Unobtrusive Real-time Heart Rate Variability Analysis for the Detection of Orthostatic Dysregulation

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Abstract— **The possibilities for wearable health care technology to improve the quality of life for chronic disease patients has been increasing within recent years. For instance, unobtrusive cardiac monitoring can be applied to people suffering from a disorder of the autonomic nervous system (ANS) which show a significantly lower heart rate variability (HRV) than healthy people. Although recent work presented solutions to analyze this relationship, they did not perform it during daily life situations. For that reason, this work presents a system for a real-time analysis of the user's HRV on an Android-based mobile device throughout the day. The system was used for the detection of an orthostatic dysregulation which can be an indicator for a disorder of the ANS. Measures for HRV analysis were computed from acquired ECG data and compared before and after a posture change. For triggering the HRV analysis, an IMU-based algorithm which detects stand up events was developed. As a proof of concept for an automatic assessment of an orthostatic dysregulation, a classification based on the derived HRV measures was performed. The performance of the stand up detection was evaluated in the first part of this study. The second part was conducted for the evaluation of the derived HRV measures and involved healthy subjects as well as patients with idiopathic Parkinson's Disease. The results of the evaluation showed a recognition rate of 90.0 % for the stand up detection algorithm. Furthermore, a clear difference in the change of HRV measures between the two groups before and after standing up was observed. The classification provided an accuracy of 96.0 %, and a sensitivity of 93.3 %. The results demonstrated the possibility of unobtrusive HRV monitoring during daily life situations.**

I. INTRODUCTION

Heart rate variability (HRV) is the ability of the human organism to adapt its heart rate over time, according to the current circumstances such as physical activity or posture changes. The change in heart rate over time is regulated by the sympathetic and parasympathetic branch of the autonomic nervous system (ANS), causing the heart rate to be increased or decreased, respectively [1].

A common indicator for the correct function of the ANS is the observation of the *orthostatic reaction* while standing up [2]. During the transition from sitting or lying to standing (also referred to as *orthostasis*), the hydrostatic pressure increases as the blood sags into the legs, resulting in a decrease of the venous backflow in the heart chambers. As the organism strives to maintain a relatively constant cardiac output, the sympathetic nervous system causes a rapid increase in heart rate. For that reason, limited HRV is a measure for orthostatic dysregulation, which in turn can be a sign for disorders of the ANS, for example Parkinson's Disease (PD) [3]. Therefore, HRV analysis based on ECG recordings has been proven to be a simple and non-invasive method for the detection of abnormalities of the ANS [4].

The growing popularity of ubiquitous computing in recent years offers new possibilities for the acquisition of biomedical signals for medical as well as fitness purposes [5], [6], [7]. Therefore, wearable health care technology is a promising method of improving the quality of life for chronic disease patients and elderly people, as well as healthy individuals, allowing an ubiquitous and pervasive monitoring of vital signs. An application for analyzing the user's ECG is *DailyHeart* [8], which was extended within this work. It is an application for Android-based mobile devices and offers several modes for cardiac feedback, from measuring the current heart rate to continuously monitoring the user's ECG throughout the day. Furthermore, it implemented methods for novel human computer interaction concepts (e.g. smart watches) in order to provide cardiac feedback to the user.

Solutions performing HRV analysis using wearable sensors were implemented for stress assessment [9], [10] or biofeedback [11]. Furthermore, several research groups like Haapaniemi et al. [3], Kallio et al. [4] and Mihci et al. [12] were evaluating the HRV of patients with PD and proved it to be a marker of a disorder of the ANS. However, they mainly performed spectral methods for HRV analysis and used long-term clinical datasets, which are both neither feasible for a continuous monitoring throughout the day nor for providing immediate feedback to the user. For that reason, there is a need for an application which is capable of performing a real-time HRV monitoring and orthostatic reaction analysis in the user's daily environment without any restrictions in activity or modification in behavior.

In this work, the range of functions of the *DailyHeart* application were extended by a mode which allows mobile real-time HRV analysis for the detection of an orthostatic dysregulation. It therefore presents an algorithm for the automated detection of the user standing up, which is utilized for the evaluation of computed HRV measures before and after posture change. Thus, the acquired data allows an assessment of a possible orthostatic dysregulation resulting from a disorder of the ANS. Furthermore, the feasibility of developing a system for an automatic assessment of orthostatic dysregulation was proved by developing a classifier

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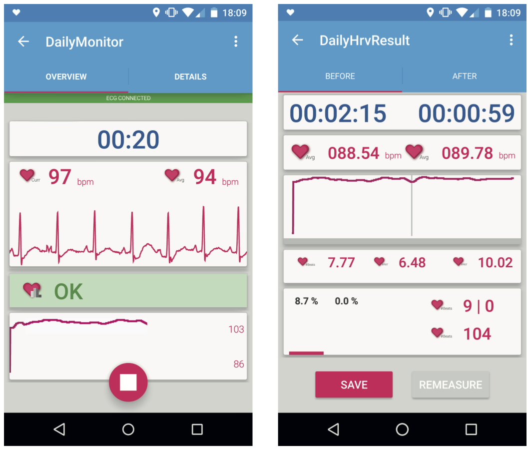

Fig. 1. **Screenshots of the DailyHeart application.** *Left:* Screen for live HRV analysis; *Right:* Screen showing the results of the HRV analysis.

