Cardio: An Edge-enabled Wearable ECG Vest for Office Worker's Heart Condition Monitoring

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Keywords: Electrocardiogram, Wearable Device, Feature Extraction.

Abstract: Heart conditions are one of the most common health problems for people aged above 50 years, with the percentage of people suffering from chronic heart diseases increasing year by year. These problems are more common in modern western societies, where sedentary life and stressful lifestyles are the norms. People at these ages are in the final steps of their professional careers and need to balance the effect of their work on their health while staying safe and productive to achieve the best future quality of life for themselves and their families. In this work, we present a novel wearable ECG Vest that can help them monitor in real-time their known heart conditions while they work, reducing stress and fear. Its operation is simple enough for the device to be worn, as a normal jacket without the need to know where exactly to connect electrodes. Its operation is also controlled with a single button without the need for any further configuration.

1 INTRODUCTION

Health monitoring is an extremely active research field, especially after the recent COVID-19 pandemic crisis that altered the lives of billions of people on the planet. Visits to hospitals have been significantly reduced, due to the COVID-19 focused operation of hospitals or even the people's fear of coming in contact with the virus. Physicians, clinics and governments have been trying to find alternative ways to provide their patients and citizens with effective telemedicine and home monitoring and home care solutions, to reduce the stress in hospitals and medical personnel. Detecting potentially dangerous health conditions quickly and with minimal effect on the people's routines and ensuring them that they are safe during their everyday interactions is now of utmost importance to everyone, as societies start to emerge from prolonged lockdowns and people start to return to their "normal" daily routines.

SmartWork is an EU-funded research project that intends to provide older workers (aged 55+) with services that help them stay safe and more productive in their professional life. Such services can offer them and their loved ones reassurances that their health conditions are not deteriorated by their work. SmartWork uses an Internet of Things (IoT) powered unobtrusive sensor network to understand and observe the older worker's health conditions, their work environments, and their productivity in real-time. This information is then used to provide suggestions for behaviors and habits that have negative effects on the health conditions of workers and their work efficiency. SmartWork achieves all that by using robust and proven in real world trials solutions for collecting, storing and processing of all the needed information using resource-constrained devices that are integrated into the final system (Chiang and Zhang, 2016).

Cardiovascular diseases, especially after the pandemic, are of extreme importance and require immediate care, as the stress and anxiety cause by stay at home guidelines can have serious negative effects. Additionally diseases of the circulatory system cause more than 1.68 million deaths every year (based on data from 2016) (cde,), with more than 10 million patients that needed hospital care in 2018, depicting the importance of early diagnosis and proper monitoring. Having access to tools and methods to effectively monitor heart conditions can give doctors the chance to save thousands of lives every year (O'Connor et al., 2015). The most common way to detect and iden-

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Amaxilatis, D., Antoniou, A. and Chatzigiannakis, I.
Cardio: An Edge-enabled Wearable ECG Vest for Office Worker's Heart Condition Monitoring.
DOI: 10.5220/0010724700003063
In *Proceedings of the 13th International Joint Conference on Computational Intelligence (IJCCI 2021)*, pages 420-426
ISBN: 978-989-758-534-0; ISSN: 2184-3236

tify these heart conditions is the use of an Electrocardiography monitoring (ECG) device. This device can monitor the electrical activity of the heart, and its electrical impulses generated by the polarization and depolarization of cardiac tissue through properly placed electrodes. ECG devices range in both sizes and accuracy from stationary hospital-grade equipment to miniature devices with lower accuracy but higher portability and comfort for the users.

The Cardio ECG Vest is one of the SmartWork IoT devices used to gather cardiological-health related information from office workers. It is a miniature ECG device designed as a wearable vest that can be used during office-related or other activities while collecting ECG data in real-time and with minimal discomfort to the office workers. It is capable of producing high quality, hospital grade, 12-channel ECG recording with additional features such as on-board data processing, real-time notifications while being comfortable to wear and easy to use. This is a huge benefit in terms of accuracy and data quality, when compared to other portable ECG devices that rely on a limited number of leads with limited accuracy, such as the AliveCor Heart Monitor[1], the HeartCheck Pen[2] or the Polar H10 Heart Rate Sensor[3]. The produced electrocardiogram (ECG) and the extracted analysis can be used in decision-support systems to assist physicians and cardiologists evaluate irregular heart rhythm, potentially diagnose cardiac abnormalities, and predict critical clinical states (da S. Luz et al., 2016).

