KAUNAS UNIVERSITY OF TECHNOLOGY

FACULTY OF ELECTRICAL AND ELECTRONICS ENGINEERING

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ESTIMATION OF HEART RATE RECOVERY TIME DURING FREE-LIVING ACTIVITIES

Master's Degree Final Project

Supervisor

prof. dr. Vaidotas Marozas

KAUNAS, 2018

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"Estimation of heart rate recovery time during free-living activities", final project

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Reikšminiai žodžiai: širdies efektyvumas, fizinis aktyvumas, fotopletizmograma, išmanieji įrenginiai.

Kaunas, 2018. 47 psl.

SANTRAUKA

Širdies sveikatos problemos yra pagrindinė mirtingumo priežastis. Daugiau nei penktadalį visų mirčių pasaulyje sukelia širdies ligos. Širdies sveikatos sutrikimai paprastai vystosi palaipsniui dėl nesveikos gyvensenos ir fizinio aktyvumo stokos. Profilaktinis, veiklos nevaržantis širdies būklės matavimo būdas gali gerokai pagerinti ankstyvą širdies ligų aptikimą. Dauguma dažniausiai naudojamų testų atliekami tik kliniškai kontroliuojamomis aplinkybėmis. Širdies efektyvumas yra parametras, kuris nustato širdies gebėjimą veikti esant stresui ir atstatyti po padidėjusio širdies ritmo, jis yra svarbus klinikinių tyrimų metu. Širdies ritmo atsistatymas tai širdies funkcija, kuri yra glaudžiai susijusi su širdies efektyvumu. Širdies ritmo atsistatymas yra svarbus širdies sveikatos vertinimo metodas, kurį įmanoma integruoti į nešiojamus prietaisus. Veiklos nevaržančio įvertinimo metodo tobulinimas gali motyvuoti žmones rūpintis savo sveikata ir padėti jiems stebėti fizinio pasiruošimo pažangą. Šiame tyrime mes išmėginsime įvertinti širdies ritmo atstatymo parametrus iš duomenų, surinktų naudojant dėvimų išmaniųjų prietaisų technologijas. Fotopletizmografija yra pasirinkta kaip galimas elektrokardiogramos pakaitalas širdies ritmo atsistatymo įvertinimui. Pateiktas ir išbandytas širdies ritmo atsistatymo įvertinimo algoritmas iš fotopletizmogramos ir elektrokardiogramos signalų. širdies ritmo atsistatymo įrašų duomenų bazė su skirtingais fizinio aktyvumo lygiais buvo surinkta iš 23 žmonių. Išbandytos elektrokardiogramos, fotopletizmogramos ir "Fitbit" registravimo metodų galimybės įvertinant širdies ritmo atsistatymo parametrus. Parametrų pakartojamumas buvo ištirtas visiems įrašymo metodams.

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SUMMARY

Cardiac health problems is the leading cause of mortality. Over one fifth of the total deaths in the world are caused by cardiac illnesses. Heart health problems usually develop gradually due to unhealthy behavior and lack of physical activity. A prophylactic, unobtrusive way of measuring heart condition could greatly improve the early detection of cardiac disease. Most of the commonly used tests are only performed clinically under controlled circumstances. Heart efficiency is parameter that determines hearts capability to perform under stress and recover afterwards, it is important in clinical studies. Heart rate recovery is an important heart function which is closely associated with heart efficiency. Heart rate recovery is a viable cardiac health assessment method to be integrated into wearable devices. Improvements in unobtrusive measurement could motivate people to take care of their health and help them to monitor progress of fitness. In this study, we will test the ability to assess heart rate recovery parameters from data gathered using wearable device technology. Photoplethysmography will be tested as a possible surrogate to electrocardiogram for heart rate recovery assessment. An algorithm for heart rate recovery extraction from photoplethysmogram and electrocardiogram signals is presented and tested. A database of heart recovery recordings under different physical activity levels has been assembled from 23 people. The performance of electrocardiogram, photoplethysmogram and "Fitbit" based heart rate signals were tested. Repeatability of parameters have been analyzed for all recording methods.

CONTENTS

INTRODUCTION

Heart rate recovery (HRR) is often proposed as an alternative of HRV to assess cardiac health. The rise in heart rate during exercise is considered to occur due to the combination of parasympathetic withdrawal and sympathetic activation. The ability of heart rate to recover after exercise is related to the capacity of cardiovascular system to reverse ANS (withdrawal of sympathetic activity) and baroreceptor adaptations that occur during exercise, often termed as vagal reactivation. Many previous studies has found a link and associations between HRR and mortality. Monitoring of HRR can help people to keep track of their fitness. The simple way of achieving unobtrusive monitoring will further motivate people to improve lifestyle and invest more time in physical activity. In this study we will test the ability to measure HRR during daily life scenario using a specialized smart wristband.

The aim of this work is to develop a novel algorithm for estimation of heart rate recovery time during free-living activities. The objectives are the following:

1. To analyze clinical significance of heart rate recovery time as a biomarker of heart efficiency and available methods for its estimation;
2. To develop a method of heart rate recovery time estimation during free living activities;
3. To create a protocol and acquire database of biosignals;
4. To study the variability of heart rate recovery under different physical activity levels;

1. BACKGROUND

1.1. Clinical importance of estimating heart efficiency

Heart efficiency is a term used to explain how effective is heart to supply oxygen to the body. Cardiac efficiency is usually split between myocardial conversion efficiency and contractile efficiency. Within these terms heart is considered as a mechanical motor or a pump which uses energy and produces a certain amount of work (Westerhof et al. 2000). Effectiveness of the heart depend on the stress level that it is used to receive and its overall health (Toorop et al. 1988). Cardiac efficiency also directly corresponds to the ability for a human body to recover to a normal state after physical activity. After physical activity heart rate is increased and stress to the heart is elevated. If heart is capable to perform efficiently under unusually high contraction rate it recovers faster in contrast to the heart of lower efficiency.

Heart efficiency as a term that describe heart ability to perform under stress and recover afterwards is important in clinical studies. The assessment of heart efficiency is not standardized. This is mostly because the factors that determine it are numerous. However, a combination of many physiological parameters allow doctors to evaluate the overall heart effectiveness and assess patient health.

Many cardiological diseases like myocardial infarction and cardiac arrhythmias are a result and often cause reduced effectiveness of heart function. Even when the main disease is treated the causes may remain and the risk of cardiological malfunction is higher than normal. Patients in rehabilitation are usually required to visit hospitals at a regular rate to perform heart evaluation tests. These experiments usually test the main heart functions related to the experienced disease. Many of the heart functions included are highly determined by heart efficiency.

1.1.1. HRR and pathophysiology

The factors that determine the ability for the heart to keep its effectiveness is under discussion. Aging and lack of physical activity are potential causes of reduced heart efficiency which usually lead to heart related diseases (Strait et al. 2012, Fleg et al. 2012). Physical activity in its own right presents a high risk to develop coronary and ischemic heart diseases (Billinger et al. 2014). Lower levels of physical activity and an increase of sedentary behavior has been previously associated with cardiometabolic risk which determines the overall chances of having and getting diabetes, heart-related disease or stroke. The combined effect of sedentary behavior and reduced physical activity has been tested for people of all ages and the relationship of developing cardiometabolic risk does pose a serious danger to young people and children as well (Imai et al. 1994, Vaisto et al. 2014).

Cardiac autonomic dysfunction has symptoms that occur in late stages of diabetes and is a marker for paroxysmal atrial fibrillation (AF) and other cardiovascular diseases (Sarafidis et al. 2017). Flawed autonomic heart functions are mainly associated by the fall of parasympathetic activity and rise of sympathetic activity. These functional differences usually lead to increased cardiac load. These drastic changes in stress and increased heart functional instability often result in higher risk of cardiovascular diseases like cardiac arrest, infarction. The tools for cardiac autonomic dysfunction assessment include HR response to pharmacological blockade (Kinugawa et al. 1991), baroreflex sensitivity estimation and HRV analysis (Gerritsen et al. 2001).

Keeping heart at the best performance level is important not only for athletes but for ordinary people as well. Cardiac problems that appear later in life ordinarily show signs of illness earlier in life. The markers that determine heart related diseases often relate to the main heart functions in general. Constant monitoring of heart efficiency can in many ways provide the earliest signs of incoming cardiac diseases. Research studies of healthy people heart efficiency monitoring at long term suggest that it is highly related to the mortality rate (Arena et al. 2008).

HRR after physical activity is an alternative vagal activity determined factor. Vagal reactivation tend to be promoted by physical exercise (Perini et al. 1998). In addition to that the slow phase of recovery period is shown to be at least partly encouraged by cardiac sympathetic withdrawal. Sympathetic withdrawal in its own right is associated with various cardiac diseases. This is the main reason HRR is related with mortality rate.

Aspects of heart rate recovery is known to be influenced by many factors. The influence of these factors may differ of intensity to different phases of recovery period. However age, gender and even race are probable factors that impact the behavior of both slow and fast phases of HRR. In general, HRR sequence is considered to be falling at an exponentially slowing rate. heart recovery time is usually modeled with an exponential function, method that is widely used in HRR research. Recovery episodes that do follow an exponential curve are considered to be normal. However, abnormal HRR instances happen more frequently in aged part of populace than in younger. Abnormality is usually explained as a result of cardiac illness and parasympathetic system malfunction.

The rate of recovery is also associated with the physical fitness of a subject. People more used to the physical stress are more likely to have better performance at HRR tests (Darr et al. 1988). Several studies has shown the difference in the rate of recovery after physical exercise between athletes and non-trained individuals (Trevizani et al. 2012). The mentioned reasons support the idea of expanded clinical use of HRR and further increase its research.