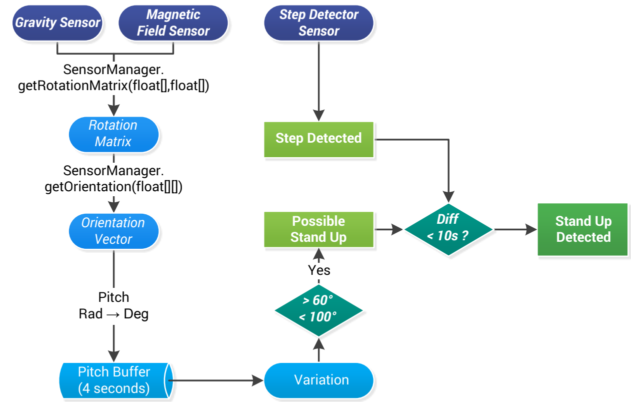

Fig. 2. **Algorithm pipeline of the stand up detector.** Overview of the pipeline which is used for detecting a posture change.

derived from the acquired HRV measures.

II. METHODS

A. Data Acquisition and Data Processing

1) Sensor Hardware: ECG data were acquired using a wearable ECG sensor system with Bluetooth Low Energy as presented in earlier work [8]. The sensor recorded an 1-channel ECG signal at a sampling frequency of 256 Hz with 3 electrodes placed according to Lead II of Einthoven's Triangle and an additional driven right leg electrode in order to eliminate electromagnetic interference. The data transmitted to the mobile device were processed by an algorithm proposed by Gradl et. al [13] which performs a real-time detection of QRS complexes in an ECG signal, followed by an automated classification into normal and abnormal heart beats.

2) Study Design: Ten subjects (age 21.40 $\pm$ 1.28 years (mean $\pm$ standard deviation)) participated in the data collection for the stand up detection. A Nexus 5 smart phone (LG Electronics, Seoul, South Korea) running on Android 6.0 "Marshmallow" (API level 23) was used for data collection which provides the required internal sensors: a gravity sensor, a magnetic sensor and a step detector sensor. The mobile device running the *DailyHeart* application was placed lengthwise in the front pocket pants of the participants. The subjects were asked to sit on a chair, stand up on command and walk forward for five meters. Each subject repeated this protocol five times.

Data for the HRV analysis was collected in the second part of the study consisting of three healthy, male subjects (age 21.70 $\pm$ 0.57 (mean $\pm$ standard deviation)) and five male patients with idiopathic Parkinson's Disease as main diagnosis (age 65.40 $\pm$ 8.55 (mean $\pm$ standard deviation)). The study was conducted at the Department of Molecular Neurology, University Hospital Erlangen, and was approved by the ethical committee of the hospital. Furthermore, all subjects gave written consent for their participation in the study. During the procedure, all subjects wore the same ECG sensor system with the default lead configuration. The data were streamed to a mobile phone running the *DailyHeart* application. Before starting the measurement, each subject was asked to sit on a chair for a duration of three minutes so that the cardiovascular system could adapt to its current posture. After the ECG measurement had started, the subjects had to remain seated for one minute, stand up on command and stand still for another minute. Each subject repeated this protocol three times.

B. HRV Analysis Extension of DailyHeart Application

The *DailyHeart* application was implemented using the *Android SDK 6.0* (API level 23). Android (Google Inc., Mountain View, CA, USA) was used because of its open source characteristics, the portability of code due to the fact that the programming language is Java, and because it is the most widely spread mobile operating system today with a market share of 84.7 % [14]. The modular structure of the application allows a simple extension by further modes for ECG recording. Within this work, the range of functions was enhanced by a special mode for performing a continuous HRV analysis (see Fig. 1). This continuous measurement was triggered by a stand up detector and subsequently performed by the extraction of specific measures in order to classify a orthostatic dysregulation.

C. Stand Up Detection

The algorithm for stand up detection is visualized in Fig. 2. It used the internal sensors of the mobile device as input. The Android framework provides built-in functions to compute an orientation vector from the raw sensor values of the gravity and the magnetic field sensor [15], [16].