A huge problem with existing solutions is the high noise added to the ECG recording by nearby electronic devices (e.g., mobile phones, electrical wires, appliances) or by the muscular movement of the wearer that can severely affect the quality of the data collected (Luo et al., 2017). The Cardio ECG Vest is equipped with specially designed noise reduction circuits that can help reduce such interference to a minimum. It can also operate for long times, at least 8 hours (the full duration of a normal workday) without the need for recharging. The data produced, are processed to a very large degree on the device itself, eliminating the need to send unnecessary personal data to a nearby smartphone or any cloud service.

Transmitting sensor data to cloud services for processing and analysis creates several security issues that need to be addressed as they are directly related to the privacy of the users (Angeletti et al., 2018; Chatzigiannakis et al., 2011) Existing portable solutions are cloud-centric: all personal data collected are stored on the cloud and, in most cases, users have reduced control over the data they produce, although certain legislative actions have given users much more power over their personal data (e.g., the EU General Data Protection Regulation, GDPR (Commission, 2018)). This cloud-focused architecture severely limits the ability of the user to maintain control of personal data. Now, more than ever, there is a need for privacy-preserving applications where users remain always in control of their sensitive data. (Angeletti et al., 2018; Angeletti et al., 2017).

The goal of this paper is to present the usage of this novel miniature ECG device and its wearable vest design in SmartWork powered office environments to provide workers with reassurance over their chronic health conditions. This is achieved using lightweight algorithms for the analysis and interpretation of ECG sensor data that can be executed in the embedded processor of the wearable device.

In this context, the wearable device becomes responsible for the extraction of features from the collected sensor data and providing actionable alerts without any dependence on cloud services. It is an evolution from the traditional cloud-based or offline (Holter ECG devices) solutions following the highly promoted wearable approach. By following this path, we do not only achieve a much more energy and processing power-efficient solution but also manage to respect users' privacy.

The rest of the paper is structured as follows: In Section 2 we present the miniature ECG device and the Vest used. Section 3 describes some basic points regarding the ECG data analysis and the steps performed to extract characterizations for the worker's heartbeats. In Section 4 and 5 we showcase the architecture of our system and the connectivity options available for integrating the ECG device with a companion smartphone application and the cloud. An evaluation of the operation and the data analysis of the Cardio ECG Vest is available in Section 6. Finally, in Section 7 we present our conclusions and next steps.

2 THE ECG DEVICE

The wearable hardware device consists of a small main board responsible for the core processing functions, communication with a smart device and ten (10) ECG sensor pads which are attached via a ribbon cable to the main board.

The main board features the ultra low power system on chip (SoC) nRF52840, with Low Energy Bluetooth capabilities, and a number of peripheral modules, such as an Real-Time Clock, an Inertial Mea-

[1] http://www.alivecor.com/

[2] http://www.theheartcheck.com/

[3] https://www.polar.com/en/products/accessories/H10_heart_rate_sensor

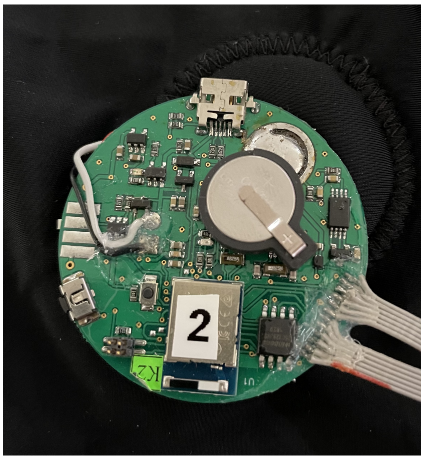

Figure 1: The main board of the Cardio ECG device.

surement Unit, an external Flash Memory module, a LED, a multi-functional push button and a power and battery charging circuit. The nRF52840 is built around a 32-bit ARM Cortex M4F CPU which, as the name indicates, has a dedicated hardware floating-point unit (FPU). It also has a Bluetooth 5, IEEE 802.15.4-2006, 2.4 GHz transceiver, which is backwards compatible with the BLE 4 communication protocol ensuring compatibility with a wide range of smart devices in the market. A MCP79411 RTC module provides timestamps for the ECG sampling sessions and can also be used to set alarms for the device to wake up at specific time or intervals in order to further reduce power consumption. The Inertial Measurement Unit is the LSM6DSRXTR module which features a 3D accelerometer and gyroscope and can provide 16 bit samples at a configurable rate and scale, based on the required sensitivity of the measurements by the application. This module also has a few embedded functions that can provide interrupts to the main SoC for events such as significant movement, or taps, which can be utilized to detect inactivity periods to put the device to sleep mode, or as wake-up signals for the device. The (W25Q128JVSIQ flash memory chip is a NOR Flash memory with a 16 MBs storage capacity, which can store up to about 46 minutes of 12bit ECG samples from 8 analogue leads sampled at a rate of 500Hz. The memory can also be used for storing user profiles and application settings, as well as pre-compiled machine learning models for the classification of the sampled data. The ECG sensor pads have electrodes that provide the eight (8) analog input signals to the internal 12bit ADC module of the nRF52840 SoC. These eight signals are used to produce the 12-lead ECG of the subject patient.

