CompRate: Power Efficient Heart Rate and Heart Rate Variability Monitoring on Smart Wearables

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ABSTRACT

Currently, smartwatches are equipped with Photoplethysmography (PPG) sensors to measure Heart Rate (HR) and Heart Rate Variability (HRV). However, PPG sensors consume considerably high energy, making it impractical to monitor HR & HRV continuously for an extended period. Utilising low power accelerometers to estimate HR has been broadly discussed in previous decades. Inspired by prior work, we introduce CompRate, an alternative method to measure HR continuously for an extended period in low-intensity physical activities. CompRate model calibrated for individual users only has an average performance of Root Mean Squared Error (RMSE) 1.58 Beats Per Minute (BPM). Further, CompRate used 3.75 times less energy compared to the built-in PPG sensor. We also demonstrate that CompRate model can be extended to predict HRV. We will demonstrate CompRate in several application scenarios: self-awareness of fatigue and just-in-time interruption while driving; enabling teachers to be aware of students' mental effort during a learning activity; and the broadcasting of the location of live victims in a disaster situation.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**; *Interactive systems and tools.*

KEYWORDS

Heart Rate, Heart Rate Variability, Accelerometer, Low Power, Inferring Stress, Photoplethysmography

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1 INTRODUCTION

Awareness of physiological parameters in daily life is vital for health and well-being. Among the physiological parameters, Heart Rate (HR) & Heart Rate Variability (HRV) are considered as important measures. Other than providing direct indicators of heart functionality, these parameters can be used to infer stress [Kim et al. 2018] and other pathologies, such as myocardial infarction [Buchanan et al. 1993] and diabetic neuropathy [Chen et al. 2015]. HR is defined as the number of heart beats per minute, and HRV is the variation in the time interval between consecutive heartbeats.

Wearables, such as smartwatches, provide a convenient way to monitor these parameters. The common HR & HRV measuring mechanism in smartwatches is based on photoplethysmography (PPG), which identifies the blood volume pulse seen in microvascular tissues [Challoner and Ramsay 1974]. However, PPG sensors are only available in high-end wearables. These sensors also consume considerably large amounts of power, making the continuous reading of physiological signs impractical. Building on ballistocardiography (BCG) [Baker Jr et al. 1950; Starr 1946], Hernandez et al. [2015], and Haescher et al. [2015], introduced a new approach which estimates heart pulse using the accelerometer and the gyroscope of a wristwatch. Their work mainly focused on measuring HR in motionless resting conditions, such as sleeping, sitting down, and standing up. Recently, McConville et al. [2018] explored long-term HR estimation of patients recovering from heart interventions using accelerometer data from a wristwatch.

Inspired by prior work, we developed a model, CompRate, that estimates HR & HRV using only accelerometer data with a lower root mean squared error (RMSE) and potentially compatible with any smartwatch. The CompRate model was trained with data obtained from an E4 wristband [1] that provided ground truth PPG data, as well as accelerometer data. The model was evaluated in an office environment with 12 participants and resulted in a lower RMSE

[1] https://www.empatica.com/research/e4/

compared to other modern accelerometer based approaches [Hernandez et al. 2015; McConville et al. 2018].

The CompRate model was then implemented in a regular smartwatch (Samsung Gear Live), to which we evaluated the power consumption, while continuously monitoring the HR. CompRate used 3.75 times less energy compared to the built-in PPG sensor. CompRate enables a wide range of applications, and we demonstrate this with three proof-of-concept application scenarios that leveraged on low power HR & HRV measuring: self-awareness of fatigue and just-in-time interruption while driving; enabling teachers to be aware of students' mental effort during a learning activity; and the broadcasting of a survivors status in a disaster situation.

The main contributions of this paper are:

- Development of an algorithm that estimates HR using accelerometer data. The model uses only accelerometer data, consuming less energy compared to conventional PPG, demonstrating suitability in the continuous HR monitoring over a long period.
- Extension of the HR estimation model building method to develop a model to estimate HRV.
- Implementation of three application scenarios (self-awareness, third-party awareness and broadcasting) to demonstrate the wide applicability of our model.

