Digital Health and Informatics Innovations for Sustainable Health Care Systems
J. Mantas et al. (Eds.)

doi:10.3233/SHTI240455

Quality of Electrocardiography Recorded with Consumer Smart Shirts

Paulo HAAS[a,1], Nicolai SPICHER[b], Joana M. Warnecke[a] and Thomas M. DESERNO[a]
[a] *Peter L. Reichertz Institute for Medical Informatics of TU Braunschweig and Hannover Medical School, Brunswick, Germany*
[b] *Department of Medical Informatics, University Medical Center Göttingen, Georg-August-Universität, Göttingen, Germany*

Abstract. Smart wearables support continuous monitoring of vital signs for early detection of deteriorating health. However, the devices and sensors require sufficient quality to produce meaningful signals, in particular, if data is acquired in motion. In this study, we equipped 48 subjects with smart shirts recording one-lead electrocardiography (ECG), thoracic and abdominal respiratory inductance plethysmography, and three-axis acceleration. For 10 min each, the subjects sit, stand, walk, and run, with a resting period of 5 min in between each activity. We preprocessed the electrocardiogram and applied a signal quality index. We analyzed the signal quality index grouped by the activity and participants. For sitting, standing, walking, and running, the ECG signals provide acceptable quality over 73.20 %, 91.85 %, 12.26 %, and 13.14 % of the recording time. In conclusion, smart wearables may be useful for continuous health monitoring of people with a sedentary lifestyle, but rather not for sportive activities.

Keywords. Fitness trackers, health trackers, mHealth, mobile health, signal quality, smart textiles, smart wearables.

1. Introduction

Personalized data is fundamental to recognize individual changes and intervene early during the development of a disease [1,2]. Regular monitoring of vital signs enables the recognition of deviations from normal ranges, facilitates timely intervention, and prevents diseases [3].

Together with sensors in other environments such as vehicles [4,5] or homes [6,7], smart wearables enable unobtrusive monitoring in daily life. Signal data can be transmitted in real-time [8], enabling the detection of health changes. Healthcare providers can intervene instantaneously, which reduces the frequency of hospital visits [9]. However, data from continuous health monitoring cannot be reviewed manually, and accurate real-time classification needs high-quality signals [8].

To measure biosignals and vital signs non-invasively, users wear smart clothes on the chest, arm, wrist, or hip [10]. The devices show promising results for many use cases ranging from personal fitness tracking to medical diagnostics [11]. However, motion artifacts lower the signal quality severely [6]. Loose-fitting garments are more vulnerable to motion artifacts, but tight fittings may cause distress and lower blood flow [12].

[1] Corresponding Author: Paulo Haas; E-mail: paulo.haas@plri.de.

Bläsing et al. [13], evaluated the performance of five smart wearables including a smart shirt. Participants needed to conduct four activities on a treadmill: standing (rest), standing with a cognitive task, walking, and running uphill. 13 subjects participated in their study. Using the newly proposed morphSQ, they rated the smart shirt's signal with sufficient quality as follows: 99.61% for resting, 86.52% for walking, 99.15% for cognitive tasks, and 77.60% for running uphill. The authors conclude the feasibility of continuous monitoring and show worsening performance with more motion.

However, Bläsing et al.'s limitations are that measurements are conducted in a controlled environment, which might not reflect real life, and with few participants, which might introduce bias. The same smart shirt was also validated in other studies [14,15], but these studies only considered the ECG-derived heart rate and not the ECG directly.

With our study, we address the research question: "What portion of the ECG signals generated by consumer-grade smart wearables is medically usable?" based on more subjects, more realistic activities, and an established SQI.

2. Material and Methods

2.1. Smart Wearable

We evaluate a consumer-grade smart wearable (Hexoskin ProShirt, Carré Technologies, Montreal, Canada), providing a single-lead electrocardiogram (ECG) (256 Hz), thoracic and abdominal respiratory inductance plethysmography (128 Hz), and 3-axis accelerometer (64 Hz). As being the most important signal, we select the ECG for further analysis.

2.2. Study design

All volunteering participants gave written consent and the Ethics Committee of TU Braunschweig approved the study under vote D 2023-05. First, the participants tried on different shirts and selected their best-fitting size. Second, we conducted a short assessment of the ECG to confirm the optimal shirt size.

Third, all participants simultaneously performed four activities – sitting, standing, walking, and running - consecutively in the same outside area for 10 min each with breaks of 5 min in between (Fig. 1). The study area was restricted, allowing participants to freely move around within it while completing activities. We recorded the start time after all participants started and the ending points before we asked the participants to stop the activity. We intended to include 50 participants and compensate them with 30 €.

2.3. Signal Evaluation

We preprocess the signals using Python (Fig. 2). We cut off the first minute of all activities and then considered the next 8 min of signal for evaluation to ensure comparability,

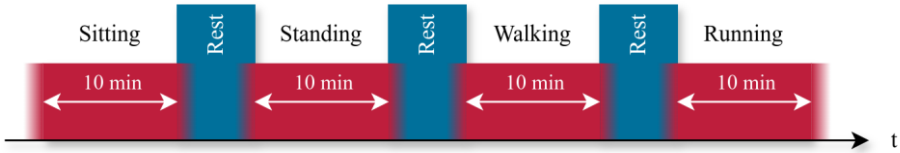

Figure 1. Timeline of the study

and skip phases where heart rate adapts. Then, we split the signal into segments of 10 s without overlap, which provides a high performance for activity recognition [16]. A 1^{st}-order Butterworth bandpass with cutoff frequencies f_L=.5 Hz and f_H=45 Hz removes baseline wander and noise. We detect the R-peaks with the STAPLE algorithm implemented in MATLAB, which combines nine state-of-the-art algorithms to perform robustly and reliably on noisy data [17].