With the support of Nordic Semiconductor's precompiled library, SoftDevice S140, which is specialized for the nRF52 SoC series, implementing the Bluetooth protocol stack and providing an easy to use API to configure Bluetooth connectivity, the application firmware can construct a custom high level communication protocol to facilitate the interactions with a client Bluetooth enabled smart device. Our protocol exposes a custom Bluetooth Service, and a number of child BLE characteristics which are used to receive commands, stream sampled or processed data and notify for device status changes and special events. Specifically, there are characteristics that handle issued commands and their execution status. Such commands include starting and stopping the sampling of ECG and IMU data, setting and reading the RTC time, resetting the device, formatting the external memory, and resetting to factory defaults. The ECG data are streamed in a dedicated BLE characteristic, with packet sizes that are set based on whether the device operates in BLE4 or BLE5 mode. BLE5 mode allows for a high throughput of up to 2Mbps, facilitating greater sampling rates. Similarly, the sampled data from the IMU are streamed from a separate characteristic and independently of the ECG sampling. Another import BLE characteristic is used to notify the calculated extracted features on the sampled data, which can be used to either form training vectors for our machine learning models or used for the classification of the active ECG data stream. Finally, auxiliary exposed characteristics include one providing information on the firmware and configuration of the device, an indicator of the device's charging status, and one notifying periodically of the current battery power level.

Figure 2: The Cardio ECG Vest.

The whole system is powered by a high capacity 402030 3.7*V* 500*mAh Lithium-ion battery cell*. It also supports battery charging via a micro-USB port and has an onboard extension port for wireless charging.

3 ECG DATA PROCESSING

The analysis of an ECG recording can be performed by many available methods in an embedded device. Most of these techniques offer low accuracy levels and result in a high number of alerts (Shah and Rubin, 2007). Machine learning techniques (Saini et al., 2013) and deep neural networks (DNN) (Kaplan Berkaya et al., 2018) have been tested and showed that can achieve higher levels of accuracy in diagnosing heart conditions using appropriate models and relying on high-performance computing infrastructures. To use them in low-power embedded hardware with limitations in memory and processing power, proper transformations are needed, using hardware ((Du et al., 2017; Gokhale et al., 2017)) and algorithmic solutions ((Luo et al., 2017; Qin et al., 2020; for the Advancement of Medical Instrumentation, 2013)).

Our processing over the sampled data on the main ECG device tries to follow the best outcomes from the above approaches to get the best accuracy with the lowest penalties on alert numbers and power consumption. Our aim is to produce a dataset of extracted features from the ECG signals recorded. These features can the be used to provide descriptive vectors on consecutive segments of an actively sampled ECG that is cross-checked and validated by a separate processing module on the client smart device or even on the ECG device itself.

In the current implementation, we use a single 12 bit lead signals as the input to extract descriptive features from. The feature extraction process takes place over ten (10) second intervals of the input signal, and employs a basic implementation of the Pan-Tompkins algorithm (Pan and Tompkins, 1985) for QRS complex detection. The extracted features include:

- the average R-R interval in milliseconds,
- the count of R peaks,
- the average R-amplitude,
- the average S-trough amplitude,
- the average R-S peak-to-peak amplitude and
- a history of the 5 most recently calculated R-R intervals

The implementation uses variables to adapt for various sample rates on the input ECG signal and noisy segments of data. The whole feature vector can be used to classify this 10-second segment in one of 3 generic groups, normal ECG recording, noisy ECG recording, marked ECG recording. The marked ECG recordings are those that display characteristics that need to be reviewed by the medical practitioner in order to understand if they are actually showing a physiological condition that needs to be further checked.

4 DEVICE TO SMARTPHONE CONNECTION

The ECG device itself has limited interaction with the user. It is equipped with an LED light for simple battery charging and operation indications and a single button used to power on the device from its deep sleep state. Starting and stopping ECG recordings is done using a companion application in the user's smartphone, with which the device is communicating over Bluetooth-LE.