1.1.2. Clinical methods for estimating heart efficiency

Cardiac efficiency is often related to the cardio-respiratory fitness. Cardio-respiratory fitness is measured through peak oxygen consumption ($V_{o_2\,max}$). Respiratory gas exchange provide the breath-by-breath oxygen consumption values. $V_{o_2\,max}$ is defined as a maximum V_{o_2} value attained in the physical activity period (Buchheit et al. 2006). Cardio-respiratory fitness, however is mostly associated with vagal-related functions that are represented by heart rate variability.

Time and frequency analysis of heart rate series are knows as heart rate variability. HRV is frequently used as a noninvasive method to evaluate cardiac functions. Analysis of parasympathetic activity which is proven to be closely related to increased cardiovascular risk. In addition to the parasympathetic studies, vagal activity is an important factor which has an affiliation to training endurance response (Hautala et al. 2003). Low frequency component (LF) of HRV frequency analysis is the main part that match the vagal activity.

Heart function to recover after physical activity has also been showed to be an index related to vagal activity. The period after physical activity show a difference in lower frequency fluctuations in healthy subjects and subjects with known cardiac disease. For normal subjects the recovery period showed a progressive increase of heart rate power which is the difference when comparing with results of ill patients. These findings propose a possibility of change to autonomic modulation for patients of cardiovascular diseases (Arai et al. 1989). For HRR analysis it is most common to identify the exponential time constant HRR_{τ} as an index of the whole recovery period, however there has been defined many complementary parameters.

As a reduction of cardiac efficiency may be the cause of appearance of certain heart arrhythmia, dysfunctions it is important to research the clinical used diagnostic methods. For cardiovascular autonomic dysfunction assessment the most commonly used tests include Valsalva maneuver, postural testing and heart rate variability analysis (Broadstone et al. 1991).

1.1.3. The need for testing heart efficiency in an unobtrusive way

Methods of estimating heart efficiency clinically are hard to apply for everyday use. The regulations and a strict protocol have advantages when researching the relations of certain physiological aspects to determine markers of illnesses. However situations that follow the proposed protocol are hard to come by in free-living activities. That makes it particularly hard to perform wider studies and include people from many different backgrounds. With the advancements in technology some of the difficulties that occur under uncontrolled situations can be eliminated or reduced. Robust signal processing techniques can be integrated into novel physiological signals monitoring devices. That makes the search for unobtrusive way of estimating persons health a highly sought research study. A new method could expand the potential of recent developments in the field of physiological signal processing.

The estimation of HRR and its applications for cardiac health evaluation show great promise for integrated applications. Wearable devices have proved that heart rate can be measured accurately. Smart wristbands are getting increasingly popular as a fashion item as well as a device to monitor heart rate. This tendency is being used extensively to integrate new technologies into smart devices.

1.2. Overview of heart rate monitoring technologies

Heart rate is determined by the duration of heart contractile intervals. Duration is usually converted into number of contractions per minute, or a unit beats per minute (bpm). Heart rate is not consistent, it usually varies depending on the oxygen needy. There are many factors which influence the variability of the heart rate, these factors include: physical activity, psychological stress, sleep, drugs and various physiological dysfunctions. Normal heart rate while resting is considered to be in the range between 50 and 90 beats per minute.

The number of factors that influence heart rate suggest the importance of researching and monitoring it. There are many ways to measure heart rate. The most common methods are electric heart potential measurement based recordings and optical measurement based methods. Each has its own advantages and disadvantages on signal quality and usability.The most commonly used methods are Electrocardiography and photoplethysmogram.

1.2.1. ECG based heart rhythm estimation

Electrocardiography is considered as one of the most reliable way of monitoring heart rate. It is described as a process of recording the electrical activity of the heart over a period of time using electrodes placed on the skin. Electrodes measure the electrical impulses that are generated in the heart itself that's why it is the most direct approach of acquiring heart rate signal.

Like all discrete signals ECG is highly dependent on the sampling rate it is recorded. Sampling rate determines the amount of information that is possible to extract and the quality of this information.

The complexity of ECG acquisition procedure is constituted by the chosen setup. There are a number of variations of ECG which mostly differ of the placement of electrodes on the body. However the conventional setup consist of 12 separate electrodes it is only performed on serious occasions. Many more commonly used techniques include lesser amount of electrodes like 10 or just 4 (Fig. 1.1).

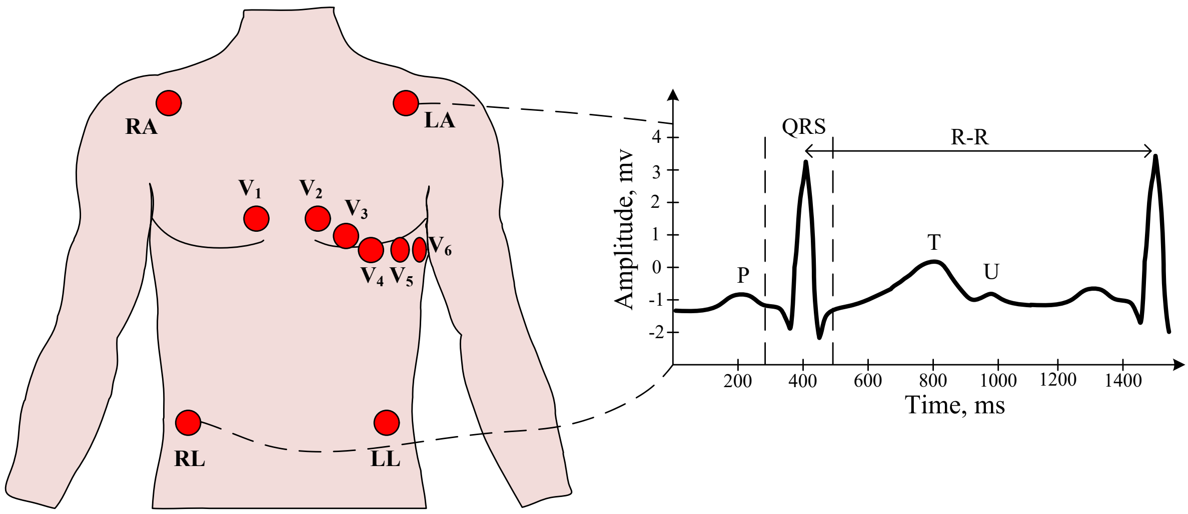

Figure 1.1 Electrocardiographic signal acquisition and QRS representation

The higher number of electrodes are used the more derivations of ECG is available for analysis. Derivations are separate leads or angles of recorded potentials. Some derivations may have supplementary information about particular part of the heart and a function associated with it.

Higher number of required derivations is useful for more in-depth analysis of the QRS complex. By interpreting ECG signal it is possible to distinguish all the parts of the heart electrical functions. Heart atrial depolarization for example represents P wave and the whole QRS complex represent ventricular depolarization. Some parts, especially QRS complex has high frequency components. To accurately assess the data provided by ECG signal it must be sampled in high frequency.

ECG additionally to heart rate provide much useful data about the functions of the heart. The downside of ECG are the need to use electrodes which might be uncomfortable for many users.

However electrodes ensure the quality of registered signal it also is less likely to get corrupted with noise.

1.2.2. PPG based heart rate rhythm estimation

A Heart rate acquisition method very popular for its simplicity is photoplethysmography. It is optically obtained plethysmogram, a volumetric measurement of an organ. A PPG is often obtained by using a pulse oximeter which illuminates the skin and measures changes in light absorption. Changes are created by the change of volume in the periphery. Each cardiac cycle pumps blood to the peripheral system, each wave of blood travels throughout the body. Volumetric changes can be distinguished and applied to the different phases of the heart (Fig. 1.2).

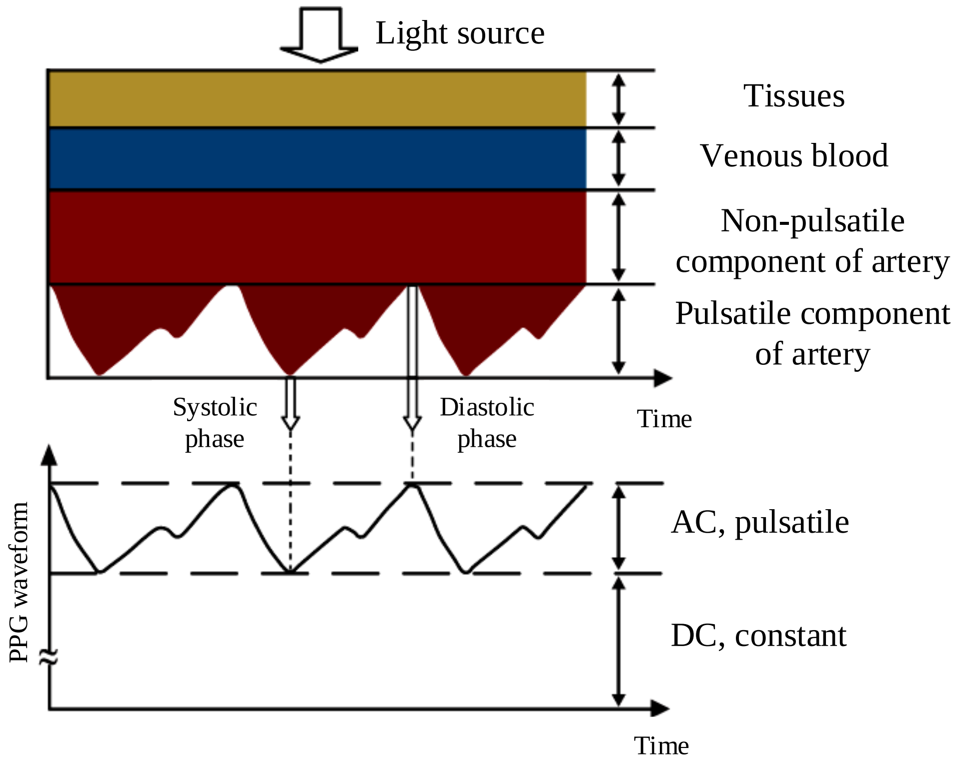

Figure 1.2 Photoplethysmography

The valleys of the PPG waveform represent systolic phase while peaks represent diastolic phase.