2 RELATED WORK

The current gold standard of heart rate measurement technologies is electrocardiography (ECG) and photoplethysmography (PPG). These two technologies are clinically used for measuring heart rate because of their high accuracy. ECG needs electrodes attached to the body [López et al. 2010; Luprano et al. 2006], while the PPG device is usually a finger-worn clip [Mundt et al. 2005; O'Donovan et al. 2009; Oliver and Flores-Mangas 2006; Shnayder et al. 2005] or a wrist-worn device [Luprano et al. 2006]. Recently, the majority of smartwatches have adapted this technology to monitor heart rate. However, PPG requires a considerably higher power consumption compared to other electronics of a smartwatch. For instance, McConville et al. claim that a PPG sensor of a smartwatch typically consumes up to 5000 times the power of an accelerometer used in a smartwatch [Elsts et al. 2018]. Therefore, using the accelerometer to sense the body's vital signs could be ideal for wearable technology in terms of battery life.

Ballistocardiography (BCG) is a non-invasive physiological measurement method that estimates a person's heart rate by capturing subtle body motions through shifts in the blood's mass in blood vessels when the heart pumps [Giovangrandi et al. 2011; Starr et al. 1939]. In BCG, these subtle motions are non-invasively captured by adding motion sensors to the body, usually near the heart [Bieber et al. 2013; Dinh 2011; Kwon et al. 2011]. Apart from adding sensors to the body, embedding motion sensors to everyday objects such as a weighing scale [Inan et al. 2009; Wiard et al. 2011] or a chair [Pinheiro et al. 2010] have also been explored. Also, in another study, researchers showed that extracting HR is possible by using the sensors inside a head-worn device, such as a Google Glass [Hernandez et al. 2014].

Motivated by the approaches related to BCG, previous researchers explored heart rate estimations using wrist-worn motion sensors for their convenience and wearability. For instance, BioWatch [Hernandez et al. 2015], estimated heart rate by utilising the accelerometer and gyroscope of a smartwatch. In their work, a controlled laboratory study demonstrated accurate heart rate measurement in 3 different resting positions (standing up, sitting down and lying down), without any motion, under relaxed and aroused conditions with a mean absolute error of 1.27 (STD 3.37) beats per minute. In a similar study, Haescher et al. [Haescher et al. 2015] explored heart rate measurements via wrist-worn accelerometers in motionless conditions. Furthermore, they compared their accuracy with commonly applied technologies and found that heart rate detection was not significantly different to current gold standards. In another study, researchers demonstrated a method which can upgrade any smartwatch to enable sensing heart rate [Haescher et al. 2016]. All these studies mainly focused on estimating HR in motionless conditions such as standing up, sitting down, sleeping or lying down. In a very recent study, researchers explored online heart rate and an HRV prediction method using the accelerometer of a wrist-worn wearable, which uses PPG heart rate sensor infrequently [McConville et al. 2018]. In their study, they asked 3 patients, who were recovering from heart interventions, to wear a smartwatch and evaluated their method using 4 weeks of in situ data. Their algorithm achieved average RMSE of 6.10 while 20% of data were obtained from PPG sensor. Despite advancements in measurement technologies, none of these works focused on exploring application domains of low power heart rate monitoring, which we will demonstrate in addition to our CompRate algorithm.

Table 1: Performance of ML models

ML Approach	Parameters	RMSE (BPM)
Linear Regression	method: qr	6.59
Neural Network	hidden: (6, 12, 3), threshold: 0.01, learning_rate: 0.01, algorithm: rprop+	3.79
Quantile Regression	tau: 0.5, method: br	6.82
Random Forest	ntrees: 500, nodesize: 5	1.76
SVM	type: eps, kernel: sigmoid, epsilon: 0.1, gamma: 0.16	6.68
XGBoost	eta: 0.3, max_depth: 6, nrounds: 128	2.23

3 COMPRATE

CompRate was primarily developed as a low-power solution to estimate HR in low-intensity physical activities, namely when a person is working in an office, in a classroom/lecture, or while driving. Similar to BCG, CompRate captures subtle motions of the body due to shifts in blood mass in the blood vessels by using an accelerometer of a wrist-worn device and estimates HR with a pre-trained model. We developed the CompRate model with a classic machine learning approach using the readings of Empatica E4 wristband. We tested our model with another smartwatch (Samsung Gear Live). We describe the data collection, pre-processing, feature extraction, training and testing of the CompRate model in the following sections.

3.1 Model Development: Data Collection

- Participants:
  12 healthy participants, 4 female and 8 male aged between 24-31 (Mean = 27.46, SD = 2.57) were recruited for the study.

