller is programmed to enter a low-power sleep mode after 50 consecutive failed attempts at connecting to any sensor, significantly conserving energy.

In line with our power conservation strategy, the sensors are set to remain in Rx mode continuously, with an optional time-out feature. For further power optimization, this timeout has been configured to activate after 3 hours of inactivity, striking a balance between energy efficiency and operational readiness. To ensure targeted communication, sensors are programmed to transmit data only upon receiving their corresponding Tx Permit, marked with their unique ID. This approach not only conserves power but also reinforces the precision and security of the data transmission process.

Overall, the proposed protocol showcases a sophisticated balance between operational efficiency, data security, and power optimization, addressing the key challenges inherent in portable ECG systems, especially in remote or dynamic healthcare environments.

In our research, we conducted simulations to analyze how various factors of the communication protocol affect its capacity to support a certain number of sensors. These simulations, depicted in Figures 6, 7, and 8, vary key parameters such as Data Per Response, Sampling Rate, and Buffer Capacity to understand their impact on the system's scalability.

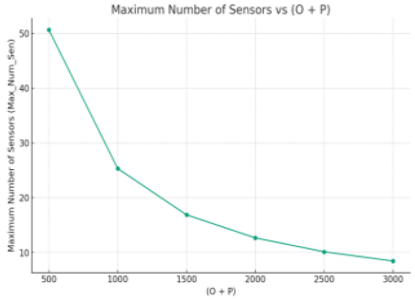

Fig. 7: Varying Data Per Response (500-3000) step size 500.

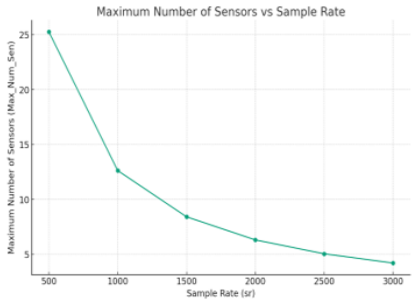

Fig. 8: Varying Sampling Rate: (500-3000) step size 500

Data Per Response Variation (Figure 6): By varying the Data Per Response (O+P: Overhead + Payload) from 500 to 3000 bytes in steps of 500, we observed a notable trend in the system's capacity to support sensors. The relationship between the Data Per Response and the number of sensors supported by the protocol follows an inverse proportion (1/x pattern). As the data per response increases, the number of sensors (Portable ECG devices) that can be effectively managed by the protocol decreases. This is attributable to the increased bandwidth and time required to handle larger data payloads, which inversely affects the number of sensors that can be accommodated within the system's operational constraints.

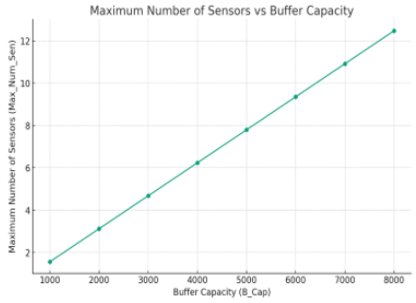

Fig. 9: Varying the buffer capacity (1000 – 8100) Step size 1000.

Varying Sampling Rate (Figure 7): A similar inverse relationship was observed when varying the Sampling Rate between 500 to 3000 samples per second, with the same step size of 500. The increase in the sampling rate leads to a larger data generation rate per sensor (Portable ECG device), which in turn reduces the number of sensors that can be concurrently managed. This outcome is consistent with the limitations imposed by the data handling capacity and transmission bandwidth of the system.

Buffer Capacity Variation (Figure 8): Contrasting with the above relationships, the variation in Buffer Capacity from 1000 to 8100 bytes (in steps of 1000) demonstrated a linear relationship with the number of ECG boards or sensors supported by the system. As the buffer capacity of each sensor increases, the system can accommodate a larger number of sensors. This linear relationship indicates that buffer capacity is a directly proportional limiting factor for the number of sensors the system can support. Higher buffer capacities allow for more data to be stored temporarily, enabling the system to handle a greater number of sensors without data loss or overflow.

