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Real Time Signal Quality Aware ECG System for Health Care Monitoring Using Raspberry Pi

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Abstract – Recently, development of wearable technologies and continuous individual electrocardiogram (ECG) monitoring indentifies of invalid data in recording. In this work, we present a signal quality index (SQI), which is intended to assess whether reliable heart rates (HRs) can be obtained from ECG signal collected using wearable sensors. The proposed quality – aware ECG monitoring system is realized on Raspberry Pi. It consists of two modules: 1) ECG signal sensing module; 2) automated signal quality index (SQI) analysis. The main objective is to design and development of a light weight ECG SQI method for automatically classifying the acquired ECG signal into GOOD or BAD and real time implementation of proposed ECG framework is tested and validates using ECG signals taken from the Physionet database.

Index Terms—Battery life, electrocardiogram (ECG) photoplethysmogram (PPG), respiratory rate (RR), signal quality, telemonitoring, wearable sensors.

1. Introduction

The greater part of tele monitors methods future in the literature has still not created their way into general clinical use. Challenge faced in the field of wearable sensor design include minimize the substance and the size of the systems to increase relieve, militating against the corruption of recorded signal by motion artifact, and maximize battery life while maintaining wear ability. Compared with conventional bedside monitoring, as used in intensive care units, the issue of identifying invalid data is of particular importance for wearable sensors, as data obtained from ambulatory patients, the patients most likely to benefit from the use of wearable sensors, are more likely to contain artifact than data from bed-bound patients. Artifact-corrupted signal has been shown to lead to a large number of false alarms which can lead to the phenomenon of "alarm fatigue" whereby ward staff become desensitized to and ultimately ignore alerts from the system. The Joint Commission, the body that accredits U.S.healthcare institutions, has recently issued a Sentinel Alert, highlighting the problem of alarm fatigue and the ECRI Institute has listed alarm hazards in10HealthTechnology their annual Top Hazards report every year since 2010. A large number of artifact detection (AD) algorithms have been developed with the purpose of assessing the quality of physiological data. Recent publications propose algorithms for deriving signal quality indices (SQIs) either based on a single channel of physiological data or by fusing information from several channels. A comprehensive review of the development and utility of AD algorithms in critical care units (CCUs) was recently published in, which reviewed 80 AD approaches published between 1989 and 2012. The authors conclude that currently published AD techniques are highly specific to a particular clinical setting and require modification for validation and reuse in a different one. Most algorithms are hard coded to monitor specific data types and frequencies, which may limit their use. Furthermore, the fact that most commercially available monitors used in the reviewed studies have undisclosed built-in preprocessing algorithms imparts an unknown bias to the output of the AD algorithms

In this paper, we propose an approach to automatically qualifying segments of electrocardiogram (ECG) collected from ambulatory patients via wearable sensors, using an SQI, extending work initially presented in. The planned algorithms are intended to provide real time assessment of the suitability of ECG and PPG signals for deriving reliable heart rates (HRs). In order to make our algorithm usable in a range of clinical environments, it was developed and evaluated on data from different clinical settings and monitors. The output of the algorithm is given in a binary format, "good" (i.e., a reliable HR can be derived) and "bad" (i.e., a reliable HR cannot be derived) to simplify interpretation and facilitate applicability. In addition, we demonstrate the utility of the proposed SQI for improving the performance of wearable sensors by proposing strategies for: 1) power saving in order to extend the battery lifetime of the sensors.