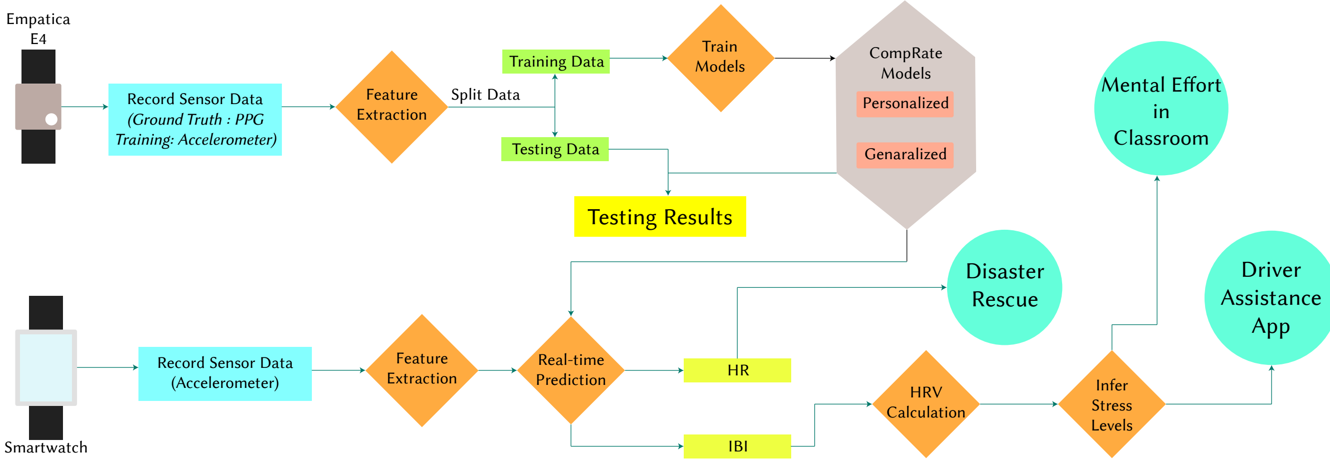

Figure 1: The figure shows the block diagram of steps we followed in developing CompRate models.

Since our goal is to estimate HR in low-intensity physical activities, we recruited participants from an office environment to collect our data. All participants are researchers at a university.

- Apparatus:
  We used Empatica E4 wristbands to collect ground truth data, given its validation in prior work [McCarthy et al. 2016]. The wristband was connected to a Samsung Galaxy A8 mobile phone via Bluetooth. A custom built Android application inside a mobile phone collected all the data. To validate our model with an external device, we used a Samsung Gear Live smartwatch.
- Task and Procedures:
  Participants were asked to wear an Empatica E4 wristband on their non-dominant hand for one full day (from 9 am to next day 9 am). During this day, they had to complete their typical daily tasks such as, working in front of a computer, soldering, walking, cooking, sleeping, etc.
- Data Collection:
  Inter beat interval (IBI) was recorded as the ground truth data from a PPG sensor of the E4 wristband with a resolution of 1/64 seconds. Accelerometer data was collected with the built-in 3-axis accelerometer of the E4 wristband with a frequency of 32Hz. The accelerometer values had an eight-bit resolution and full-scale range of $\pm 2g$. Each individual data set was partitioned into training and testing data sets. Training data sets were then used to train the models, as described in the subsection below.

3.2 Model Development: Training

In the preprocessing stage, each axis of the training accelerometer data was normalised using the Z-score within a moving window to give all axes the same relevance [Hernandez et al. 2015]. Incomplete data points were omitted as part of the data cleaning process. HR values were derived using recorded IBI values ($HR = 60/IBI$). HR values were smoothed with a moving average because they were calculated for each inter-beat-interval values. We tried smoothing window sizes in the range of 5 - 120 seconds and found that 40 seconds was the optimal window size for smoothing.

The median and standard deviation were extracted as features for each axis of a window of an arbitrary period of 60 seconds, resulting in 6 features per window. Using these six features and the heart rate derived from the IBI using the E4 data as the ground truth, we identified the most suitable algorithm among six machine learning algorithms: SVM, Random Forest, Linear Regression Model, Neural Network, Quantile Regression Model and XGBoost. From these algorithms, Random Forest demonstrated the lowest RMSE (Root Mean Squared Error) as shown in the Table 1. Hence, we selected the Random Forest as our preferred machine learning algorithm to implement in the CompRate model.

To identify the optimum feature window size, we tested the performance of the model over different sizes, such as 5s, 10s, 15s, and up to 120s. We confirmed that an 80-second window is the smallest window size that results in the lowest prediction error.