These simulations provide crucial insights into the scalability and limitations of the proposed communication protocol. Understanding these relationships allows for informed decisions when configuring the system for different operational scenarios, ensuring optimal performance and reliability of the portable ECG network.

B. ECG Placement/Labeling Problem

In Section IV, Subsection B of our research, we focus on the implementation of a 'Correctness Measure' for accurately labeling ECG leads obtained from portable ECG Boards. This measure is based on the premise that there is a quantifiable

correlation between ECG leads, which can then be utilized in determining the most accurate lead labeling through permutations.

In the scope of our study, attention was directed towards three specific ECG leads: I, II, and III. The objective was to validate the correlation among these leads and to subsequently incorporate this understanding into our proposed 'Correctness Measure'. To achieve this, we utilized a comprehensive dataset, referenced in our study as [12]. This dataset was chosen for its extensive coverage and relevance to the leads in question. It provided a robust foundation for analyzing the correlations of Leads I, II, and III, thus contributing significantly to the development and validation of our Correctness Measure.

Dataset Composition

- Contains 827 ECG tracings from diverse patients.
- Annotations provided by cardiologists, residents, and medical students, constituting a 'Golden-Standard' for analysis. This is needed as we only export leads that were marked for healthy subjects as a baseline for the correlation measure.

Significance in Research

- Utilized in the study "Automatic diagnosis of the 12-lead ECG using a deep neural network", published in Nature Communications.
- The dataset's reliability and diversity make it a valuable resource for validating our Correctness Measure.

Covered ECG Abnormalities

- 1st degree AV block (1dAVb)
- Right bundle branch block (RBBB)
- Left bundle branch block (LBBB)
- Sinus bradycardia (SB)
- Atrial fibrillation (AF)
- Sinus tachycardia (ST)

Technical Details of ECG Signals

- Sampling rate: 400 Hz.
- Original 10s signals, each comprising 4000 samples.

The employment of this dataset is pivotal in establishing the correlation between Leads I, II, and III, thereby enabling the fine-tuning of the Correctness Measure for the most accurate lead labeling.

As a proof of concept, we implemented two correlation functions:

1) **Pearson Correlation**:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}} \tag{8}$$

Where r is the Pearson correlation coefficient, X_i and Y_i are the individual sample points indexed with i, $\bar{X}$ and $\bar{Y}$ are the means of X and Y respectively. Pearson correlation coefficient works well under certain conditions: Linear Relationship: Pearson correlation measures the strength and direction of a linear relationship between two variables. It works best when the relationship between the variables is linear. Continuous Variables: It is most appropriate for continuous variables. While it can be used with discrete variables.

2) **Spearman Correlation**:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)} \tag{9}$$

Where ρ is the Spearman's rank correlation coefficient, d_i is the difference between the ranks of corresponding variables, and n is the number of observations. Spearman correlation coefficient works well under certain conditions: Detects: The Spearman coefficient measures the strength and direction of the monotonic relationship between two variables. Continuous Variables: It is most appropriate for continuous data. Robustness: It's less sensitive to outliers.

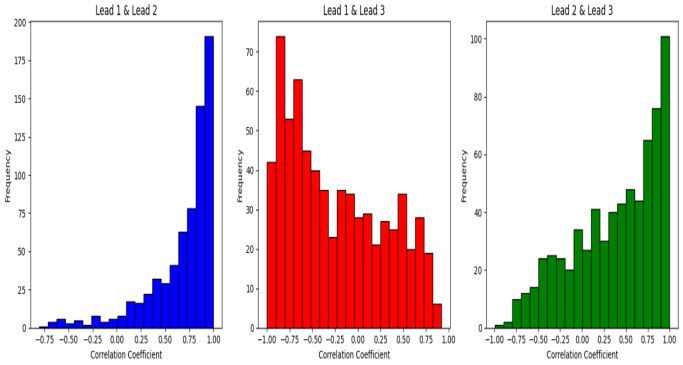

Fig. 10: Pearson Correlation.