2. Motivation and Related work

In real-world applications, the majority IoT-enabled devices function on inadequate power batteries for extended time periods. Theenergy consumption becomes a essential design thought toimprove the whole network life span consequently controllingdata exchange can minimize the energy expenditure and furtherimprove network utilization. [1] Studied thepotential of data-driven event triggering in a real-world publictransport tracking scenario. The study showed that the data drivenevent triggering has great potential to improve energycompetence and network use [2]. A long-term continuous cardiac health monitoring system highly demands more battery power for real-time transmission of electrocardiogram (ECG) signals and increases bandwidth and treatment costs and diagnostic server traffic load. The event-triggering is a promising paradigm that has the potential to adequately address the aforementioned key challenges. In our previous works, an automated low-complexity robust cardiac event change detection method was proposed for long-term healthcare monitoring applications [3]. Literature studies showed that the battery lifetime of IoT-enabled devices is highly influenced by the power consumption of the communication network utilization for continuously sharing the sensor data to cloud server and the on-device embedded processor for event detection and modeling in real-time. Therefore, intelligent solutions are demanded to improve battery lifetime of IoT devices and to Reduce diagnostic traffic load and bandwidth utilization costs. In practice, the ECG signals are corrupted by various kinds of artifacts and noise including, flat line (FL) due to the electrode disconnection, baseline wander (BW) due to the Respiration, abrupt change (AC) due to the physical activities, muscle artifacts due to the muscle contraction, power line interference (PLI) and recording instrument noise [2]. The disturbances due to muscular activity (i.e., electromyography (EMG) or muscle noise) that is ubiquitous in wearable cardiac health monitoring devices under ambulatory and high-intensive exercise ECG recordings [4]. Consequently, the muscle artifacts degrade the signal quality, spectral resolution and resultsin large amplitudes. For example, the small amplitude local waves (P, T, U and small QRS complex) are obscured by the larger amplitude muscle artifacts. Thus, it is difficult for the physicians to visualize and locate the presence or absence of these low-amplitude local waves that can provide significant clinical information required to diagnose certain heart abnormalities. Moreover, it is also difficult to perform more accurate and reliable measurement of morphological parameters such as amplitude, duration, pause interval, timings, polarity, and shapes of the local waves that are most important for accurate heart rate monitoring, arrhythmia detection and heartbeat pattern recognition [1]. Further, transmission of bad quality ECG signals to the cloud server can reduce lifetime of on-device battery in body area networks as well as increases false alarm rates in unsupervised health monitoring applications.

3. Signal quality indices

The SQI we propose is intrinsically linked to the ECG and the PPG peak detectors used since an assessment of their performance is used in the development of the SQI. For R-peak detection, we used the widely accepted Hamilton and Tompkins algorithm, and for PPG pulse-peak detection, we used a three-point peak detector with a set of empirically determined. Thresholds. To develop the ECG SQI, we used 1500 10-second segments of ECG, comprisin500 segments randomly drawn from each one of the PCinC, JRD−ECG, and JRE−ECG databases. For the development of the PPG SQI, we used 1500 10-second segments of PPG, comprising 750 segments randomly drawn from each one of the JRE−PPG and JRN−PPG databases. All 3000 segments were manually labeled.

1) Labeling of ECG and PPG Signals: Labeling was carried out in three stages. In the first stage, two assessors categorized the 3000 samples based on the following rule: “An ECG or PPG segment is labeled as ‘clinically usable’ if a human expert can confidently derive a reliable HR from it, by counting the number of salient features(such as R-peaks or PPG pulse peaks) over fixed time intervals. Otherwise, it is labeled as ‘clinically unusable.” When there was disagreement between the two assessors, a third assessor reviewed the ambiguous samples and gave the decisive label. 991 ECG samples (66%) were ranked as “clinically usable,” and 509 (34%) were ranked as “clinically unusable.” In the case of the PPG, 828 samples (55.2%) were ranked as “clinically usable” and 672