While the phone is in the vicinity of the ECG device it can receive in real time both the full ECG recording, IMU data, results from the on-board feature extraction, battery levels and notifications (ECG or device related). Each one of these sources is a separate BLE characteristic that the smartphone can subscribe to, in order to receive it form the ECG device according to the BLE5 specification. In order to fit all these data in the BLE notification packets and avoid hardware related restrictions, we attempted to limit as much the number of notifications generated by the device, increasing the amount of data we send in batches during each notification. For this, each ECG data notification contains a total of 19 ECG samples with each sample consisting of 8 12-bit values, while each IMU data notification contains 19 full samples with each sample containing 6 values of 2 bytes. In this configuration, we manage to keep a constant flow of data from the ECG device to the smartphone with minimal packets lost. For example, in a 3 minute recording window, the number of packets lost less than 300 out of a total of 90000 (around 0.003%). The same behaviour is observed with the IMU data packets, where in the same period, around 50 packets are lost out of a total of 18000 (again around 0.003%). Similar numbers are achieved even when only one of the notifications is enabled, letting us believe that this behavior is not related to the actual BLE medium but to the handling of the packets on the smartphone side or the generation of the packets in the ECG device's side. As this was observed using multiple phones with different specifications, the most probable cause is the later.

The smartphone application itself does minimal processing on the received data. It displays the received ECG in a simple graph for the user to see that everything is operating normally, the battery level of the ECG device, and some of the features provided by the device. The most important task is the storage of the real-time ECG recording on the phone's storage so that it can then be shared with a medical practitioner as needed. The file is stored in a properly encrypted format to avoid any usage without the direct consent of the worker.

5 SMARTPHONE TO CLOUD CONNECTION

To provide the data collected on the phone to their medical practitioner, users have two options. The first one is the most simple, by physically giving their phone to their doctor to review the data collected. This is no a very sophisticated approach but simplifies all the actions needed to safeguard personal data, as no information leaves the user's phone ever. The second option is to properly share the recordings with the medical practitioners via our cloud services. In this flow, the user uploads the recording to the Cardio service and shares it with the doctor's account. The doctor by accepting the recording receives the keys to access it and sends a data access receipt to the worker/patient. During the whole flow, the data are encrypted, and the worker has the option to revoke access at any time.

This whole flow is implemented using Amazon Web Services[4]. In more detail we are using Amazon Cognito & IAM to manage users and their permissions, Amazon S3 to store and share recordings, AWS SNS for sending notifications to users, and Amazon Lambda to implement our serverless API for sharing and getting access to ECG recordings and user information (such as access receipts).

6 EVALUATION

To prove our system's operation we performed a series of tests on the ECG devices using both ECG simulators and in-lab test patients. As soon as the system's operation is proven, we will extend our testing during the SmartWork's trials, where workers will use the ECG vest to perform a number of recordings of variable intervals to help us understand better (1) the ease of use of the ECG Vest itself, (2) the ease of use of the Cardio application interface, (3) the quality of the data recorded on various body types, (4) the quality of the feature extraction algorithms with real world data.

[4]https://aws.amazon.com/

From the performed in-lab tests we performed, we hereby present some results that depict the key features of the operation of our system.

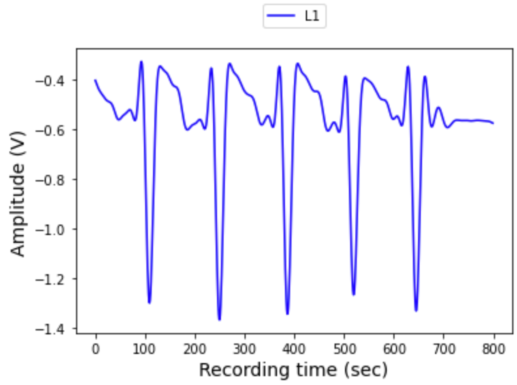

Figure 3: Recorde ECG pulses - L1 channel.

Fig. 3 and Fig. 4 show 5 consecutive recorded heartbeats recorded from an in-lab test patient during a larger recording. These figures give us a better understanding of how heartbeats are depicted in different channels and how their PQRST characteristics look like. Based on this view we are able to extract the needed characteristics (as we described in Section 3), like R-R interval, the R-amplitude or the R peak count.

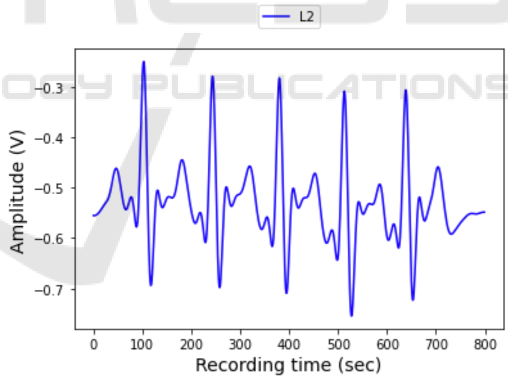

Figure 4: Recorde ECG pulses - L2 channel.