PPG can be performed in light transmission or absorption methods. Transmitted light mode is more common and considered more reliable. In addition to heart rate photoplethysmography can be used to measure oxygen saturation in blood. By comparing PPG and ECG signals it is possible to measure latency of the pulse wave also called pulse arrival time. Pulse arrival time is associated with arterial stiffness.

The downsides of photoplethysmography are the low amplitude alternating component that transmits the pulse information. That means this method is responsive to occurring motion artifacts. On the other hand this method is easy to use, in general requiring only light emitting diode (LED) and photodiode. For its simplicity this method of heart rate measurement is used widely in smart wearable device market. Photoplethysmography technology is advancing and the task of robust PPG recording is more achievable.

1.3. Methods of HRR evaluation

The number of studies on HRR is increasing, especially in the last two decades (Pecanha et al. 2017). This rate of growth in research is attributed to the potential of HRR as an easily measured biomarker of heart function. Most of these studies focus on the mechanisms of HRR and its development in the field of clinical monitoring and prognosis (Jouven et al. 2005, Kannankeril et al. 2000). Throughout the years there have been many developments in the process of assessing the data that lies in the heart recovery signal. Parameters that have the most significant meaning have been distinguished. The most commonly used methods and parameters will be presented and discussed in this study.

1.3.1. Fast-slow phase transition estimation

One of the most common methods of HRR estimation is estimation of fast-slow phases of heart recovery. This method separates recovery signal into two parts, a primary-fast phase lasting up to 60 seconds and a secondary-slow phase that lasts up to 5 minutes (Rosso et al. 2014). Fast phase and slow phase estimation reflects the rapid vagal reactivation and sympathetic withdrawal (Imai et al. 1994).

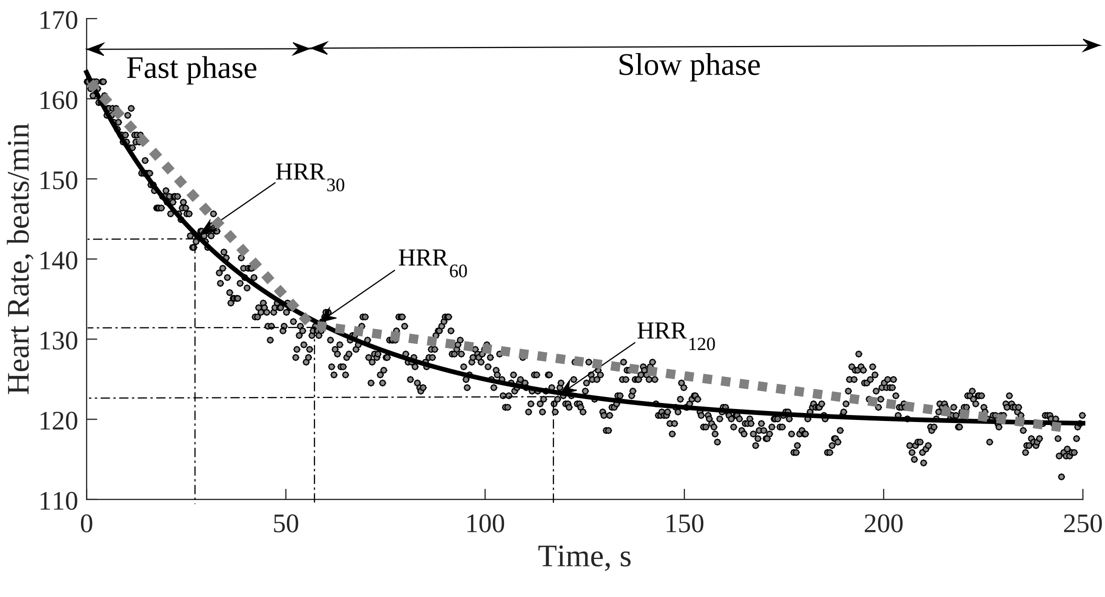

Figure 1.3 Decay of heart rate over time, parameters at different phases

Parameters are usually separated into two groups, containing only fast phase and the other containing fast and slow phase together. Fast phase parameters include an index of heart rate 30 and 60 seconds after the start of recovery. These parameters could be represented as heart rate value at this instance, a difference from maximum heart rate or a proportional difference from the maximum heart rate (Fig. 1.3). In this study we will use the last representation approach. Studies have shown HRR60 parameter to highly reflect parasympathetic reactivation (Pecanha et al. 2017). A lower HRR60 measured can be a predictor of mortality (Nanas et al. 2006).

1.3.2. Exponential estimation method

Heart rate recovery signal can be modeled using a first term exponential function as it has been shown in previous studies (Perini et al. 1989, Bartels et al. 2015). By applying an exponential fit we extract the most significant part of heart rate recovery signal and filter out the constantly appearing variation. The model of exponential recovery has a parameter of time-constant τ which is used as a marker defining recovery rate (Fig. 1.4).

$$\tau = HR_0 + HR_\Delta e^{\frac{-t}{\tau}} \tag{1.1}$$

In the equation HR_0 is the asymptotic value of HR, HR_Δ is the difference between peak of HR and HR_0.

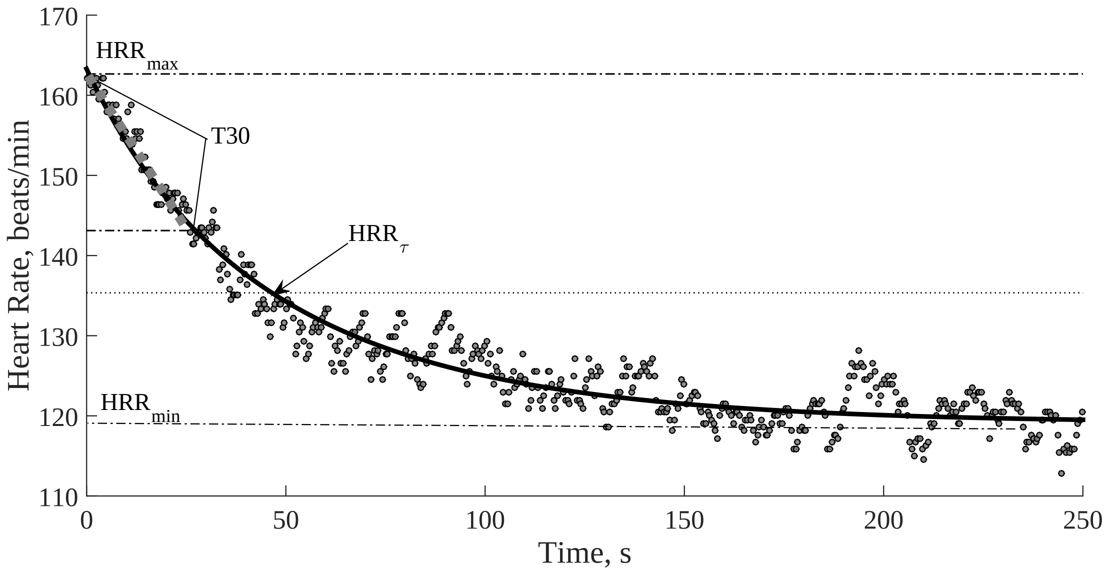

Figure 1.4 Exponential time-constant

A time-constant τ quantifies the rate of recovery decay over the entirety of curve. It is important to chose the right duration for exponential curve estimation. Length of the recovery vary from person to person and can be in range between 60 and 300 seconds. The average of recovery time is considered to be around 120 seconds (Imai et al. 1994).

1.3.3. Slope steepness

HR decay is notably important during the first minute of heart recovery. Because HRR curve acts in an exponential way, we can apply a logarithm to linearize the HR sequence. This method allows to extract the first order polynomial line which corresponds to recovery behavior as a whole. First degree polynomial function fitted on heart rate provides a line. Steepness of this line quantifies the rate of change over time which is considered as a reliable index. The T30 parameter estimates the slope during first 30 seconds of recovery and T30min estimates the 30 second duration interval which exhibits the greatest steepness during the first minute of recovery (Fig. 1.4). In order to apply heart rate recovery in a real time system the algorithm must be optimized correctly. Slope steepness method is easily adaptable and very suitable to automatic applications.

2. MATERIALS AND METHODS

2.1. Data and acquisition protocol

In order to test the algorithms performance on different types of signals and under different levels pf physical activity we must acquire a database of reliable data. We will be using different devices to record signals of various acquisition methods and sampling rate and perform a physical activity experiment with resting phases before and after.

2.1.1. Acquisition devices

The developed wrist-worn device (Biomedical Engineering Institute, Kaunas University of Technology, Kaunas, Lithuania) is capable of synchronously acquiring PPG, 3-lead ECG, barometric pressure, and motion signals (Fig. 2.1). ECG and PPG are sampled at 500 Hz and 100 Hz, respectively.

Figure 2.1 Custom made physiological signals registration device

The developed device was compared to the commercial smart wristband Fitbit Charge 2 (Fitbit Inc., san Francisco, CA, USA), which provides minute-by-minute accumulated steps, as well as pulse rate at intervals of 5 s or longer, depending on PPG signal quality (Fig. 2.2). In contrast to the developed wrist-worn device, the commercial smart wristband does not provide an instantaneous pulse rate for each heart contraction, but rather averaged values over the time interval.

ECG recorded by a custom smart wristband will be used as a reference signal because of greatest sampling rate and good quality. The objective will be to examine the availability of PPG and Fitbit recorded signals to be used as a reliable substitution to widely recognized ECG recording.