We trained 12 personalised models only using each participant's data. To examine the generalisability across users, we used the leave-one-out method, where the data of 11 participants are used to train a model to predict the left-out participant's HR. Also, to compare the performance of prediction results, we generated a baseline predictor, which always output the mean HR value of the corresponding training data set. A summary of the steps of model training is seen in Figure 1.

Table 2: Performance of HR prediction models against the baseline models.

Model	Average RMSE (BPM)	Best Performing Model RMSE (BPM)
Personalised CompRate	1.58 (*SD= 0.58*)	0.88
Personalised Baseline	6.78 (*SD= 2.81*)	2.29
Generalised CompRate	10.85 (*SD= 4.67*)	4.41
Generalised Baseline	14.13 (*SD= 6.28*)	6.25

3.3 Model Development: Testing

Trained personalised models were used to predict HR values of the testing dataset of each participant. To examine the generalisability of the method, models were trained using the leave-one-out method to predict HR values of the corresponding left-out person. A comparison of the predicted and expected HR values for 12 personalised models and generalised models are visualised in Figure 2. During the data collection session, we allow participants to engage in their daily activities. The variation of HR over time depending on physical activity level and psychological state is also visible in the same figure.

Along with personalised and generalised CompRate model predictions, we used baseline models to predict the baselines. A summary of the HR prediction results against baseline models is tabulated under the Table 2

3.4 Model Validation with an External Device

After a week, to validate the derived models with an external device, all the participants were again asked to wear both Empatica E4 and the Samsung Gear Live smartwatch on their non-dominant hand for one full day, following the same procedure as before. The participants wore the Samsung watch in a position approximately similar to that of the previous session. The E4 was used to collect validation HR values only, while the CompRate model was implemented on the Samsung Gear Live smartwatch.

We fed Samsung Gear Live smartwatch accelerometer data directly to the personalised models of each participant that we derived earlier for the E4 device. Furthermore, we calculated the RMSE for each participant for the generalised and personalised models in both E4 and the Samsung Gear Live smartwatch (*Figure 3*).

Also, a one-way ANOVA revealed a main effect between the RMSEs of the estimated heart rate values by using personalised and generalised models in the E4 and Samsung Gear Live smartwatch. ($F_{3,44}$=23.80; $p < .01$). A Tukey's HSD post-hoc analysis revealed that RMSEs of the estimated heart rates are significantly better for personalised models than generalised models for both E4 and the Samsung Gear Live smartwatch. However, regardless of device, there was no significant difference between RMSEs of HR values estimated from either personalised models or generalised models (See Figure 3).

According to the above results, average RMSEs of personalised (M= 1.58, SD = 0.58) models were better than other machine learning approaches found in recent literature [McConville et al. 2018]. Furthermore, we developed a generalised model, which had an average RMSE of 10.85 (SD = 4.67). Also, we found that estimated heart rate values in the Samsung Gear Live smartwatch were not significantly different to estimated heart rate values in E4 when using the same generalised and personalised models. This shows that the models are possibly compatible with other smartwatches. Furthermore, there was a significant difference between the values estimated from generalised models and personalised models. However, well-trained personalised devices are sufficient for most of the applications, since a smartwatch is a personal device.

3.5 Power Consumption Analysis

Power consumption of CompRate against PPG sensor was investigated using Samsung Gear Live smartwatch while continuously monitoring the heart rate. The device had a 300mAh battery and operated with Android Wear OS. Information extracted from Android debug reports were used to calculate power consumption data. USB debugging mode of the Android watch was enabled. Before each data gathering session, debug reports of the smartwatch was reset using Android Debug Bridge (ADB) [2]. The watch was set to continue monitoring HR monitoring mode through a custom build application. A participant was requested to wear the smartwatch for one hour. A debug report was later extracted using the ADB. Above steps were repeated for 20 sessions (10 sessions using PPG; 10 sessions using CompRate). Retrieved debug reports were analysed using Battery Historian tool[3] which is an opensource Android log analysing tool. We extracted the available energy capacity (out of 300mAh) of the smartwatch before and after each session. Energy utilisation was calculated per session. The results indicated that the device consumes 13.94 mAh power per hour with PPG, though CompRate-based approaches only consumed 3.71 mAh per hour. A student t-test revealed that power consumption is significantly less than PPG based approach (T(18) = 7.6565, p<0.005)

3.6 Extension of the Method for HRV

The fundamental method was built to predict HR using accelerometer readings. The possibility of extending the original method to predict HRV was also tested. In order to calculate HRV, the time intervals between consecutive beats are required. Therefore, modifications were performed according to the initial method to predict IBI values instead of HR values. The following summarises changes to the initial method,