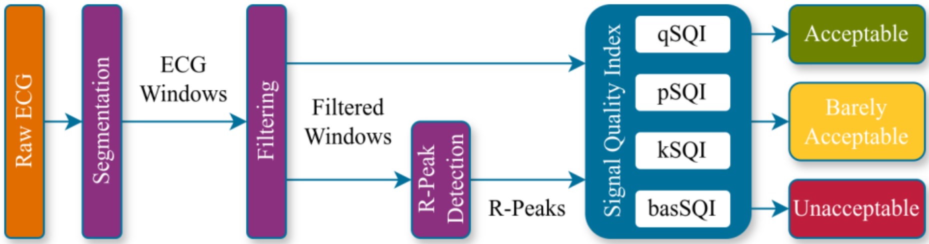

Figure 2. Data preprocessing and evaluation pipeline.

As Tan et al. recently demonstrated reliable performance over the Physionet Cinc Challenge 2011 database in comparison to 11 SQIs [18], we apply the fuzzy SQI suggested by Zhao & Zhang [19], which is implemented in NeuroKit2 [20]. The algorithm outputs a ternary classification: acceptable, barely acceptable, and unacceptable. Acceptable means applications can use the signal without further processing, barely acceptable means the signal needs re-evaluation, and unacceptable means the signal needs more denoising or is unusable. Therefore, we merge barely and unacceptable quality.

3. Results

Due to the available shirt sizes and the participants' required sizes, we conducted our experiment with 48 healthy subjects (gender: 29·m/18·f/1·not specified, age: 23.3±4.3 years, weight: 72.2±13.5 kg, height: 175.0±9.2 cm, BMI: 23.5±3.2).

Table 1. Total quality classifications per activity.

Activity	Acceptable quality	Unacceptable quality
Sitting	73.20 %	26.80 %
Standing	91.85 %	8.15 %
Walking	12.26 %	87.74 %
Running	13.14 %	86.86 %

In ten cases, the STAPLE algorithm failed to detect any R-peaks because these signals were too noisy. We manually classified them as unacceptable quality.

Standing and sitting have the most windows with acceptable quality (Tab. 1). Walking and especially running have many unacceptable windows. When examining the signal quality per participant disregarding the activities, we observe one outlier: one participant had an exceptional quality with an acceptable quality rate of 100 %. All other participants' acceptable quality was between 25 % and 79.76 % (52.19±15.57 %).

The qualities per participant and activity give more insights (Fig. 3). While standing has on average the highest quality, the distributions per participant are scattered. There are participants whose performance drops below 50 % while standing. The lowest performance was 57.14 % while sitting. The quality rate for walking is dispersed (35.27 %) and low on average (26.65 %). The results for running (9.22±19.87 %) are worse than walking, which is expected because of more motion, but also has a few exceptions providing high quality: the average quality for running was above 50 % for two participants.

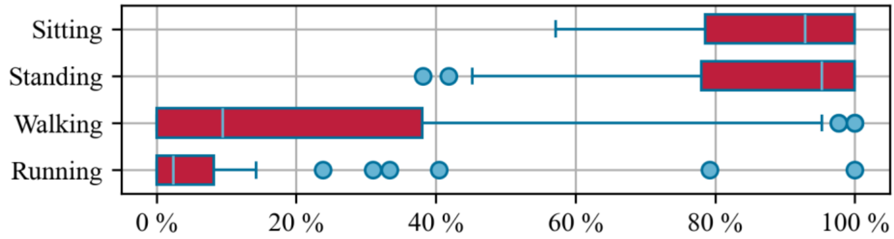

Figure 3. Signal qualities by participant and activity. Outliers from the quartiles are marked as blue dots.

4. Discussion

If smart wearables are worn all day, the signal quality would be suitable for continuous monitoring and we expect to have at least 4 h of signals with high quality (assuming the low quality of constantly running). However, sitting and standing for office jobs, and lying due to sleeping make up most of the day, we consider the real timespan to be even longer. Even short segments over a long period will allow early detection. Integration with other sensors and signal fusion could even increase accuracy and useable time.

In this work, we used a purely signal-processing-based signal quality indicator. It would also be possible to evaluate the signal quality with machine learning approaches. These approaches already show accurate results [21] and could autonomously learn to classify signals but require much training data and currently lack explainability.

The signal quality per participant diverges a lot. In retrospect and based on our data, we believe the fittings of the shirt or the way the activities were executed to be the reason for the high variation. Some participants could not run for 10 min straight and switched to swift walking, which further falsified the results. Another reason could be that it is recommended to apply conductive cream to obtain accurate results, which we did not. We will analyze the reasons for the low quality and sometimes the exceptionally high quality in our future work.

Further development of the sensors will improve the signal quality and offer more flexible solutions [22]. Integration with other sensors also enables fault-resistant generation of high-quality signals.

5. Conclusions

Motion significantly decreases the signal quality. Longer recording periods can compensate for this and achieve the same length of usable data. Due to shirt fitting and body constitution, the signal quality strongly depends on the subject. The signal quality needs to be assessed before the recordings to ensure meaningful data. The signal quality of smart wearables is suitable for continuous monitoring, as batches of high quality can be obtained.

Appendix

The German Federal Ministry of Transport and Digital Infrastructure (BMVI) funded this work under grant #VB5GFWOTUB. All procedures performed were in accordance with the 1964 Helsinki Declaration, as revised in 2013.

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