Figure 2.2 Fitbit smart wristband

2.1.2. Acquired data

Database includes 23 people, performing 5 different tests of walking, stair climbing and step test. These experiments have been chosen to best represent different possible physical activity episodes that happen during real-life situations (excluding step test). The most common physical activity that people perform daily is climbing stairs would it be to work of home. Monitoring HRR after climbing stairs could be a possible non obtrusive way of estimating heart efficiency.

Subjects comprise of 8 women and 15 men with and average age of 25 $\pm$4,8 years, average height of 178,5 $\pm$10 meters, average weight of 76,2 $\pm$17,2 kilograms and an average body mass index of 23,7 $\pm$4.1.

The device setup of experiment consists of previously described custom smart wristband and Fitbit commercial wristband (Fig. 2.3).

Experiment is separated in 5 parts that consist different types physical activity (Fig. 2.5). Each recording is 9-10 minutes of length and contains a wide variety of physiological signals and ambient parameters recordings.

Each part consist of three phases: rest, physical activity and a longer resting phase once again (5 minutes) to record whole heart recovery period. The experiment begins with walking exercise at a normal speed of no less than 72 steps per minute. Stair climbing is performed at three different speeds of climbing at: 48, 72 and 96 steps per minute. Subject is set to climb from 1st to 5th floor, in total 72 steps. Different speeds of climbing will be helpful to distinguish the effect of the intensity of physical activity to HRR results. The climb at the highest speed of 96 steps per

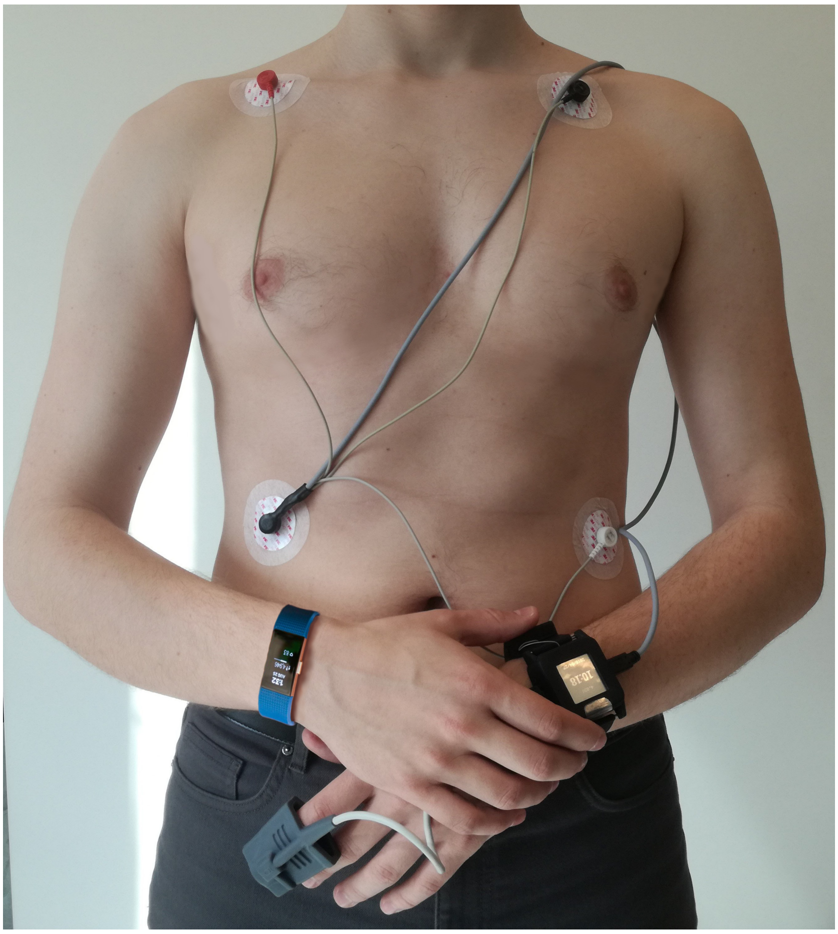

Figure 2.3 Registration setup

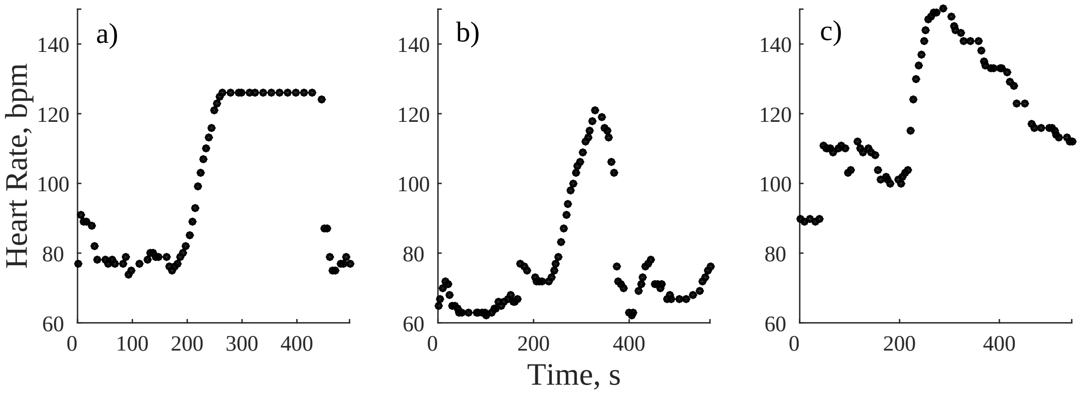

Figure 2.4 Errors in Fitbit signal. a) Signal limits restraint, b) missing parts of series, c) recovery period extension

minute is repeated three times consecutively, with a short break of 5 minutes between each test. The final part of experiment is step test, which is considered as a standard physical activity test in many studies. However during the resting phase after step test is performed while sitting other than standing.

Full database consists of 23 subjects performing 7 tests of HRR recorded with 3 different methods. In total, 161 instance of HRR under various physical activity levels and 483 considering different acquisition methods.

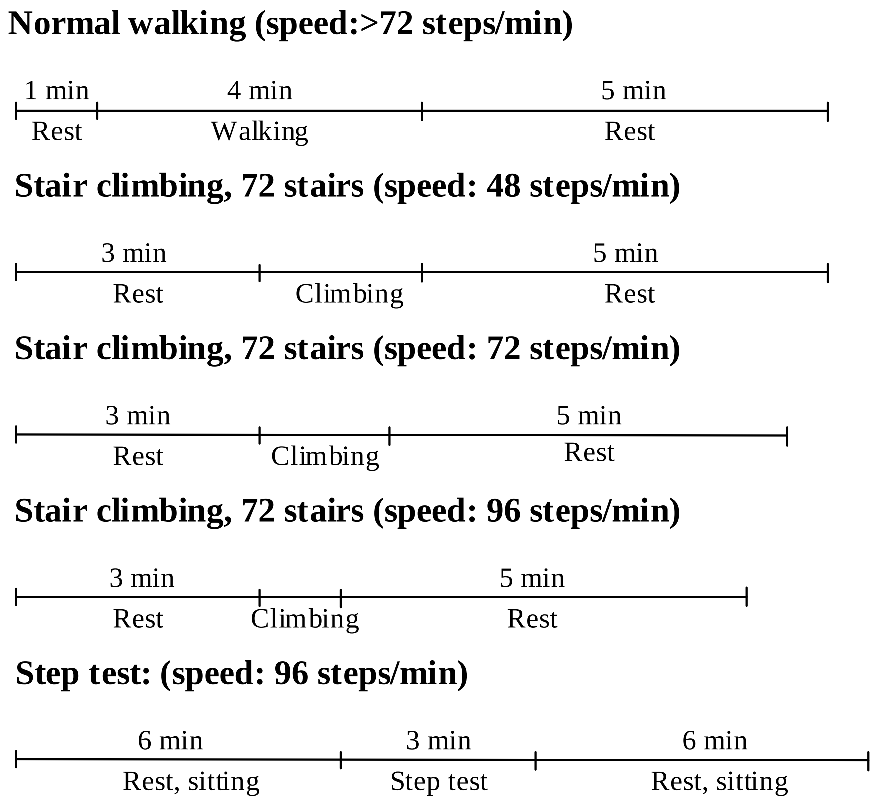

Figure 2.5 Experimental protocol

Experiment consisted of a portion of signals which have a faulty recording because of sensor or calculation failure. The device particularly influenced by technological errors is commercial Fitbit device. Some instances of either blank spaces in HR signal or limitation in HR are recorded. These errors resulted in a part of recordings that are not available for analysis (Fig. 2.4).

High quality wrist based PPG device is notoriously hard to design, there are a lot of technological and physiological problems. That is apparent in the recorded database, even though PPG signal during rest phase is acceptable, motion artifacts and occasional sensor-skin contact problems make signal highly noise contaminated.

2.2. Proposed algorithm for HRR estimation

The algorithm of HRR analysis is developed with the intention to be integrated into smart wearable devices in the future. Analysis and development process of algorithms each step of process is described in detail (Fig. 2.6). Gathered database provides us a variety of different signals that are synchronized in time. The main advantage of database is multi-modal heart rate signal. Heart rate is recorded in three different ways: heart rate from electrocardiogram signal, pulse rate extracted from finger photoplethysmography signal and pulse rate acquired from a commercial Fitbit device.

Proposed algorithm is suitable for analysis for all mentioned HR recording types.

