OMsignal Heart Rate Variability Detection

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***Abstract*—The purpose of this work was to develop a personalized method of categorizing heart rate variability (HRV) from recordings taken during daily life while participants wore the OMbra. Low HRV has been associated with increased stress levels and a wide array of adverse health outcomes. Twenty women wore the OMbra several times a week during their daily life. HRV was calculated on 5 minute windows when participants were in a still, seated position. Personalized HRV zones were calculated based on the relationship between HRV and heart rate (HR) during the first 100 HRV segments that were recorded for each participant. Participants had on average 23.1% (+/-9.8) high HRV, 55.3% (+/-13.2) average HRV, 16.1% (+/-7.1) low HRV and 5.6% (+/-6.9) very low HRV periods during their daily life recordings. This work presents a novel method of obtaining high quality HRV metrics as people go about their daily lives using the OMbra. A novel method is proposed to provide personalized HRV ratings that take into account changes in HRV due to increased or decreased HR.**

***Keywords*—heart rate, heart rate variability, electrocardiogram, bio-sensing textile.**

I. Purpose and Scope

Heart disease is the leading cause of mortality in North America [7]. A common challenge with identifying individuals who are at risk of a coronary event is that their electrocardiogram (ECG) is only recorded for a short period if they happen to visit their doctor. The vast majority of the population lives on without having their heart signals reviewed. Advances in sensor and textile technology mean that accurate ECG signal can be obtained from the OMbra while women go about their normal lives. This data can be used to assess the cardiac health of the women and can be used as an early warning sign when changes begin to occur that might mean declining heart health. The OMbra has the added benefit that it is designed specifically for women, who as a gender, are under- diagnosed for cardiac issues [7].

Cardiac autonomic dysfunction is a risk factor for cardiovascular disease development and can be measured via HRV. HRV is the result of parasympatheic and sympathetic nervous systems causing changes to heart rate [8]. Low HRV has been associated with a variety of health issues; such as mortality in patients post-myocardial infarction [15]. Low HRV has also been associated with a 32-45% increased risk of a first cardiovascular event in populations without known cardiovascular disease [5].

Hypertensive patients have been shown to have reduced HRV [11]. HRV has been shown to be reflective of an individual's psychological resiliency and behavior flexibility, indicating a person's ability to adapt effectively to changing social or environmental demands [2]. Low HRV has also been linked to increased stress levels in laboratory experiments [6]. It has also been shown that HRV is related to HR; as a person's HR increases, their HRV will naturally decrease [13]. For this reason, it is important to take into account HR when analyzing HRV outside of a controlled environment.

The goal of this work is to create a model to obtain personalized low HRV zones from remote monitoring ECG data while accounting for HRV fluctuations due to HR.

II. Methods

This data was collected as part of the OMsignal My Heart project. Participants were instructed to wear an OMbra for several days a week, over the course of six weeks. The OMsignal system measures electrocardiogram (ECG), HR, HRV, respiration as well as movement. Data is wirelessley transferred from the OMsignal box that is clipped onto the OMbra to the users mobile phone where the OMsignal App saves the data, displays results to the user and sends data to the OMsignal cloud. Data from 20 participants are included in the present work.

A. Heart Rate Variability

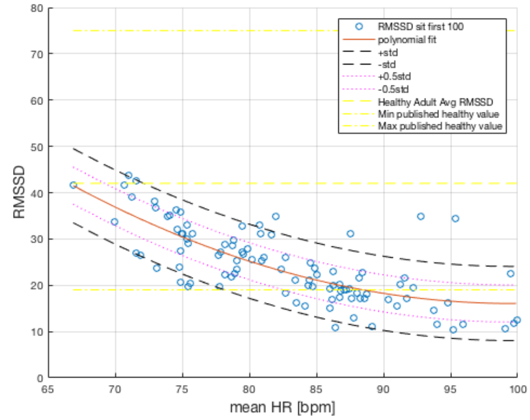
The OMsignal box that clips onto the OMbra has firmware that analyses the ECG signal and detects heart beats based on a gold standard heart beat detection algorithm [9]. These beat locations and associated RR-intervals are transmitted to the participant's mobile phone. RR-intervals are processed off line to obtain HRV. HRV is analyzed in 5 minute segments in which there is clean ECG signal, the participant was not moving and was in a seated position. The accelerometer is used to determine the orientation of the user to ensure that they are in a seated position as well as to determine that they are not moving. Ectopic beats were removed according to standard HRV analysis methodologies; which consisted of rejecting beats if they differed by more than 20% to the previous RR-interval [1]. The resulting signal is referred to as normal to normal (NN) intervals. Standard deviation of the NN-intervals (SDNN) as well as root mean square of the successive differences between normal heart beats (RMSSD) were calculated, based on gold standard processing methods [3]. Frequency domain HRV metrics have been left out of the current analysis due to recent debate in the literature as to how to interpret them correctly [4] [10].