- In the preprocessing stage, we omitted IBI to HR conversion and data smoothing steps. This step was taken to increase the resolution of data that is required for IBI prediction.
- Since the initial set of features did not have entropy to provide sufficient accuracy, following new features per each x,y and z were introduced. The mean of absolute values, the number of zero crossings, skewness, kurtosis, median and standard deviation after z-score normalisation, skewness, kurtosis, mean, standard deviation after log scale normalisation. Z score normalisation was used to omit the effect of gravitational force, while the log normalisation was introduced to reduce effect of higher accelerations.
- The feature window size was recalculated following the same procedure of the original feature window detection stage. We discovered that the optimal feature window size for IBI prediction was 120 seconds.

Table 3: Performance of IBI prediction models against the baseline models.

Model	Average RMSE (ms)	Best Performing Model RMSE (ms)
Personalised CompRate	61.39 (*SD= 16.03*)	41.58
Personalised Baseline	107.31 (*SD= 43.80*)	52.73
Generalised CompRate	116.69 (*SD= 35.80*)	76.66
Generalised Baseline	189.59 (*SD= 70.01*)	137.31

The final steps of feature extraction and splitting datasets were conducted based on the previous HR prediction method. Twelve

[2] https://developer.android.com/studio/command-line/adb
[3] https://github.com/google/battery-historian