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(44.8%) as "clinically unusable." The third assessor reviewed 12.2% of the ECG data and 13.6% of the PPG data. In the second labeling stage, the R-peaks and PPG pulse peaks of the "clinically usable" samples were manually identified by the two human experts using a custom annotation GUI written in MATLAB (Math Works, Natick, MA, USA). As in the first stage of labeling, the third assessor reviewed annotated samples for which annotations of the first two assessors differed. The third annotation was then taken to be the correct one. 103 ECG samples (10.4%) and 127 PPG samples (15.3%) had to be reviewed by the third assessor. The third labeling stage involved comparing the output of the R-peak and pulse-peak detectors applied to the "clinically usable" ECG samples with the annotations obtained from the second stage of labeling. As a result of this process, the samples had a second label applied to them according to the following rule: "An ECG segment is labeled as being 'bad' if more than one R-peak is missed by the R peak/PPG pulse-peak detector, or if more than one instance of artifact is mistakenly identified as an R-peak/PPG pulse-peak by the R-peak/PPG pulse-peak detector. Otherwise, it is labeled as 'good'." This rule is deliberately conservative: if more than one R-peak in a 10-s sample is missed, or more than one noisy peak is mistakenly identified as an R-peak.The HR value ultimately derived from this sample will have a large error.

2) SQI Algorithm:A flowchart of the SQI algorithm is shown in Fig. 1. The different steps are explained in detail in the following section.

a) Feasibility rules: The first step of the SQI algorithm is to perform R-peak/PPG pulse-peak detection on a sample and to compare the output of the detector with a set of physiologically relevant rules. The following three rules are applied sequentially, and if any is not satisfied, the sample is classified as "bad."

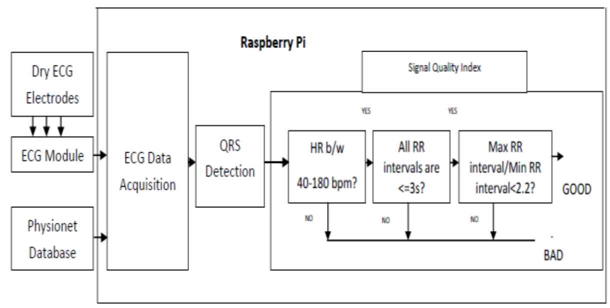

Figure 1: Block Diagram

1) Rule 1: The HR extrapolated from the 10-s sample must be between 40 and 180 beats per minute (bpm). (Though it is theoretically possible to have HRs outside of these values, this is the physiologically probable range of HR for the adult population likely to use wearable sensors.)

2) Rule 2: The maximum acceptable gap between successive R-peaks/PPG pulse-peaks is 3 s. (This rule ensures no more than one beat is missed.)

3) Rule 3: The ratio of the maximum beat-to-beat interval to the minimum beat-to-beat interval within the sample should be less than 2.2. (This is a conservative limit since we would not expect the HR to change by more than 10%in a 10-s sample. We use a limit of 2.2 to allow for a single missed beat.) If all the three rules are satisfied.

4. Implement on raspberry

The Raspberry Pi Foundation designed this little board here, the Raspberry Pi, to address a lost generation of computer programmers and hardware engineers. So, this little board here is low cost, it's easily accessible, it's very simple to use. When you power it up you get a nice little desktop environment, it includes all of the things that you need to do to get started to learn programming. There's lots of information out there on the internet that you can take away and start programming code in to make things happen.

The great thing about these boards as well is in addition to software, you can play with hardware. So these little general purpose pins here allow access to the processor and you can hang off little hardware projects that you build and you can control via the code you are writing through the software application. So, this is a great tool for kids to learn how computers work at a grassroots level.