For each one of the features, we present here the calculated values from the onboard algorithm. We start with the R-R interval, which gives us an estimate of the heart rate of the patient and its variance during each interval. Fig. 5 shows the calculated R-R interval from the ECG device (tumbling R-R) and the calculated value using a sliding window (sliding R-R) instead of a tumbling one as they are calculated on the smartphone application. As we see, values using the tumbling window are more smooth than the sliding one, as they are not so much affected by noise in the ECG signal.

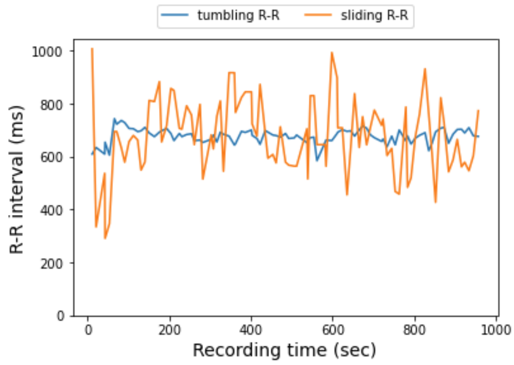

Figure 5: R-R interval using tumbling and sliding windows of 10 seconds.

Fig. 6 shows the number of R peaks detected from our algorithm in each 10 second window the ECG device detects. These values do help us detect both the number of heartbeats and the location of these heartbeats inside the window, helping find the exact start and end locations of each heartbeat, information that will help us in the future of our research. Using the R counts we can calculate the heartrate of the wearer ($10\text{-}sec\text{-}R\text{-}count \times 6 = heartrate$), so in our test, this results in a heart rate of around 90 beats per minute.

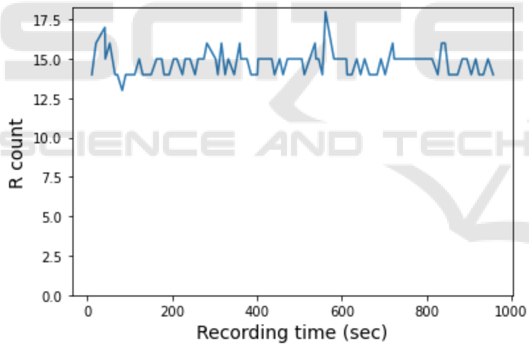

Figure 6: R count in each 10 second tumbling window.

Finally, Fig 7 depicts the average R peak amplitude, S amplitude, and RS amplitude for each of the tumbling windows. As we see, these values are quite stable, as expected, during the whole recording given that this recording is from a test patient with no chronic heart condition diagnosed.

7 CONCLUSIONS

In this work, we showed how a wearable ECG monitoring device is used in the context of SmartWork to provide information and feedback on office workers with chronic heart conditions regarding the effects of their works in their everyday lives and their diagnosed

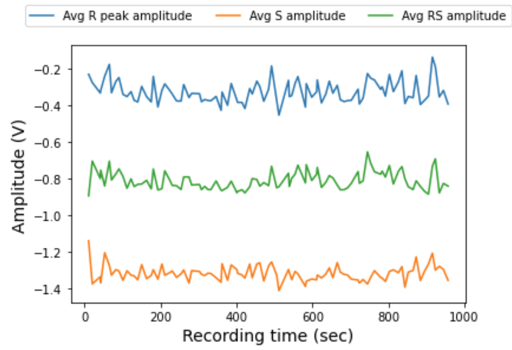

Figure 7: R, S and RS amplitudes in each 10 second tumbling window.

conditions. We presented how the device operates in order to generate such conclusions based on the ECG input signals and how the resulting events are transferred to SmartWork to properly notify the worker's doctors. We showcased the resulting data from the ECG recordings and the results of the analysis done on the ECG device.

As our next steps, we plan to further increase the analysis of the ECG traces on the device itself, providing more accurate detection and heartbeat characterization by identifying the possible problems in each heartbeat, instead of a general alert characterization. We also plan to test our system with real users, during the SmartWork's trials that are currently being executed to gather as much user feedback regarding the usability of our system and the quality of the whole experience.

ACKNOWLEDGEMENTS

This work has been partially supported by the SmartWork project (GA 826343), EU H2020, SC1-DTH-03-2018 - Adaptive smart working and living environments supporting active and healthy ageing.

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