B. Model Creation

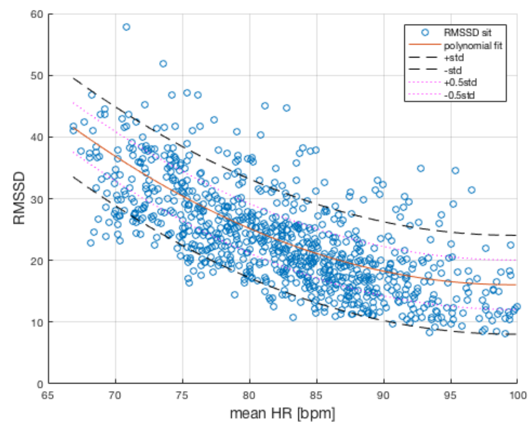
Personalized models were created to determine the relationship between HR and HRV for each participant. RMSSD was used because it had a stronger relationship to HR than SDNN. The first 100 HRV segments during usage (with mean HR less than 100bpm) from each participant were used to create the model. A second order polynomial line was fit to the HRV / HR data. Standard deviation was obtained from the HRV data from the first 100 segments. Previous work looking at HRV in a remote monitoring use case categorized low-HRV by identifying periods in which participants HRV was two standard deviations below their average HRV value [14]. The disadvantage with this method is that it does not take into account the fact that HRV changes can be due to fluctuations in HR, which can be a major factor in uncontrolled, remote monitoring data. Figure 1 shows an example of the HRV-HR model on one participant in the present study.

C. HRV Categorization

The HRV categorization methodology proposed in this work builds upon previous categorization methodologies [14] by including a personalized model to account for HRV changes due to changes in HR. HRV was categorized into high, average, low and very low values based on the standard deviation values at a given HR. A HRV value was classified as high if the HRV value was more than 0.5 standard deviation above the model value at a given HR. A HRV value was classified as average if the HRV value was between -0.5 and +0.5 of a standard deviation at that heart rate for that participant. A HRV value was classified as low if it was below -0.5 standard deviation and above - 1 standard deviation at that HR value. A HRV value was classified as very low if it was below -1 standard deviation at a given HR value. HRV segments that are associated with HR values that are outside of the HR range seen in the personalized model are excluded from analysis. Figure 2 provides a visual explanation of how the HRV zones are calculated.



(a) An example of the first 100 HRV segments used for HRV-HR model creation. The hoirzontal yellow lines represent upper, mean and lower normative healthy HRV values from the literature [8].



(b) The model created on the left with all of the participants HRV data included.

Fig. 1: Model creation is displayed on the left (a) in context with healthy adult normative data. The right figure (b) shows the model applied to all of the users data in the study. Dashed black lines represent +/- one standard deviation of HRV. Dashed magenta lines represent +/- half of one standard deviation of HRV.

III. Results

Table I shows HR, breathing and HRV categorizations along with mean and standard deviation of HRV values for each participant in the study.

IV. Discussion

In this work a method was proposed to categorize HRV into four personalized zones from high to very low HRV while accounting for HRV changes due to increasing or decreasing HR. Low HRV has been shown to be associated with increased levels of stress as well as with a variety of adverse health issues [12]; providing feedback to participants when they are in a low or very low HRV zone may have positive health benefits.

In the current study, HRV was normalized according to the first 100 HRV segments that a participant recorded. A 2nd order, polynomial fit model was created between HRV and HR on this data. The actual HRV value observed at a given HR value was then assessed according to how close it fell to the model fit line, while using standard deviation on the first 100 HRV segments as a discrimination factor. This model is very dependent on the state of participants during the first 100 HRV segments. If they are over-stressed during this period, then the model will be skewed lower and result in all high HRV values post-training. The opposite would be the case if participants were in a very relaxed period during the model training. In the future, other methods will be investigated for the creation of a correction model between HRV and HR. First, only neutral or positive days will be included in the model, with the goal of being able to identify negative stress days. Second, it could be possible to use more data in the model, such as the first 200 HRV segments. Third, the use of published

TABLE I: Summary table of HRV, HRV categorizations as well as average HR and breathing rate during HRV segments