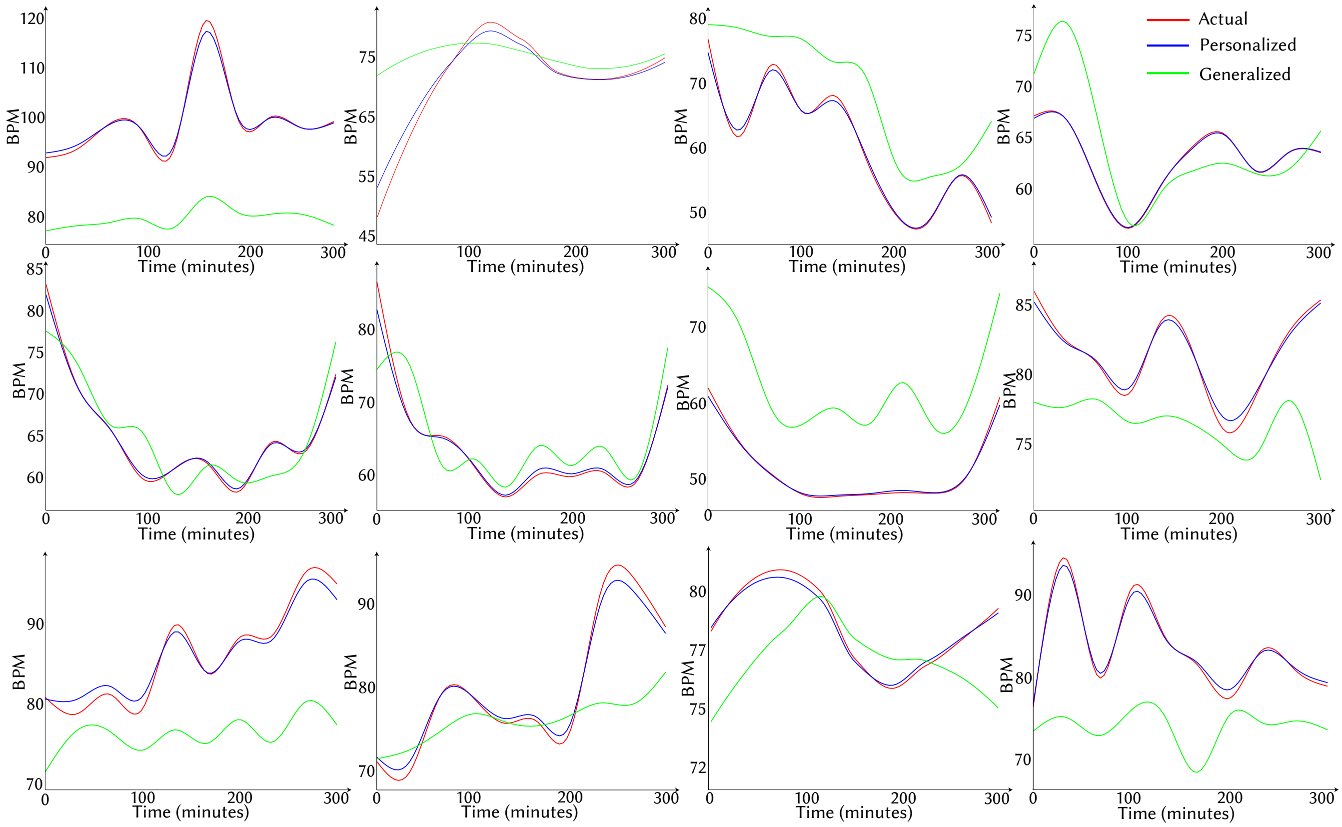

Figure 2: The figure compares the actual heart rate (red), the predicted heart rates from personalised models (blue), and the generalised (green) models of each participant.

personalised IBI prediction models were trained along with twelve baseline models. Personalised IBI prediction models were evaluated with the corresponding testing datasets. Also, the generalisability of the IBI predictor was assessed using the leave-one-out method. Results of the evaluation are presented in the Table 3.

We observed that the personalised IBI prediction models had 1.75 times better RMSE compared to the baseline while the generalised model outperformed the baseline by 1.62 times. Furthermore, we observed an error rate of less than 1.90 times in the personalised predictor compared to the generalised predictor.

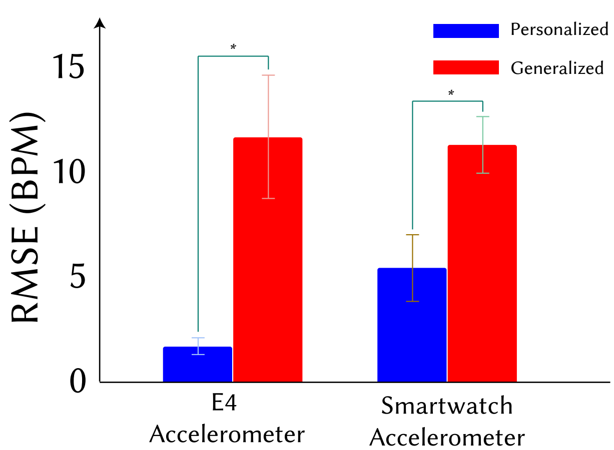

Figure 3: The figure compares the RMSEs of estimated HR values by using personalised and generalised models. The models were run in both E4 and the Samsung Gear Live smartwatch.

4 APPLICATIONS OF COMPRATE

The low power consuming heart rate monitoring capability of CompRate opens up a wide range of applications. Fundamentally, CompRate enables HR & HRV measuring abilities on affordable devices, which do not contain a PPG or ECG sensor.

Other than the trivial application, we identified 3 application areas in which CompRate may have the most substantial impact: 1) Self-awareness of fatigue and stress levels during attention-critical tasks such as driving; 2) Third-party awareness about cognitive load such as during a learning activity; and 3) Broadcasting of vital data in a rescue situation such as during a natural disaster.

Below, we show example applications for each category and initial user feedback.

4.1 Self-Awareness of Fatigue for Just in-time Interruption while Driving

In the last few decades, researchers have shown that HRV can be used as an indicator of stress levels [Kim et al. 2018; Taelman et al. 2009].

StressHacker is a recent study which explored stress monitoring in the wild by using smartwatches [Hao et al. 2017]. In this work, they have utilised an inbuilt PPG sensor to measure HRV and demonstrated that they can infer the stress dynamics of a person fairly accurately. However, as previously mentioned, PPG sensors are not power efficient and also unavailable in every smartwatch. In fact, HRV measures could potentially be used to predict whether an individual is at an increased risk of attention failure because of sleepiness [Chua et al. 2012; Healey et al. 2005; Michail et al. 2008]. Continuous monitoring of HRV will help avoid harmful situations, such as falling asleep while driving for a long duration and over long distances.

To address this, we leveraged on the CompRate model and developed a smartwatch application which provides vibration feedback on the wrist and auditory feedback when a driver is at the risk of attention failure. Also, the system suggests the driver to take a rest, if attention failure is identified based on LF/HF elevation compared to baseline [Chua et al. 2012]. We envision that the same information can be used to shift the driving control between manual and automated driving depending on the driver's condition.

To get initial insights, we asked 3 male drivers (26, 31, 28 years old) to drive a car on a road with low traffic for half an hour while wearing a smartwatch with our application (*see figure 4*). The application provided feedback about HRV every five minutes. Although the envision system provides feedback whenever the user experiences attention deprivation, we provide HRV feedback every five minutes in the pilot study to understand the applicability of the feedback system. Since our subjects were not sleep deprived, we did not see much LF/HF variance. All the participants appreciated the importance of an application that increased self-awareness of fatigue when driving. Software architecture of the application is shown in the Figure 5.