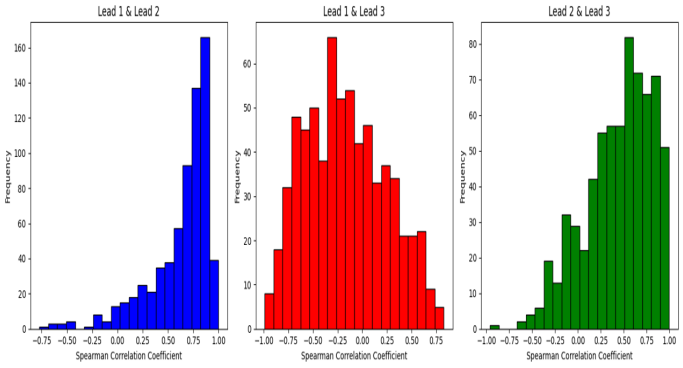

Fig. 11: Spearman Correlation

In Figures 10 and 11, we present histograms that depict the correlation between the three ECG leads: I, II, and III. These visual representations clearly demonstrate the degree of correlation among the leads. It is evident from the histograms that Lead I and Lead II exhibit a high degree of linear correlation. However, the correlation between Lead I and Lead III, as well as between Lead II and Lead III, does not appear to be linear.

This observation suggests the need for employing other correlation algorithms to fully understand the relationships among these leads. Nonetheless, the evident correlation between Lead I and Lead II serves as a proof of concept that correlation analysis can be a valuable tool in lead labeling. For instance, if we were presented with three unlabelled leads I, II, and III,

the high linear correlation between two of these leads could be used to infer which one is Lead III. Leads showing high linear correlation would be identified as Leads I and II, thereby aiding in the correct labeling of the leads.

Such inference is crucial for the implementation of a Correctness Measure in our study. It demonstrates the practical application of correlation analysis in determining the accurate labeling of ECG leads, a key step in ensuring the reliability and clinical utility of ECG readings obtained from portable ECG devices. These correlation functions validate the presence of a correlation between ECG leads, which is integral to our Correctness Measure.

VI. Factors Affecting Accuracy of EKG Signals

Before delving into the intricate details of preprocessing EKG signals, it is essential to first address several factors that can significantly impact the accuracy of EKG signals.

A. The Importance of Effective System-Level Design in Noise Rejection"

Effective system-level design plays a critical role in noise rejection when it comes to portable ECG devices. The design of the hardware components of a portable ECG device, including the instrumentation amplifiers, shielding, and cables, significantly impacts the accuracy of ECG signals. One of the critical components of an ECG device is the instrumentation amplifier, which amplifies the tiny voltage signals produced by the body. Instrumentation amplifiers with high common mode rejection ratios, typically 100dB or more, can effectively reject noise signals that are common to both the positive and negative input terminals of the amplifier. This rejection reduces the common-mode noise level, which is crucial in improving the overall accuracy of the ECG signals. In addition to using high-quality instrumentation amplifiers, shielding is another crucial aspect of effective system-level design for portable ECG devices. Metallic shields can prevent high-frequency RF signals from being coupled into the device's circuitry, which can interfere with the accuracy of the ECG signals. Shielding can be applied to the device's circuit board, cables, and connectors to improve noise rejection and reduce the possibility of interference. Moreover, the cables used to acquire the ECG signals should be shielded and driven with a common voltage to minimize noise. Common-mode noise, which results from electrical interference from other equipment or external sources, can be rejected by using cables driven with a common voltage. Shielded cables can further reduce noise levels by preventing interference from external sources.

In summary, effective system-level design is essential in noise rejection for portable ECG devices. Incorporating high-quality instrumentation amplifiers, shielding, and shielded cables can improve the accuracy of ECG signals, resulting in more reliable diagnostic outcomes. Therefore, it is crucial to consider the design of the ECG device's hardware components to ensure the accuracy of ECG signals in portable devices.