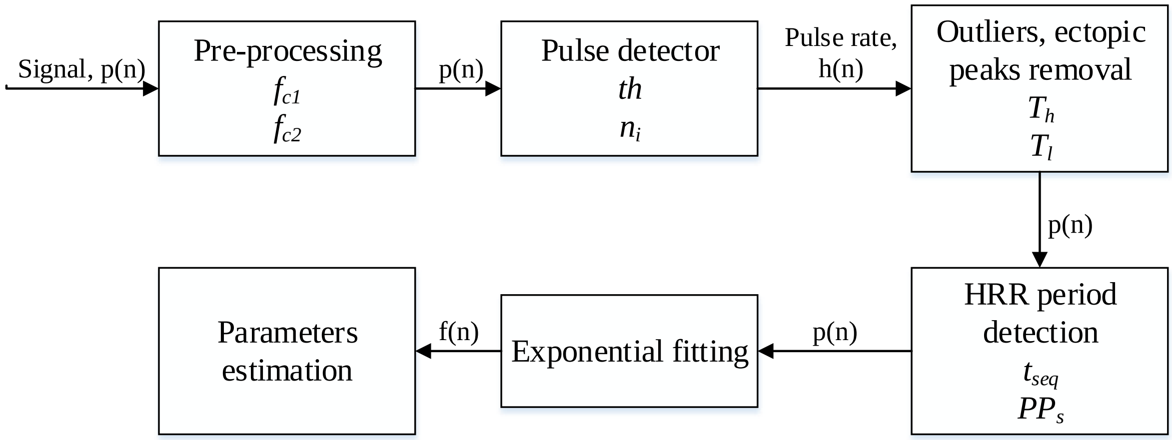

Figure 2.6 Main structure of algorithm

2.2.1. Pre-processing

ECG and PPG signal is filled with high frequency noise which comes from motion and sensor contact issues as well as low frequency base line. The signal preprocessing stage consists of two parts: a low-pass filter for high frequency noise removal and an adaptive high-pass filter for baseline removal. ECG signal is filtered with a band-pass filter of 10-th order and kaiser window. The pass band is between 0.8 and 20 Hz, it filters the valuable signal part and removes noise artifacts. Frequency response of filter is represented in a figure below (Fig. 2.7).

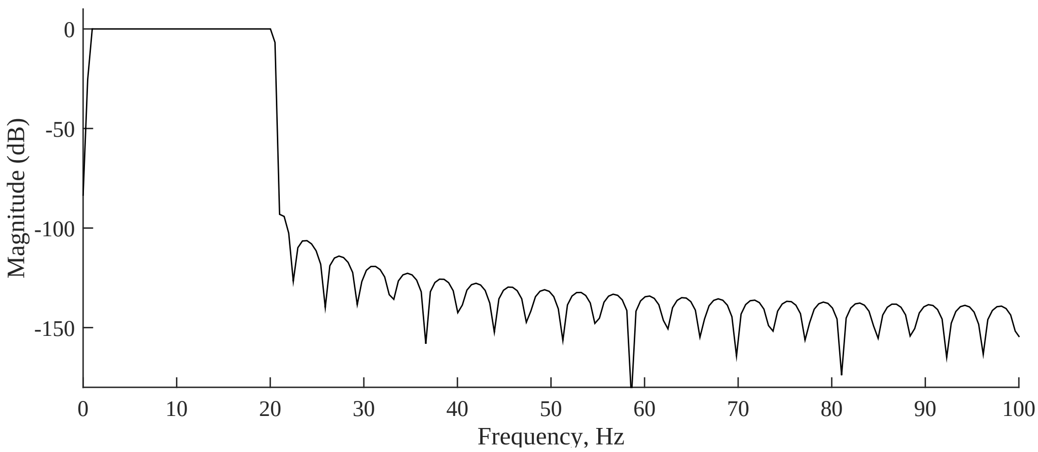

Figure 2.7 Bandpass filter frequency response

For PPG filtering a different filter with upper cut-off frequency of 15 Hz is used. PPG signal does not have as much useful information in high frequency parts and is recorded in lower frequency as well. The result of ECG signal before and after filtering is represented in figures (Fig. 2.8).

The filter applied on a personal computer based analysis is not suited for smart device integration purposes, it is too advanced. For integrated purposes it is advised to use more efficient filtering technique for faster performance.

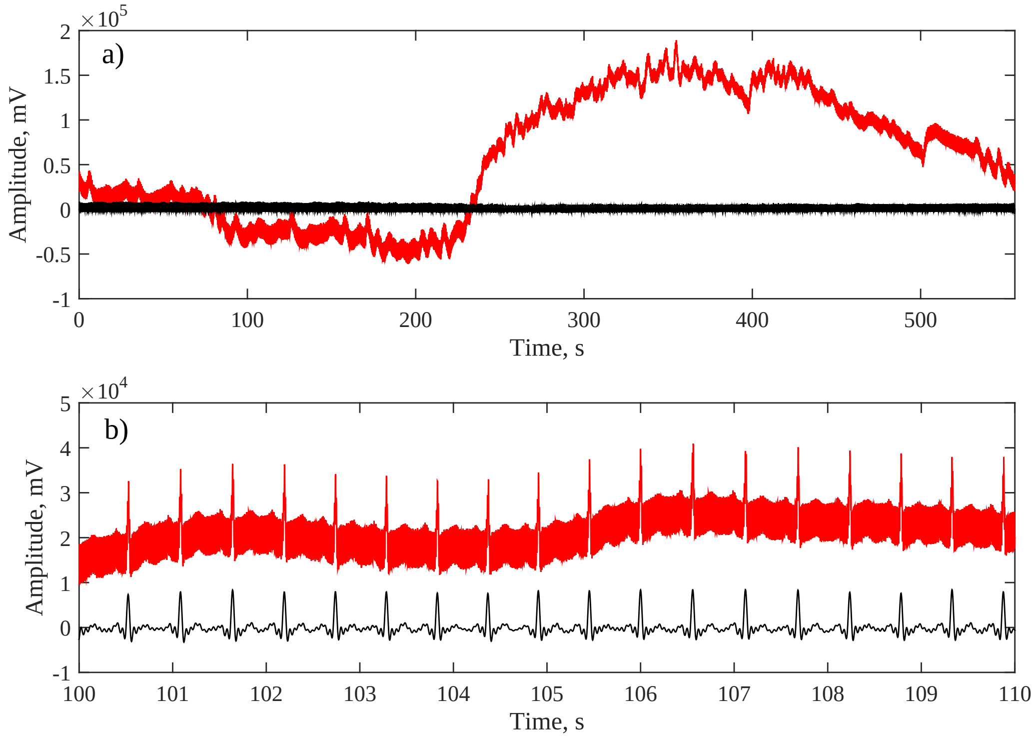

Figure 2.8 ECG signal before and after filtering

2.2.2. Heart rate estimation

Peak detector of ECG and PPG signals is based on local maximum detection of peaks which exhibit the greatest instances of energy. These peaks are usually the highest amplitude R peaks (Thiamchoo et al. 2016). The peak detection representation on an ECG signal is presented in (Fig. 2.9). Red line represent the signal before filtering and black represent it after filtering.

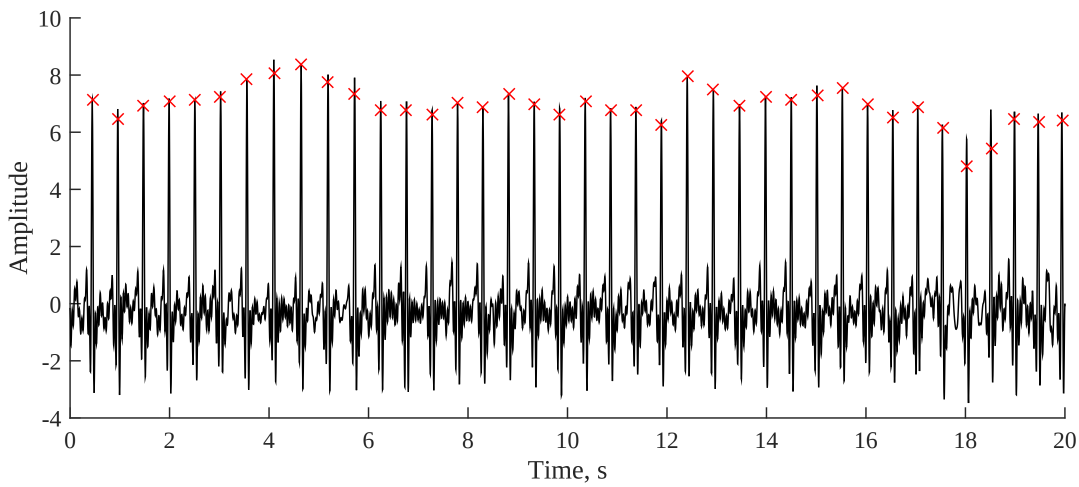

Figure 2.9 Detected ECG peaks

Detector is robust under different types of ECG signal types and performs relatively fast. Values of parameters like threshold *th*, and inactivity interval n_i can be tweaked according to the signal quality and type.

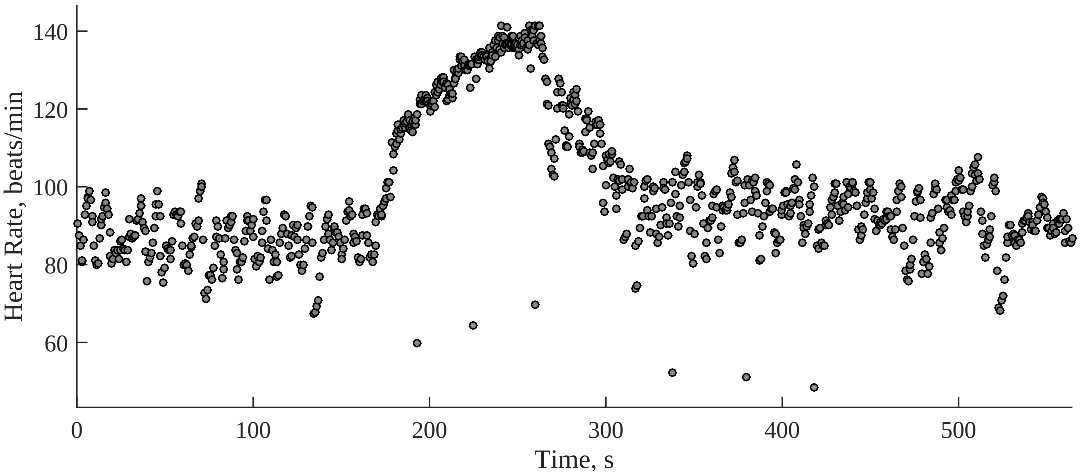

Figure 2.10 Raw heart rate series

The resulting heart rate signal usually is not ideal and requires further filtering. However, these artifact as seen in illustration (Fig. 2.10) cannot be easily avoided during detection part. Extreme motion instances and possible heart arhythmias result in minor heart rate outliers.