So there are two versions available of the Raspberry Pi currently. This is the Model B; this is the first one that came out, and this is pretty much like any other computer: it plugs in to your television; it has a keyboard and a mouse input here; you can connect it to the internet; and it runs an operating system off the SD card here. The Model A, which has come along more recently, is pretty much the same as the Model B, but it's removed some of the functionality so there is no connection hardwired to the internet and they've removed the device that controls that as well. So it's a slightly cheaper board and it's much lower power, so if you wanted to do some handheld applications or battery-powered, for example, it's a much better solution to go for. It was originally intended to go for children, and what happened was that this got a massive following from a wider base of people, kind of the hobbyists and the hackers if you like out there, and what they've done is they adopted it very quickly because of the price, the accessibility, the fact that it's fully featured and you can do lots with it. So from a very basic level if you are a child in your bedroom and you want to learn just basic computer programming, or you want to turn it into a media centre where you can play videos and audio, or if you want to take it to the next level and you're a DIY tech guy, for example, you might want to replace some Electronics around the house that was broken, you might want to control your heating timer, you could dial into it from the internet, you could control your heating, your lights, you could make a home automation control box from this. And not only has it been adopted by the hobbyist space, but also from a commercial world, people are actually adopting this to put into their finished applications. So you might decide that you want to put it into an industrial control product. So, as I say, the hard work is already done, you just need to hang off a few peripherals from this, stick it into a box and you've got your construction so when you get your Raspberry Pi, it comes in a nice little box, like this, well open it up here, and here it is. So, this is what you get and you need a few things to get it going. Let's start by connecting up the USB keyboard and mouse; we have our HDMI cable here for connection to our television;

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we have the power; and we have our SD card. And that goes in the back; that's what holds the operating system. The working system we have got in here, they're Linux-based operating systems, and they're Raspbian which is a distribution of Debian. You need a few accessories to get it running; if you haven't got those lying around the house then you can buy those from RS or Allied. And once you're in you can do anything you can do on a regular computer. You can do documents, Word processing etc. and that's a great little platform for children to start learning computer programming as well with the built in packages that come with it. You can connect it to the internet. There is a Pi store that's already loaded on to the Raspberry Pi itself and that gives you access to lots of applications and you can pull those down for free at no extra cost.

5. Results and discussions

This sensor is a cost-effective board used to measure the electrical activity of the heart. This electrical activity can be charted as an ECG or Electrocardiogram and output as an analogy reading. ECGs can be extremely noisy, the AD8232 Single Lead Heart Rate Monitor acts as an op amp to help obtain a clear signal from the PR and QT Intervals easily. TheAD8232 is an integrated signal conditioning block for ECG and other bio potential measurement applications.