B. The Impact of Portable EKG Electrode Placement, Patient Movements, and Biological Conditions

Proper electrode placement is essential to ensure accurate EKG signal acquisition and to minimize noise. To avoid signal artifacts caused by improper electrode placement, which can distort the signal and introduce noise, it is crucial to follow the standard electrode placement protocol. Several studies [13] have been conducted to determine the proper locations to place small portable EKG devices for better accuracy for lead V1-V6. However, additional research is necessary to study the proper placements for leads I, II, and III. Apart from proper electrode placement, patient movement and biological conditions can also affect EKG signal quality. Patient movements, including muscle contractions, can generate interference signals that can be picked up by the EKG electrodes, leading to noise in the EKG signal. Therefore, it is important to instruct the patient to remain still during the EKG measurement to reduce the introduction of noise in the signal. Additionally, biological conditions, such as sweat, can create a conductive pathway between the electrodes, leading to noise in the EKG signal. Hence, it is necessary to clean and dry the skin before electrode placement to avoid this interference.

Furthermore, some patients may have conditions, such as obesity, lung disease, or heart disease, that affect their EKG signal quality. In such cases, alternative electrode placement methods may be necessary to ensure accurate EKG signal acquisition. Moreover, the use of high-quality EKG devices with advanced filtering algorithms can help reduce noise and improve signal quality in patients with biological conditions that affect EKG signals.

In conclusion, proper electrode placement, patient cooperation in remaining still, and taking into account biological conditions affecting EKG signal quality are crucial in ensuring accurate EKG signal acquisition. These factors, along with the use of high-quality EKG devices with advanced filtering algorithms, can help reduce noise and improve EKG signal quality, resulting in more reliable diagnostic outcomes.

C. Dataset Size Considerations for EKG Signal Data Collection: Implications for Machine Learning Models and Signal Processing

Collecting sufficient electrocardiogram (EKG) signal data is crucial for developing accurate machine-learning models and effective signal processing techniques. However, the appropriate dataset size for EKG signal data collection can vary depending on multiple factors, including the research question, analysis approach, and complexity of the machine learning model.

Assuming that the EKG signals are sampled at the standard clinical rate of 1000Hz, it is recommended to collect at least 10 seconds of EKG data to capture sufficient heartbeats and prevent data loss from artifacts and noise. Consequently, a minimum of 10,000 data points is advised to capture adequate data for processing and analysis. Some studies recommend collecting more extended EKG signals, such as 30 seconds or more, to enhance the accuracy of the analysis and represent a more comprehensive sample of cardiac activity.

Furthermore, the size of the dataset needed for EKG signal analysis is contingent upon the intricacy of the machine learning model utilized. In particular, deep neural networks may necessitate a greater number of samples to acquire an understanding of the fundamental patterns and correlations within the data. Additionally, increasing the size of the dataset can assist in mitigating overfitting, which is a frequently encountered problem in machine learning wherein the model performs well on the training data but inadequately on new data. To generalize EKG signal processing techniques, it is typical to collect data from a large number of subjects. For instance, some studies [13] have used data from 256 subjects, while others have conducted 25 long-term EKG recordings of human subjects, with each recording lasting 10 hours. In general, larger datasets consisting of thousands or even millions of EKG recordings are preferred to enhance the accuracy and generalizability of the analysis.

VII. ECG Leads Preprocessing and Denoising

This section focuses on ECG signal processing and lead mapping efforts. The primary goal is to enhance the accuracy and comprehensiveness of cardiac signal interpretation by extending the application of correctness measures and lead correlations to the full spectrum of the 12-lead ECG.

Initial Steps and Dataset Utilization:

- ECG samples were acquired using the ESE Lab's portable EKG PCB. The dataset consists of ECG signal amplitudes recorded using chest electrodes for limb leads I and II. Lead III was excluded as Lead II adequately represented it.
- The dataset comprised 49 packets for Lead I and 43 for Lead II, each containing 1500 samples.