2.2.3. HR outliers filter

HR outliers appear for physiological and technological reasons. Ectopic hear beats cause inconsistencies in HR and a peak in signal might be missed in HR detection phase. To handle possible HR outliers a median filter is applied. It detects and removes outstanding HR beats.

For ECG a N-sample median filter is used, when N= 20 consecutive beats, with an output of:

$$y(n) = median[x(1:N)], \quad when \quad y(n) > x_{median} + T_h \tag{2.1}$$

Threshold T_h determines if the beat y(n) is between allowed interval of differential heart rate. In the case of electrocardiogram signal, T_h is equal to 20 beats of difference to the median value. For PPG signal a N= 10 median filter is used and T_h threshold is changed to 30 beats, because of smaller sampling frequency and higher scattering rate.

Median filter reliably removes HR outliers, a cleaned PPG pulse rate is displayed in (Fig. 2.11). White dots represent beats that have been detected as outliers. This method is also effective for ectopic beats removal.

2.2.4. Recovery onset detection

Automatic recovery detection presents a big problem because of different possible situations and artifacts that can happen in uncontrolled free-living situations. At times HR recovery sequence can be sporadic, filled with random heart rate variability. These factors highly depend on physical activity at the time of recording. Recovery period has a distinct indication of falling heart rate episode of approximate duration of between 60 and 200 seconds. The time of full HR recovery is proportional to the level of physical activity performed beforehand.

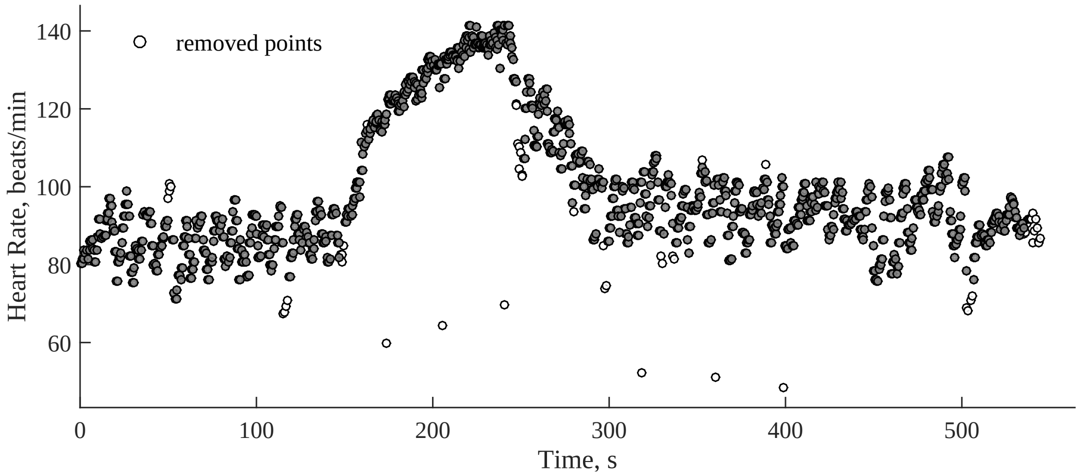

Figure 2.11 Filtered beats of heart rate with a median filter

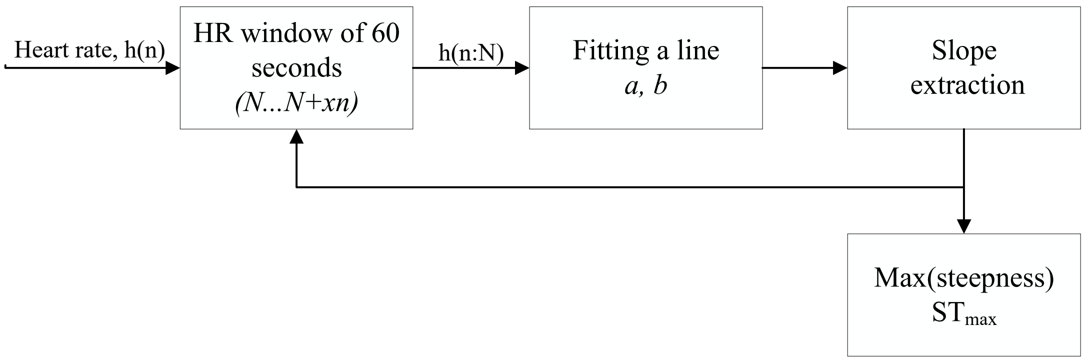

Figure 2.12 Recovery detection algorithm

Firstly we detect approximate location of recovery phase. A useful method to detect the falling curve of HR recovery is to adapt a 1st degree polynomial line fitting and evaluate its parameters to determine slope of the function. Vandermonde matrix is used to calculate polynomial fit of designated window.

$$\begin{vmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{vmatrix} p = \begin{vmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{vmatrix} \tag{2.2}$$

Vandermonde matrix V for 1st degree polynomial with *n* number of rows is presented in a linear system (eq. 2.2). Coefficient p, representing the slope of the linear function is calculated:

$$p = \frac{V}{y} \tag{2.3}$$

A form of 1st degree polynomial equation:

$$y = ax + b \tag{2.4}$$

Wearable devices require fast processing and efficient algorithms to provide results with less processing power. 1st degree polynomial on its own is a simple mathematical operation and in this case it provides very useful information about particular part of the signal. In order to detect the recovery episode, we slide the signal with the step of one beat and apply a window of 60 seconds which is the effective minimum of HR recovery time.

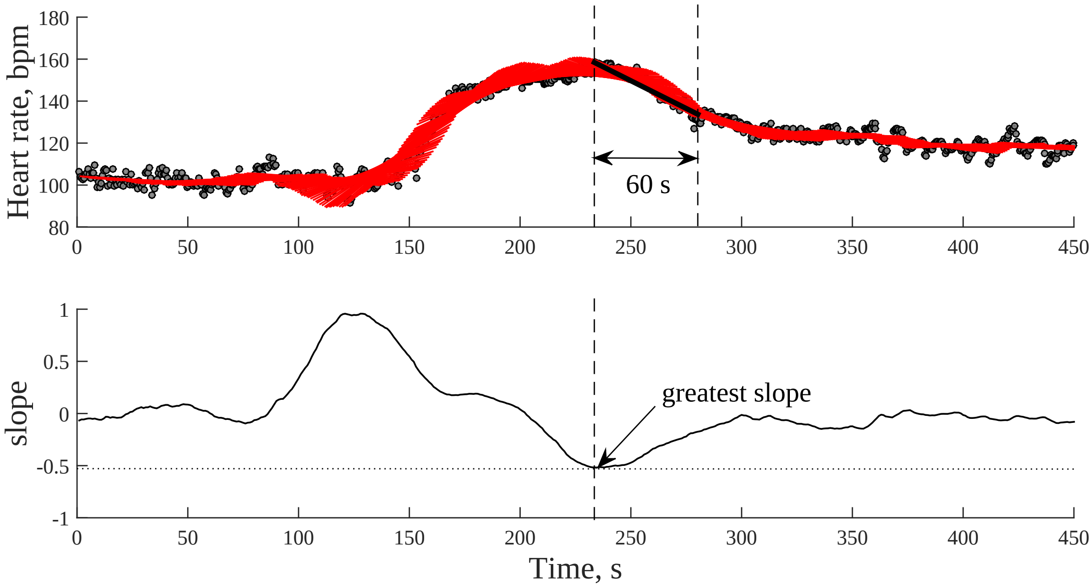

Figure 2.13 Detection of greatest slope

By sliding the window, we acquire a series of polynomials which hold information of its steepness. The representation of the cycled signal is presented in (Fig. 2.13).

The polynomial which has the highest steepness and a slope to the correct direction has the highest probability of being the part of HR recovery.

2.2.5. Assessment of HRR onset

Steepest slope extraction provides us an approximate position of the start of heart rate recovery. Start of the steepest polynomial function is the new start of the recovery phase. To more precisely locate instance of the start of the recovery phase a window of 50 seconds is adapted. The start of recovery phase is a peak of heart rate after which the recovery process begins. The problem is that it might not be the highest peak nor the last in the defined window.

Firstly, the higher, 6th order polynomial fit is applied to the defined period of heart rate sequence. Higher degree Vandermonde matrix is applied:

$$\begin{vmatrix} x_0 & x_0^2 & \dots & x_0^m \\ x_1 & x_1^2 & \dots & x_1^m \\ \vdots & \vdots & \vdots & & \vdots \\ x_n & x_n^2 & \dots & x_n^m \end{vmatrix} \begin{vmatrix} p_1 \\ p_2 \\ \vdots & \vdots \\ p_{m+1} \end{vmatrix} = \begin{vmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{vmatrix} \tag{2.5}$$

In this case m is the degree of polynomial applied and n the length of the signal.