Figure 4: Self-awareness app for drivers: Samsung Gear Live smartwatch with CompRate model provides feedback when the driver needs to rest. To get initial feedback, we developed an app which provided HRV feedback every 5 minutes.

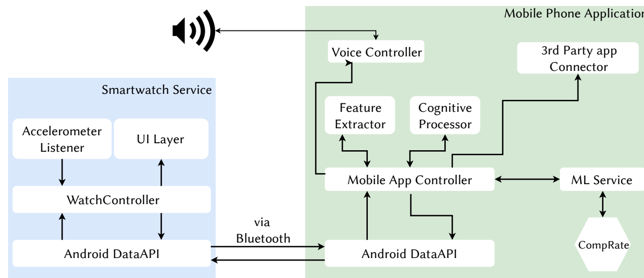

Figure 5: System architecture diagram of the self-awareness application for drivers

4.2 Enabling Teachers to Become Aware of Students' Learning Engagement

Recent work found that low-frequency (LF) to high-frequency (HF) ratio of HRV might be an indicator to identify the cognitive load and used to identify mental attentiveness towards a task [Sridhar et al. 2018]. Motivated by prior work, we implemented an example application which estimated the cognitive load during a lesson in a classroom using a simple accelerometer wristband. Also, we implemented this in such a way that only the teacher will receive feedback, not the other students. This was important to avoid self de-motivation among students.

We used an off-the-shelf accelerometer break out MPU9250 from SparkFun[4] to build our model. We then used a low-power 1.4-inch 128×128 TFT LCD display without front polariser. The IMU and the LCD display was connected to Adafruit pro trinket which has an ATmega328P microcontroller. The microcontroller was programmed to run our model. All these devices were embedded into a wristband like device as shown in Figure 7. When a student wears the wristband, the device will change the colour of the display according to the estimated cognitive load. This change is not visible to the naked eyes of the students.

Since the LCD does not have a front polariser, the content of the display is only visible through polarised filters. We developed a separate pair of glasses with polarising filters for the teacher (*see Figure 7*). In this way, a teacher can identify the student's cognitive load and use this information to provide a better learning experience. The main components of our application are distributed according to the Figure 6.

To gain initial insights on our application, we gave the system to 3 primary school teachers. We demonstrated its functionality and asked a few questions about: value of understanding student engagement, current methods they are using, advantages of the proposed method over current methods, and additional requirements.

[4]https://www.sparkfun.com/products/13762

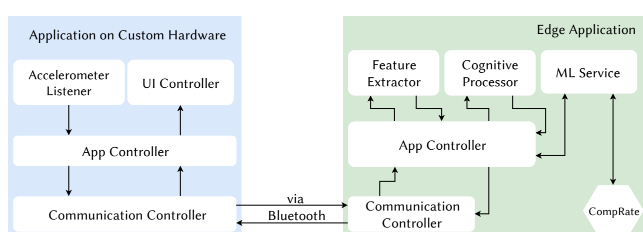

Figure 6: System architecture diagram of the student engagement monitoring system

Figure 7: Enabling teachers to be aware of the students' learning engagement: Custom wristband for students which has a display without a polariser. A teacher wears a special polarised glass to get feedback about students stress levels.

According to the teachers, they typically use a self reporting method to identify the stress levels of students during a teaching lesson. Since it is purely based on students' self-reporting, it is difficult to rely on this information to improve learning methods. Therefore, all the teachers highly appreciated the system, as it provided them with real-time, objective indication of the cognitive load. They also mentioned that limiting the visualisation of the cognitive load to teachers was highly important to avoid de-motivating students. Furthermore, the teachers suggested that the device should provide some form of a self feedback to students as well.

4.3 Broadcasting of Vital Data in a Disaster Situation

Low power heart rate sensing in vital situations is important, especially in situations with limited power. In such a situation, a smartwatch with CompRate will help broadcast heart rate to relevant people to get immediate attention. For instance, disasters such as earthquakes, tsunami, and hurricanes cause numerous casualties. The major cause of such casualties in urban areas is the collapse of buildings [Coburn et al. 1992], trapping people for many days before rescue teams are able to locate them.