Figure 2: Sensor Pad location on Body

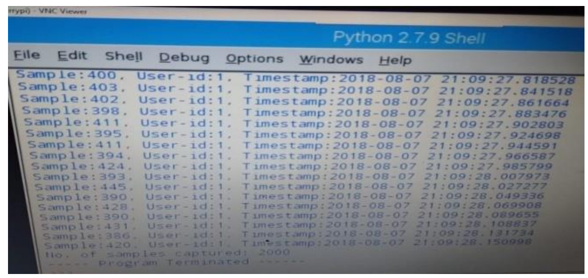

Figure 3: Output of Hart Bert Samples

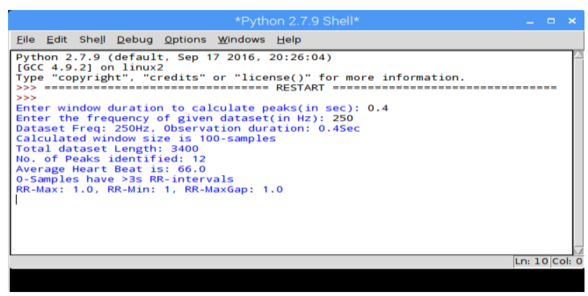

Figure 4: signal 1 frequency 250 in Hz window

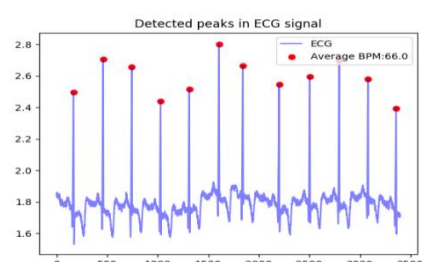

Figure 5: Detected peak in ECG signal

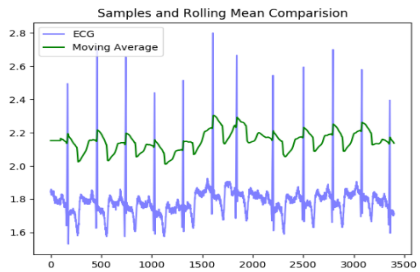

Figure 6: Samples and Rolling mean comparison

6 Conclusions:

We have presented an SQI for the ECG which is intended to provide real-time assessment of the suitability of ECG and PPG signals for deriving reliable HR values. We evaluated the SQI on data from a range of wearable physiological sensors and achieved sensitivities and specificities of 94% and 97% for the ECG .The proposed SQI is intrinsically linked to the peak detector used meaning that using other peak detectors would change the performance of the SQI. We then proceeded to propose two applications of the SQI in order to improve the performance of wearable physiological monitoring systems. We first proposed a power-saving application utilizing the SQI in order to increase the battery lifetime of wearable monitors. Our proposed approach assumes that a single reliable HR value is required in every 5 min of ECG recording. In particular, the device is turned off after a "good" segment of data is obtained and then on again after a predetermined period of time has elapsed.

7 Future works:

Empirical Mode Decomposition very recent techniques. Hence a lot of research needs to be done on the properties so that we can come up with still simpler methods for ECG signal Analysis. Feature extraction is yet another field in ECG signal Analysis untouched by us. But it is very important for classification of Arrthymia. Hence our future work will be dedicated to feature extraction and classification. The process of enhancement can be modified using more evolved techniques. Research needs to be done for finding more efficient methods for signal enhancement.

References:

[1] G.Clifford and D.Clifton, "Annual review: Wireless technology in disease management and medicine," *Ann. Review Med.*, vol. 63, pp. 479 492, 2012.

[2] V. Nangalia, D. Prytherch, and G. Smith, "Health technology assessment review: Remote monitoring of vital signs-current status and future challenges," *Crit. Care*, vol. 14, no. 5, pp. 1–8, 2010, DOI: 10.1186/cc9208.

[3] C. L. Tsien and J. C. Fackler, "Poor prognosis for existing monitors in the intensive care unit," *Crit. Care Med.*, vol. 25, pp. 614–619, 1997.

[4] ECRI. (2013). Alarm safety resource site: Guidance and tools to help healthcare facilitiesimprovealarmsafety[Online].Available:https://www.ecri.org/Forms/Pages/Alarm_Safety_Resource.aspx

[5] S. Nizami, J. R. Green, and C. McGregor, "Implementation of artifact detection in critical care: A methodological review," IEEE Rev. Biomed.Eng., vol. 6, pp. 127–142, Jan. 2013, DOI:10.1109/RBME.2013.2243724

[6] E. I. Shih, "Reducing the computational demands of medical monitoring classifiers by examining less data," Ph.D. dissertation, Dept. Elect.Eng.Comp. Sci., Mass. Inst. Technol., Cambridge.USA, 2010.

[7] T. Bonnici, C. Orphanidou, D. Vallance, A. Darrell, and L. Tarassenko, "Testing of wearable monitors in a real-world hospital environment: What lessons can be learnt?" in Proc. BSN, 2012, pp. 79–84,

[8] M. A. DeVita, G. B. Smith, S. K. Adam, I. Adams-Pizarro, M. Buist, R. Bellomo, R. Bonello, E. Cerchiari, B. Farlow, D. Goldsmith, H. Haskell, K. Hillman, M. Howell, M. Hravnak, E. A. Hunt, A. Hvarfner, J. Kellett, G. K. Light hall, A. Lippert, F. K. Lippert, R. Mahroof, J. S. Myers, M. Rosen, S. Reynolds, A. Rotondi, F. Rubulotta and B.Winters "Identifying the hospitalized patient in crisis—A consensus conference on the afferent limb of rapid response systems," Resuscitation, pp. 375–382, 2010.