1. Removing DC Offset in ECG Signal: DC filtering was implemented to remove baseline wander or DC offset in ECG signals. This step is critical for accurate signal analysis and interpretation. A second-order high-pass filter with a cutoff frequency of approximately 0.5 Hz was used, proving effective in eliminating low-frequency noise. As seen in Figure 12 **(Due to confidentiality and privacy, I cannot disclose patient EKG details.)**

2. Cross-correlation for Time Alignment: Time alignment is needed for two ECG signals before mapping them in order to synchronize the signals in time. This is necessary because the ECG signals may have been recorded at slightly different times or with slightly different sampling rates, which can cause small time shifts or phase differences between the two signals. If the two signals are not properly aligned in time, it can lead to inaccurate or misleading results when trying to compare or map the signals. By aligning the signals in time, we can ensure that corresponding features or events in the signals (such as heartbeats) are properly matched and accurately compared. This is especially important for tasks such as detecting abnormalities or patterns in the ECG signals, where accurate mapping and comparison of the signals are crucial. A cross-correlation method is a valuable tool for aligning signals that have similar patterns but may be out of phase with each other, such as ECG signals obtained from different devices. In our experiment, we aim to map the lead Truth signal to the ECG board signal obtained by the portable PCB. To accomplish this, signal pre-processing is necessary, including aligning the signals to synchronize them in time. One approach to achieving this is to calculate the cross-correlation between the two signals and use it to determine the time shift, which can then be used to align the signals based on the time shift. Time alignment of ECG signals was achieved using the *np.correlate* function. This method aligns signals based on their cross-correlation, ensuring that corresponding features in the signals are accurately matched for analysis. As seen in Figure 13. **(Due to confidentiality and privacy, I cannot disclose patient EKG details.)**

3. Denoising/Filtering: Electrocardiogram (ECG) signals can be contaminated with various types of noise, such as power line interference, muscle artifacts, baseline drift, and other types of physiological noise. This noise can make it difficult to accurately interpret ECG signals and extract meaningful information from them. Therefore, denoising is an important step in ECG signal processing.

There are many methods that have been developed for ECG denoising, with some of the most commonly used methods including Kalman filtering, Chebyshe filters.

These methods can be applied individually or in combination, depending on the specific characteristics of the noise and the ECG signal. Since it is important to carefully evaluate the performance of any denoising method to ensure that it does not introduce artifacts or distortions into the ECG signal we have selected our denoising filters carefully. **An Effective Denoising Approach for ECG Signals to Reduce Baseline Wander, Respiration, Electrode Impedance and Motion Noise** Electrocardiogram (ECG) signals are commonly utilized in clinical settings to diagnose various heart diseases. However, these signals are often plagued by multiple sources of noise, including baseline wander, respiration, electrode impedance, and motion artifacts. This leads to a decrease in diagnostic accuracy.

The Linear Kalman filter is a state-space model that estimates the underlying ECG signal and eliminates noise based on this estimate. It is widely used in many fields such as control systems, signal processing, and robotics, owing to its ability to provide a precise estimate of the signal, even in the presence of noise. This filtering method has significant implications in clinical applications, as it can enhance the accuracy of diagnosis and reduce the need for repeat measurements, leading to a reduction in time and resources.

We deployed the Linear Kalman filter as an effective denoising approach for ECG signals. The Kalman filter works by using a mathematical model of the system, represented by transition matrices and observation matrices, to estimate the state of the system at each time step. The filter also uses the initial state covariance to indicate the trust we have in the model in the prediction step. Specifically, it describes the covariance matrix of the errors in the initial estimate of the state vector. The observation covariance value is used to indicate the trust we have in the model in the update step. Specifically, it describes the covariance matrix of the measurement errors. The third parameter to tune in Kalman

filtering is the transition covariance values. Specifically, it describes the covariance matrix of the errors in the transition model used to predict the next state of the system. All these variables are utilized to adjust the trust in the model and the measurements. In our implementation, we set the value of 0.5 for the initial state covariance, indicating a moderate amount of uncertainty or error associated with the initial estimate of the state vector. A larger initial state covariance would indicate even more uncertainty, while a smaller initial state covariance would indicate a more confident estimate. The observation covariance is also set to 0.5 in our project, indicating a moderate amount of noise or uncertainty associated with the measurements. A larger observation covariance would indicate even more noise or uncertainty, while a smaller observation covariance would indicate more precise measurements. A suitable initial value for the transition covariance matrix for ECG signals is typically relatively high, such as in the range of 0.1 to 0.5. This is because ECG signals are often characterized by high variability and susceptibility to various sources of noise. However, the optimal value for the transition covariance matrix may vary depending on the specific characteristics of the ECG signal being analyzed.