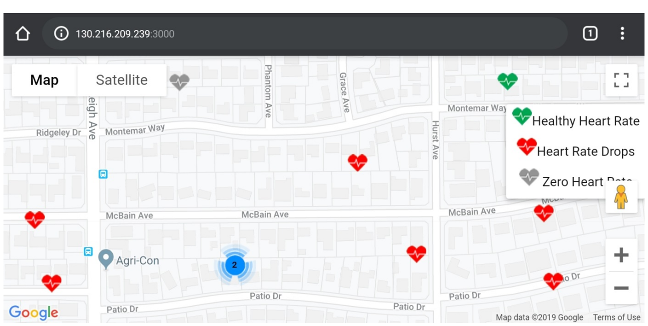

Figure 8: Broadcasting of vital data in a disaster situation: Figure shows a screen shot of the disaster rescue application. The heart icon indicates the locations of the victims and the colour scheme shows the condition of the HR; the blue colour icon shows the number of people in close by proximity.

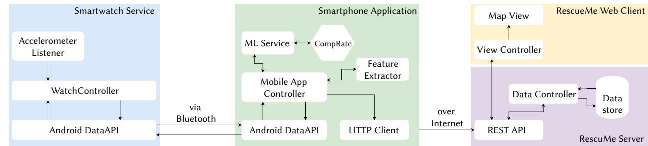

Figure 9: System architecture diagram of the disaster rescue application system

Some of the current methods used in rescue missions are ad-hoc searches, where the search for survivors is performed by scanning vital signs, such as the heartbeat and breath sounds [Landau 2015], and thermal scanning. Due to a limited range of these sensing technologies, these scans usually require rescue teams or Unmanned Aerial Vehicles (UAVs) to operate in close proximity of the disaster, jeopardising the safety of the rescuers and the functioning of the UAVs. Remote and real-time information like the survivors' locations and the vital signs of survivors, would facilitate better coordination and focus in rescue missions. A device which broadcasts heart rate to a central application could be beneficial for rescue teams to identify live victims and also victims who have a greater chance of survival and require immediate attention.

To accomplish this, we developed a smartwatch application which estimates HR and broadcasts it to a central application (Figure 8). In the pilot application, we defined HR above 60 BPM as healthy HR, 0 to 59 BPM as HR drops, and 0 BPM as zero HR. Software architecture of the system is visualised in the Figure 9. The system has four main components: application on smart watch to capture accelerometer data, application on mobile phone to predict the HR using accelerometer data, web application which stores the individual HR data, and a website that visualise the locations and HR values of the users.

5 LIMITATIONS & FUTURE DIRECTIONS

- Cross Validation with Only One Device:
  Currently, we validated our model with only one device, a Samsung Gear Live smartwatch. For a better understanding of the accuracy of our model in the future, we aim to test our model with a few other popular smartwatches such as Pebble, Apple Watch, Xiaomi Amazfit, etc.
- Small Number of Users:
  For the model training, we had 12 participants and when we removed one participant for generalised models, only 11 participants remained for model training. Although this is a considerable amount of participants for a generalised model, more participants will generate a better model to obtain higher accuracy. Cross device validation was also done with 12 participants. Having more participants will help gain a better understanding of the accuracy of our model.
- More Studies of the Application Scenarios:
  The demonstrated application scenarios provided us with preliminary insights for future developments. We will conduct more in-depth investigations of the usability of those applications.
- Estimation of HR while Performing High Intensity Activities:
  The current model was developed to estimate the heart rate,

only while the user performs low-intensity activities. In high-intensity activities, such as walking, jogging, running, the IMU signals generated from micro-movements can be hidden by higher amplitudes of relatively lower frequency components. For example, with jogging, the heart rate will typically exceed 100 BPM. Therefore, micro-movements will also generate a frequency closer to 100 cycles per minute. However, IMU signals generated by hand movements will be relatively lower than this frequency. Analysing an FFT and filtering out these low-frequency components will help to extract the heart rate values.

6 CONCLUSION

This paper presents CompRate, a low power solution to estimate HR for an extended period while the user is engaged in low-intensity activities. The experiment results indicate that accelerometer-based HR prediction has comparable accuracy compared to PPG-based approaches. Furthermore, the personalised prediction models are easily generalisable across people and hardware. Also, using an accelerometer instead of a PPG sensor to detect HR improves the battery life expectation of a wearable by threefold, enabling the potential of continuously monitoring physiological signs for an extended period. The method used to build HR prediction model can be extended to develop an HRV prediction model. Lastly, we demonstrate the possibility of enabling an extensive amount of impactful applications with the continuous monitoring of HR & HRV.

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