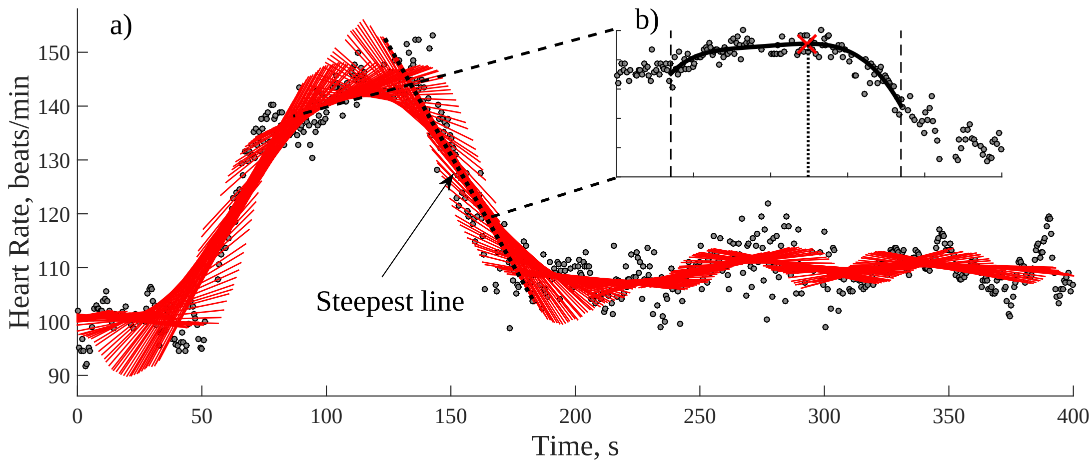

Figure 2.14 Estimation of the start of heart rate recovery after physical activity

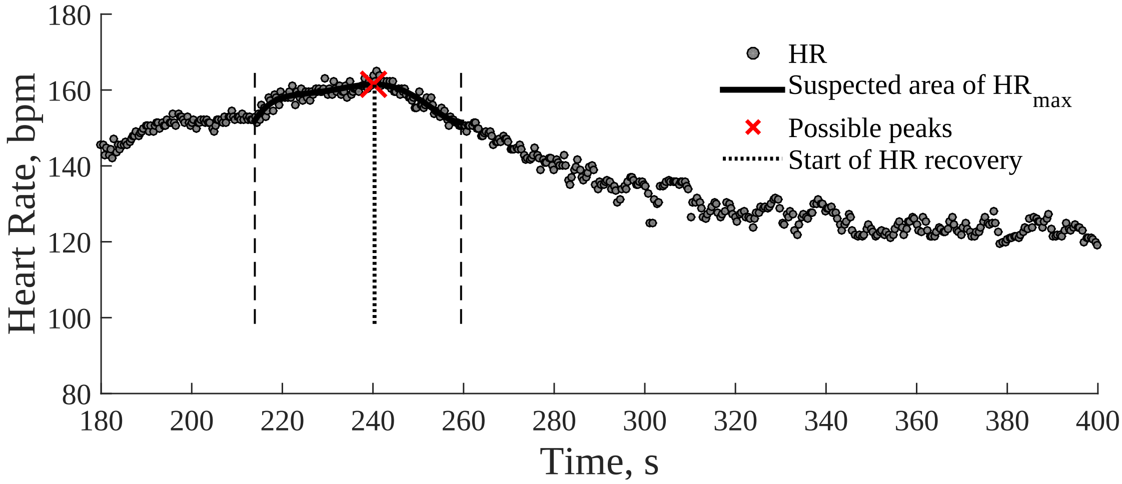

Figure 2.15 Estimation of the start of recovery phase

Secondly, the peaks that appear in the defined window are detected. Under normal conditions the last peak that appears in the interval is considered the start of the recovery (Fig. 2.15).

2.2.6. Exponential fitting

Exponential fit is applied to the period of 5 minutes, which is expected to be enough for full Heart rate recovery after any level of physical activity (Fig. 2.16). Exponential function to model HR change is the following:

$$x_e(t) = x_0 + x_\Delta e^{\frac{t}{\tau}} \tag{2.6}$$

Where x_0 is the asymptotic value of HR, x_Δ is the difference between peak vale and x_0 and τ is the time-constant.

An important parameter of the fit is its quality of match with the original signal. A determination coefficient is estimated for each exponential fit applied and the values of R^2 that are over 0.5 are considered to be adequate for further analysis. If R^2 happened to be of lower value than 0.5 the an adjustment of the beginning of recovery window usually improves the quality of the fit

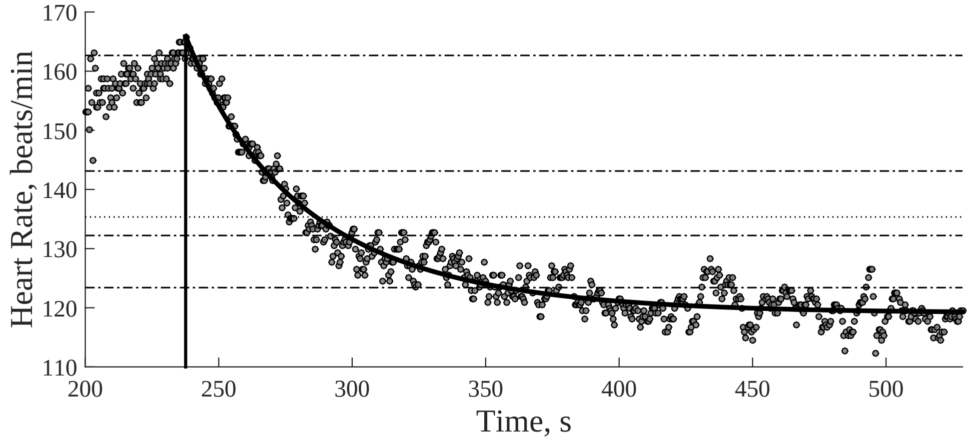

Figure 2.16 Exponential curve fitting on heart rate recovery signal

(Fig. 2.15). Adjustment is performed by increasingly varying the onset time in each direction and estimating the exponential fit quality each time.

2.2.7. Estimation of HRR parameters

A simple method to assess HR recovery rate of the fast phase is to estimate the HR that dropped from the peak to the 60 s mark. The difference can be shown in the percentage of HR decline as related to the peak value. Studies have shown HRR_{60} parameter to highly reflect parasympathetic reactivation (Pecanha et al. 2017). A lower HRR_{60} measured can be a predictor of mortality (Nanas et al. 2006).

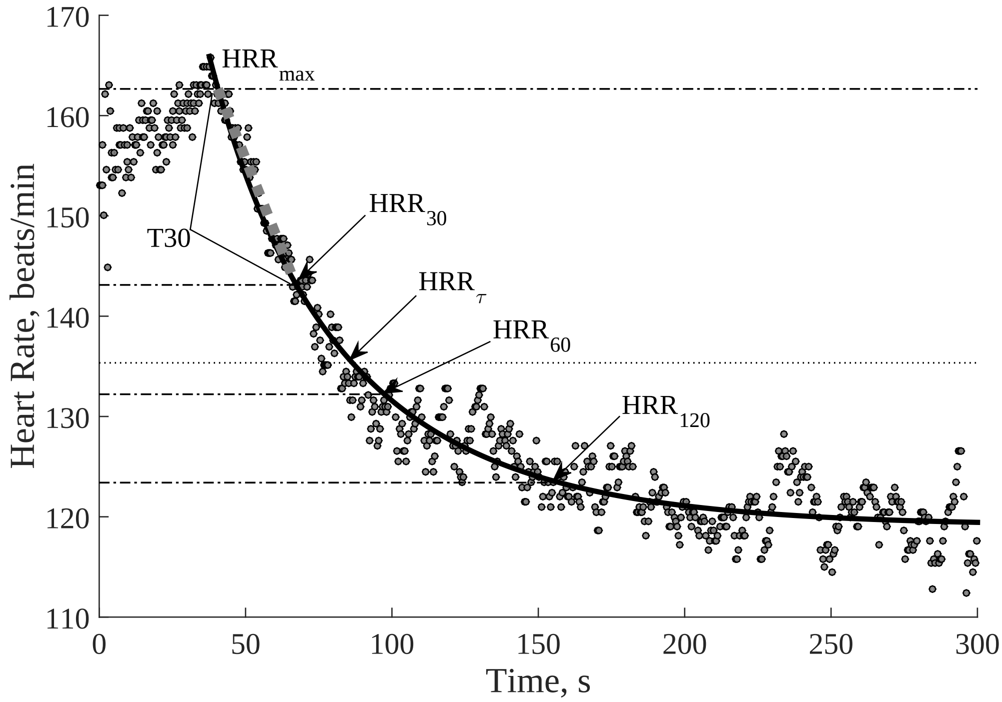

Figure 2.17 HRR parameters representation

HRR has been shown to represent the decay of exponential curve HRR_{τ} so it can be modeled with a first-order exponential. Using a model it is viable to estimate a time-constant of the curve

HRR_τ which evaluate the HRR decay. HRR_τ has shown to be an index that reflect parasympathetic reactivation and sympathetic withdrawal (Pierpont et al. 2000).

First degree polynomial function fitted on recovery part of heart rate provides a line. Steepness of this line quantifies the change over time which is a reliable index. T30 parameter estimates the slope during first 30 seconds of recovery and $T30_{min}$ estimates the 30 second duration interval which exhibits the greatest steepness during the first minute of recovery. T30 parameter values are often impaired by unexpected HRR behavior at the start of recovery therefore $T30_{min}$ has higher reproducibility.

The parameters of T30 is calculated by fitting a 1st degree polynomial curve in the first 30 s of recovery. This parameter is expressed as a steepness coefficient of the curve. T30min is estimated by cycling through recovery interval with a window of 30 s and calculating steepness of each episode.

2.3. Automatic HRR evaluation

The goal of the study is to test the developed algorithm its ability to detect and analyze the HR recovery episodes from longer signals. Algorithm is tested with signals recorded during free-living conditions. The main parts for this process is quality estimation and heart recovery period detection.

2.3.1. Signal quality evaluation

Physiological signals have a tendency to be have highly unpredictable recording quality. Quality depends on recording device onset precision, motion level and recording method. An estimation of signal quality and noise level is necessary to provide user accurate results and possibly inform any possible device error. Possible signal quality assessment methods:

- Signal energy calculation.
- Hjorth parameters method.