In our particular implementation, we set the initial value of the transition covariance matrix to 0.5, which allowed us to assess the performance of the filter. We then fine-tuned this value by experimentation to achieve the best outcome of the filter, which in our case was achieved by reducing the transition covariance matrix to 0.02. This approach allowed us to optimize the filter's performance and effectively reduce the impact of noise on the ECG signal.

Reducing Electrical Grid Noise in ECG Signals: A Denoising Approach In the field of signal processing, one of the main challenges is extracting the underlying signals from noisy data. In particular, electrocardiogram (ECG) signals are often contaminated by various sources of noise, including interference from the electrical power grid. The frequencies of 50/60 Hz are common sources of such noise, which can obscure important features of the ECG signal. To mitigate this issue, one common approach is to use a bandstop filter to remove the unwanted frequencies from the signal. In this context, we have utilized an IIR filter bandstop Chebyshev Type II (Cheby2) filter to suppress the 50/60 Hz noise from the ECG signals. The IIR filter is a digital filter that utilizes feedback to achieve its filtering operation. The Cheby2 filter is a type of IIR filter that provides a steeper roll-off in the stopband compared to other filter types. This means that it can effectively suppress unwanted frequencies without distorting the desired ECG signal. Additionally, the Cheby2 filter provides a higher degree of selectivity than other filter types, making it well-suited for this application. The choice of the filter order depends on several factors such as the desired attenuation in the stopband which in turn determines the sharpness of the filter's transition band and the computational complexity of the filter. A higher filter order will result in a sharper transition band, but also in a longer computational time. In general, a higher filter order can provide better suppression of unwanted noise but can also result in longer processing times. In our implementation, we have used a filter order of 60 which has been found to provide a good balance between performance and computational efficiency. Another parameter to tune is the window parameter which specifies the type of window used to design the filter, which affects the passband and stopband ripple of the filter. In our implementation, we have chosen a window of $49 - 51$ and $59 - 61$.

Our implementation of the IIR bandstop Chebyshev Type II filter proves to be an effective method for removing unwanted 50/60 Hz noise from ECG signals. This filter significantly enhances the accuracy and reliability of ECG signal analysis, which is crucial for medical applications.

To denoise the ECG signals, we employed both Linear Kalman filters and Chebyshev filters. These methods effectively reduce baseline wander, respiration artifacts, electrode impedance noise, and motion artifacts, thereby improving signal clarity and diagnostic accuracy. The Kalman filter was fine-tuned with initial state covariance and observation covariance both set at 0.5. The transition covariance matrix was initially set at 0.5 and subsequently optimized to 0.02, as illustrated in Figure 14. **(Due to confidentiality and privacy, I cannot disclose patient EKG details.)**

In summary, the comprehensive preprocessing approach adopted above, encompassing DC offset removal, time alignment through cross-correlation, and various denoising techniques, has markedly enhanced the quality of the ECG signals. This improvement is not merely a step in signal processing but a significant stride towards the ambitious goal of 12-lead ECG mapping. These methodologies collectively contribute to refining the ECG data, ensuring that the signals used in our analysis are not only accurate but also reliable. This refined data is crucial in our pursuit of developing advanced mapping techniques for 12-lead ECGs, which is paramount for detailed cardiac analysis and diagnostics.

VIII. Conclusion

In this project, we have achieved a significant milestone in demonstrating the practicality of a portable ECG board by addressing three fundamental challenges: developing a robust communication protocol, utilizing signal preprocessing techniques, and solving the lead placement/labeling problem. Our proposed communication protocol effectively ensures accurate and synchronized data collection across a network of portable devices, significantly enhancing their utility in clinical practice.

This advancement not only extends the reach of cardiac monitoring to previously inaccessible environments but also opens new possibilities for patient care. Furthermore, our approach to signal preprocessing represents a crucial step towards mapping ECG signals while preserving their integrity, thereby ensuring the reliability of the diagnostic information. Additionally, the placement and labeling of leads have been addressed through the implementation of correlation functions and the Correctness Measure. Through comprehensive analysis, simulations, technical and theoretical proofs, and the development of protocol code, this project has been a successful and enriching learning experience.