Subj	HR (bpm)	Resp-Rate	RMSSD Mean	RMSSD Std	Good HRV %	Avg HRV %	Low HRV %	Very low HRV %
1	90	19.1	18.9	6.2	29.9	48.8	16.8	4.4
2	82	21.1	23.4	8.1	16.0	50.5	26.1	7.4
3	72	21.3	18.2	5.7	10.6	42.4	37.1	9.8
4	76	20.8	37.5	11.8	21.3	56.3	19.0	3.4
5	70	19.3	24.5	8.4	8.3	68.8	18.3	4.7
6	63	18.1	43.6	8.9	19.7	26.9	20.7	32.6
7	66	23.5	36.1	12.0	36.2	53.1	8.7	2.0
8	75	24.2	38.6	12.2	26.3	53.6	13.4	6.7
9	64	22.0	61.5	14.8	13.5	68.9	16.5	1.1
10	63	17.6	38.3	10.2	37.2	51.9	8.8	2.1
11	71	22.6	32.8	11.1	44.4	34.5	14.5	6.6
12	67	19.4	31.2	9.0	22.3	53.5	20.3	3.9
13	83	20.1	17.3	5.5	24.2	54.4	15.3	6.0
14	72	19.0	27.3	8.1	36.0	50.0	10.2	3.8
15	74	20.3	33.8	11.9	13.0	78.2	8.3	0.5
16	71	20.3	54.5	25.5	22.3	70.3	7.1	0.3
17	72	22.4	31.6	10.7	24.5	52.7	17.8	5.0
18	70	22.5	22.8	7.7	25.5	45.8	20.1	8.5
19	80	21.0	28.4	9.6	15.1	71.7	12.2	1.0
20	69	23.2	59.4	23.0	15.2	72.6	10.9	1.3
Mean	72	20.9	34.0	11.0	23.1	55.3	16.1	5.6
Std	7	1.8	12.9	5.1	9.8	13.2	7.1	6.9

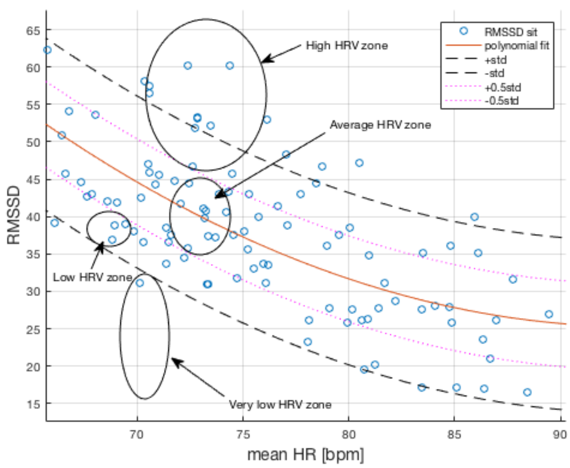


Fig. 2: A visual example of how HRV zones are calculated. Good HRV is classified when the HRV at a given HR is above one standard deviation. Average HRV is classified when the HRV is between -0.5 and +0.5 of a standard deviation. Low HRV is when the HRV is below -0.5 of a standard deviation, but above -1 of a standard deviation. Very low HRV is categorized when HRV is below -1 of a standard deviation at a given HR.

normative data will be included in the model instead of relying completely on personalized data. If a participant always has very low HRV (ie - 15 RMSSD), then this should not be categorized as average or high HRV because it is well below the published normative data for healthy adult HRV values [8]. In the current work, standard deviation of the RMSSD values in the first 100 HRV segments will also have a large affect on the HRV-categorization model.

Participant 6 had the highest levels of very low HRV percentage. This was due to the fact that the first 100 HRV segments for this participant included mainly HR values on the lower end of what was seen in all of her data. The model was not able to accurately model this participants HRV-HR relationship at higher heart rate values because there were not enough of them in the model creation. This problem should be taken into account in future iterations of model creation.

Very little work has been done investigating HRV while people go about their day to day life. The majority of HRV knowledge comes from HRV in supervised settings, while patients are in a sedentary state in a clinic or laboratory. This supervised research has shown the power of HRV to predict adverse health events and stressful mental conditions. Monitoring HRV in peoples everyday life poses a difficult challenge in understanding the context in which HRV measurements are obtained. The OMbra provides a unique way of providing context to HRV segments via the breathing sensor as well as the on-board accelerometer. The accelerometer is used to determine when a participant is in a seated, still position. This ensures that HRV outlier segments are not included in the data analysis.

Previous research in the area included movement data in the remote monitoring HRV analysis and did not account for HRV changes due to changes in HR [14]. In this work, we chose to only consider HRV while participants were in a still, seated position and we also developed a method to take into account HRV changes that were due to an increased or decreased HR.

V. Conclusion

The OMbra provides an unobtrusive way to obtain accurate HRV data in a remote monitoring setting with relevant contextual information. In this work a novel method for categorizing periods of low HRV is proposed that accounts for HRV changes due to an increased or decreased HR. Such a categorization would be useful in a bio-feedback scenario to allow users to observe how much time and when during a day they are in unhealthy low-HRV zones.

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