Every second, the current value of the rotation around the negative X-axis (also known as pitch) according to the coordinate system defined in Fig. 3 was stored in a ring buffer with a capacity of $N = 4$ elements. Once a new value had been added to the buffer, the variation Δ_{pitch} (defined as the sum of the difference between consecutive buffer entries) was recomputed according to (1):

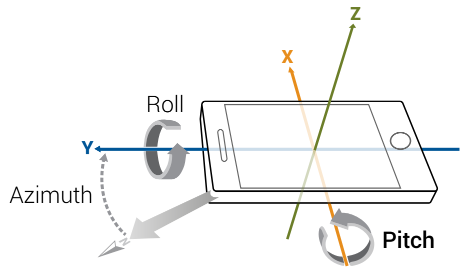

Fig. 3. **Coordinate system for the smart phone orientation** *Pitch:* Rotation around the negative X-axis; *Roll:* Rotation around the Y-axis; *Azimuth:* Rotation around the negative Z-axis.

$$\Delta_{pitch}(i) = \sum_{k=1}^{N-1} \text{buf}[(i-k)\ \%\ N] - \text{buf}[(i-k-1)\ \%\ N]. \tag{1}$$

The computed variation had to be between 60 ° and 100 ° in order to detect a *possible stand up event*. The thresholds were chosen empirically as they describe the change of leg angle between sitting and standing position. In order to reduce false detections, the algorithm was combined with the step detector sensor provided by the Android framework. Therefore, a stand up event was only triggered if a step was detected within ten seconds after a possible stand up.

D. HRV Measures

The measures used for HRV analysis were selected according to guidelines of *The European Society of Cardiology* and *The North American Society of Pacing and Electrophysiology* [1] and are listed in Table I. In order to minimize computational load, only statistical measures in the time-domain were chosen. They can be divided into those which are derived directly from the measurement of the RR intervals (*AvgRR, StdRR*) and those which are derived from the difference of two successive RR intervals (*AvgSD, StdSD, RmsSD*). Except *pRR20*, all measures were computed for non-overlapping windows of ten seconds in order to continuously provide feedback to the user.

TABLE I
SELECTED MEASURES FOR HRV ANALYSIS

Variable	Description	Unit
AvgRR	Average of RR intervals	ms
StdRR	Standard deviation of RR intervals	ms
AvgSD	Average of successive differences	ms
StdSD	Standard deviation of successive differences	ms
RmsSD	Root mean square of successive differences	ms
pRR20	Number of successive differences $\geq$ 20 ms divided by all RR intervals	%

E. Feature Extraction and Classification

Each acquired HRV measure was averaged over all windows before and after stand up event, resulting in two values per measure. The features were extracted by computing the difference of both values for each HRV measure. Finally, the features were used to train a C4.5 decision tree. The feature normalization and classification was performed using the Embedded Classification Software Toolbox (ECST) [17].

III. Evaluation

A. Stand Up Detection

The goal of the stand up detection was to correctly detect stand up events and subsequently trigger the measurement for the HRV analysis. All subjects performed the proposed procedure of sitting, stand up and walking. The actual stand up events were manually labeled by observation. The parameters which were evaluated were the recognition rate of the algorithm and the time difference between the detection of a stand up event and the manually labeled event. This difference was calculated by using two synchronized clocks.

B. HRV Measures

Acquired data were written to the internal storage of the mobile phone and exported to MATLAB® (The Mathworks, Inc., Natick, MA, USA) for further analysis. The parameters to be evaluated were the changes of HRV measures during stand up and the most distinct HRV feature to be used for separating both groups.

C. Classification

The evaluation of the decision tree was based on a leave-one-subject-out cross-validation. Accuracy, sensitivity and specificity of the classifier were computed from the results.

IV. Results

A. Stand Up Detection

During the evaluation of the stand up detection algorithm, 45 out of 50 stand up events were correctly detected. Therefore, the recognition rate was 90 % with a time difference of 0.54 s ± 0.63 s (mean ± standard deviation). It could be observed that standing up too fast and in a slanted manner could cause the algorithm not to detect a stand up event. An incorrect placement in the pocket pants showed the same effect.

B. HRV Measures

Example heart rate data recorded while performing the study protocol of the HRV analysis is visualized in Fig. 4 for a healthy subject and a PD patient, respectively. Table II shows the change of the selected HRV measures for healthy subjects and PD patients. Furthermore, the difference between the both groups was computed for each measure.

C. Classification

The decision tree obtained from the classification step achieved an accuracy of 96.0 % with a sensitivity of 93.3 % and a specificity of 100.0 %.