IX. Future Directions

As this project progresses into its next phase, several key areas could be explored to enhance its impact and efficacy. One promising direction is to extend the application of correctness measures and lead correlations to the entire spectrum of the 12-lead ECG. This extension could lead to a more comprehensive and accurate interpretation of cardiac signals, providing a broader understanding of heart health.

Concurrently, refining our communication protocol for sensor-controller mode operation presents a significant opportunity. Enhancing this protocol would improve its effectiveness when sensors are utilized outside the lab setup, extending beyond the current debug mode. This improvement is crucial for real-world applications, ensuring reliable data transmission and sensor performance in diverse environments.

A significant advancement could be the integration of Artificial Intelligence (AI) technologies. The use of AI could revolutionize the interpretation of health data, particularly in the early detection and diagnosis of cardiac and related diseases. This integration aims to enhance diagnostic accuracy, marking a shift towards a more proactive and predictive healthcare approach. Leveraging AI for deeper and more insightful interpretations of health data could fundamentally change patient health management and understanding.

These potential endeavors represent a pathway toward advancing cardiac monitoring and diagnostics. By integrating cutting-edge technology, we can potentially improve patient care and outcomes, making significant strides in the field of cardiac health.

References

[1] Fisch C. Evolution of the clinical electrocardiogram. J Am Coll Cardiol. 1989 Nov 1;14(5):1127-38. doi: 10.1016/0735-1097(89)90407-5. PMID: 2681318.

[2] Fisch C. Centennial of the string galvanometer and the electrocardiogram. J Am Coll Cardiol 2000; 36: 1737-1745.

[3] W. Einthoven, The telecardiogram, American Heart Journal, Volume 53, Issue 4, 1957,Pages 602-615,ISSN 0002-8703, https://doi.org/10.1016/0002-8703(57)90367-8. (https://www.sciencedirect.com/science/article/pii/0002870357903678)

[4] Einthoven W. Le Telecardiogramme. Arch Int Physiol 1906;4:132-6

[5] Einthoven W. Weiteres uber das Elektrokardiogramm. Pfluegers Arch 1908:122:517-8

[6] . Burch EG. DePasquale NP. A History of Electrocardiography. Chicago: Year Book Medical Publishers, 1964: 164.

[7] Wilson FN, Johnston FD. Rosenbaum F, et al. The precordial electrocardiogram. Am Heart J 1944;27: 19-85. IS.

[8] Kossmann C. Unipolar electrocardiography of Wilson: a half century later. Am Heart J 1985;l lO:9Ol-4.

[9] Centers for Medicare and Medicaid Services (CMS): Medicare provider utilization and paymentdata. (2015). Accessed: April 27, 2019: https://data.cms.gov/Medicare-Physician-Supplier/Medicare-Provider-Utilization-and-Payment-Data-Phy/utc4-f9xp/data.2020 Rehman et al. Cureus 12(7): e9040. DOI 10.7759/cureus.9040 8 of 8

[10] DOI 10.7759/cureus.9040 Precordial ECG Lead Mispositioning: ItsIncidence and Estimated Cost to Healthcare

[11] Alain Rudiger, Jens P. Hellermann, Raphael Mukherjee, Ferenc Follath, Juraj Turina, Electrocardiographic artifacts due to electrode misplacement and their frequency in different clinical settings,The American Journal of Emergency Medicine,Volume 25, Issue 2,2007,Pages 174-178,ISSN 0735-6757,https://doi.org/10.1016/j.ajem.2006.06.018.

[12] Rehman M, Rehman NU. Precordial ECG Lead Mispositioning: Its Incidence and Estimated Cost to Healthcare. Cureus. 2020 Jul 7;12(7):e9040. doi: 10.7759/cureus.9040. PMID: 32656045; PMCID: PMC7343296.

[13] Puurtinen, M., Viik, J. Hyttinen, J. Best Electrode Locations for a Small Bipolar ECG Device: Signal Strength Analysis of Clinical Data. Ann Biomed Eng 37, 331–336 (2009). https://doi.org/10.1007/s10439-008-9604-y