TABLE II

CHANGE OF HRV MEASURES DURING POSTURE CHANGE. THE MOST DISTINCT MEASURE IS WRITTEN IN ITALIC.

Measure	Healthy	PD patient	Abs. Difference
AvgRR	−15.24%	−6.23%	9.01
StdRR	+43.64%	−11.57%	55.21
AvgSD	+46.23%	−5.10%	51.33
StdSD	+19.75%	+1.58%	18.17
RmsSD	+21.74%	−1.03%	22.77
pRR20	*+68.81%*	*−25.77%*	*94.58*

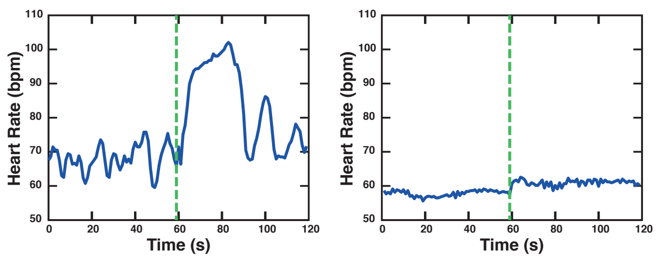

Fig. 4. **Course of heart rate over time during a stand up event.** *Left:* Example recording of healthy subject; *Right:* Example recording of subject suffering from PD; *green, dashed:* Stand up event.

V. DISCUSSION

A. Stand Up Detection

Despite the high recognition rate of 90 % stand up events were missed occasionally, because the variation of the pitch value did not reach the threshold. Including the remaining two orientation values roll and azimuth (as visualized in Fig. 3) into the algorithm could further increase the recognition rate. Additionally, suitability for daily use could be further improved. For instance, the stand up detection should only trigger an event when having rested for a certain period of time so that the cardiovascular system could adapt to the current posture.

However, the results prove that the proposed algorithm is suitable for triggering a HRV analysis during posture change in daily life situations. Furthermore, the algorithm only used the internal sensors of the smart phone and therefore did not rely on additional hardware. Due to the fact that several stand up events occur throughout the day, the achieved recognition rate is sufficient for performing an accurate HRV analysis which does not require every stand up event to be detected.

B. HRV Measures

As seen in Fig. 4, subjects suffering from idiopathic Parkinson's Disease show a considerably lower orthostatic reaction than healthy subjects. Likewise, evaluation results show a clear difference in the change of HRV measures between PD patients and healthy subjects with *pRR20* being the most distinct measure for the assessment of an orthostatic dysregulation. Limited HRV is not only an indicator for a disorder of the autonomic nervous system but can also be analyzed for the diagnosis of cardiovascular diseases, diabetic neuropathies, or acute myocardial infarction [18], [19] which can be examined in future work.

The measures used for HRV analysis within this work were computed in real-time on the testing device. The temporal resolution could be improved by implementing overlapping windows for the computation of HRV measures. Furthermore, future work could include other time-domain measures (e.g. geometric measures) or perform a spectral analysis [1] on the complete data acquired during posture change.

C. Classification

The decision tree obtained from the classification step yields an accuracy of 96.0 %, a sensitivity of 93.3 %, and a specificity of 100.0 %, and hence can distinguish clearly between healthy subjects and PD patients. However, in future work the amount of training data should be increased in order to develop a more robust classification system.

Results show that the system presented in this work allows an unobtrusive HRV analysis during posture change during daily life activities. It is a mobile and cheap solution for giving an assessment regarding a orthostatic dysregulation and a possible disorder of the autonomic nervous system in real-time. It is clearly not intended to replace a neurological examination, but could provide additional information for the physician without the effects of the *"white coat syndrome"* [20].

VI. CONCLUSION AND OUTLOOK

Within this work, the range of functions of *DailyHeart* was enhanced by a special mode for performing a continuous analysis of the user's heart rate variability in order to detect an orthostatic dysregulation. An algorithm for stand up detection with a recognition rate of 90.0 % was developed and used to trigger the comparison of HRV measures during an orthostatic reaction. The evaluation showed that the presented solution is capable of detecting subjects with limited HRV like patients diagnosed with Parkinson's Disease. The classification showed an accuracy of 96.0 %, a sensitivity of 93.3 % and thus demonstrated the possibility of performing a mobile HRV analysis for the detection of disorders of the autonomic nervous system. Based on these promising results, the next steps will be to collect more data in order to develop a more robust classifier for the detection of an orthostatic dysregulation which could be included in the application. So far, the stand up detection algorithm and the analysis of the orthostatic reaction have been evaluated separately. As a next step, the performance of the combination of both featured throughout the day will be examined. To this end, a long-term study will be conducted.

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