Artifacts detection is important parts of signal processing. Usually signals that are contaminated with movement artifacts are unusable and must be discarded. Artifacts seen in Figure 1 PPG signal are unstable and unpredictable. There can be distinguished two main artifacts types. Some signal parts has highly varying amplitude, so it most likely is result of movement however, other parts has almost no unusual amplitude variation, but pulse rate is extremely high or not detectable at all. This type of artifacts is commonly visible in either PPG or ECG signal, but not both. So it is safe to conclude that artifacts also appear because of bad sensor or electrodes contact with skin surface. We will implement and test two methods of signal artifacts types. The first one is Hjorth parameters method (Gil et al 2009) and the second is energy calculation method. The principle behind the Hjorth parameters detector is that when the signal differs largely from an oscillatory pulse signal, it is very likely an artifact. So we estimate frequencies that appear in the signal and by having frequency boundaries we can determine which parts are most likely an artifact. Hjorth parameter H1 has been proposed as an estimation of the central frequency of a signal and H2 as half of the bandwidth, these parameters are calculated from different orders of spectral moments:

$$\bar{w}_i = \int_{-\pi}^{\pi} w^i S_{xPDC(e^{I\omega})d\omega} \tag{2.7}$$

where w is the spectral power.

$$H_1(n) = \sqrt{\frac{\bar{w}_2(n)}{\bar{w}_0(n)}} \quad and \quad H_2(n) = \sqrt{\frac{\bar{w}_4(n)}{\bar{w}_2(n)} - \frac{\bar{w}_2(n)}{\bar{w}_0(n)}} \tag{2.8}$$

When analyzing long signals oscillatory frequency can change drastically especially during high noise intervals and high amplitude body movements. In case both parameters threshold adaptiveness during signal is required. A window of 2-3 minutes is chosen for each estimation of parameters.

The biggest problem is that each case of recording has a high variability in frequencies observed in the signals. That makes this method less robust because parameters H1 and H2 thresholds in some cases must be lower or higher especially in signals containing heart rate recovery. However, recordings with lower intensity of artifacts are processed quite well. Parts of the analyzed signal that steps out of the defined thresholds are considered artifacts.

Method works quite well in signals that does not contain extreme movement artifacts or sensor misplacement episodes. But in some cases algorithm detects perfectly good parts of signal as artifacts or vice versa.

Other method to detect signal artifacts is by estimating energy. As movement artifacts are usually a cause a high amplitude variation, the signal energy at that instant is higher as well. By estimating energy at defined periods in the signal we can locate high energy intervals and consider them as artifacts.

$$E_i = \sum_{n=0}^{N} x_n^2 \tag{2.9}$$

$$A = \begin{cases} 1, & if \quad E_i > 3E_M \\ 0, & if \quad E_i < 3E_M \end{cases} \tag{2.10}$$

Energy is calculated in the defined windows (1-10 seconds). The part of the signal is considered an artifact (A) if estimated energy is higher than the defined threshold. Threshold in this case is 3E$_M$ (E$_M$ as a median of local energy).

Energy artifacts detector is better at detecting long lasting artifacts (absolute energy of the signal), however Hjorth energy detector is better at detecting short instances of noise and periodic motion noise intervals which exhibit different frequency band than expected heart rate signal. Algorithm determines the parts which are unsuitable for further analysis and removes them. Shorter instances of noise (up to 5 seconds) can be interpolated in HR series, parts of longer duration are removed completely. HRR detection part of analysis is is provided with high quality HR series.

2.3.2. HRR detection in signals acquired during free-living conditions

In order to make HRR estimation system more suitable for commercial use, that do not obstruct free-living automation must be ensured. Proposed algorithms main purposes is to detect recovery period and estimate HRR parameters. Usually an integrated medical device like a smartwatch records data and stores it in memory until it is available for uploading to separate system for analysis. However devices more suited for healthy people needs to be more flexible, informative and easier to use.

The biggest problem of adapting HRR estimation algorithm for automatic use is the reliability of detected periods of recovery. Heart recovery periods have a high variability between people and can be easily corrupted. Possible short instances of motion noise while leaving most of the signal intact can can leave the crucial parts of the heart rate recovery series faulty. On the other hand even when motion noise is negligible any physical activity highly effect the speed of heart recovery.These problems can be eliminated by evaluating the quality of each extracted period of heart rate recovery, the signs that show possible corrupted HRR data:

- Poor exponential curve fitting quality (below 0.5).
- Low rate of detected pulses, which define bad signal quality.
- HR drops drops slowly (less than 30% recovery after 1 minute).
- HR highly inconsistent, drops and rises randomly, indicating unwanted physical activity.
- Heart rate is not recovered to 80% of normal HR.
- Ambiguous onset of the recovery instance.

This set of signs are taken in consideration while designing robust HRR estimation algorithm. The representational signal of 1.5 hours length includes part of physical activity (climbing stairs) and two types of resting positions: standing and sitting. Resting while standing has certain implications to the recovery as HR does not reach normal state while the person is sitting (Fig. 2.18). The same can be said about supine resting position as well. The position of body drastically affect the resting HR. However it does not change the main parameter of HRR the exponential coefficient τ.

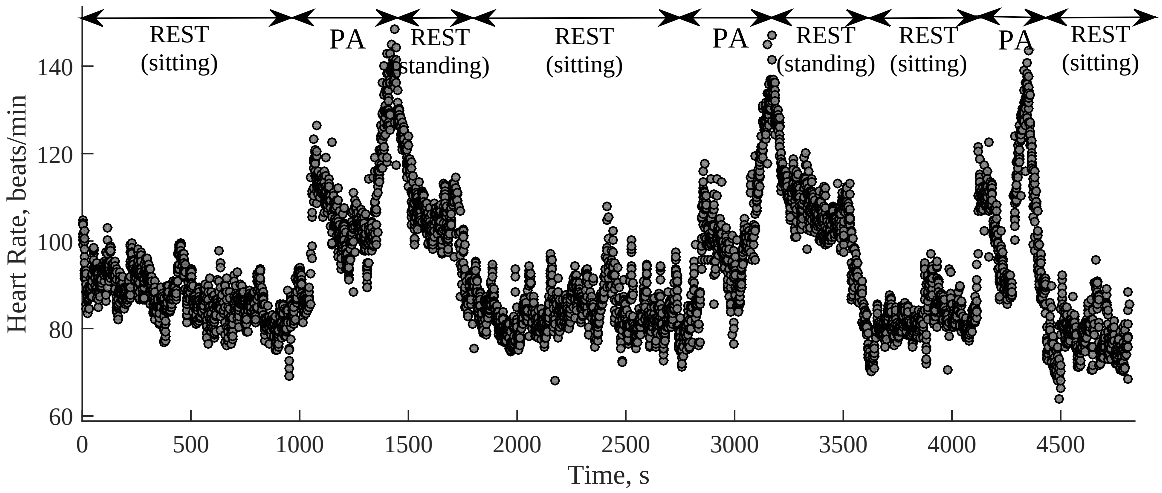

Figure 2.18 ECG signal with occurring physical activity and HR recovery

Recovery period detection part works by analyzing the entire signal in parts. A window of 60 second is applied to the HR series and sequenced with a step of 1 pulse beat. Window of 60 seconds length is chosen because it is the first minute of the recovery that have a property of linearity. For each of the 60 s parts we apply a 1st degree polynomial fit. The process is the same as described in the recovery detection part of proposed algorithm.

In this part of signal the algorithm detected 5 instances of recovery which could be safely used for parameter estimation (Fig. 2.19).

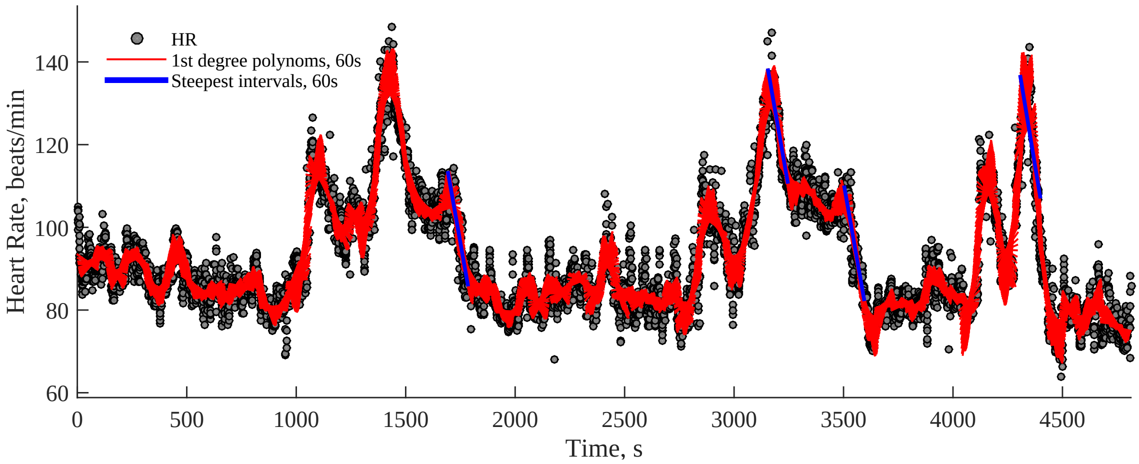

Figure 2.19 Automatic detection of HR recovery

We can observe that the detected parts also include the ones that appear after changing resting position from standing to sitting. For some people the effect of changing resting position can be lower and for some even higher. This difference highly depends on fitness of a person, height and age. The detected parts of heart rate recovery are extracted when the exact start of the recovery phase has been detected. The start and end of recovery that will be used for further analysis is represented in dashed and solid lines (Fig. 2.20). The length on window applied is 5 minutes that are enough for estimation of main parameters of HRR.

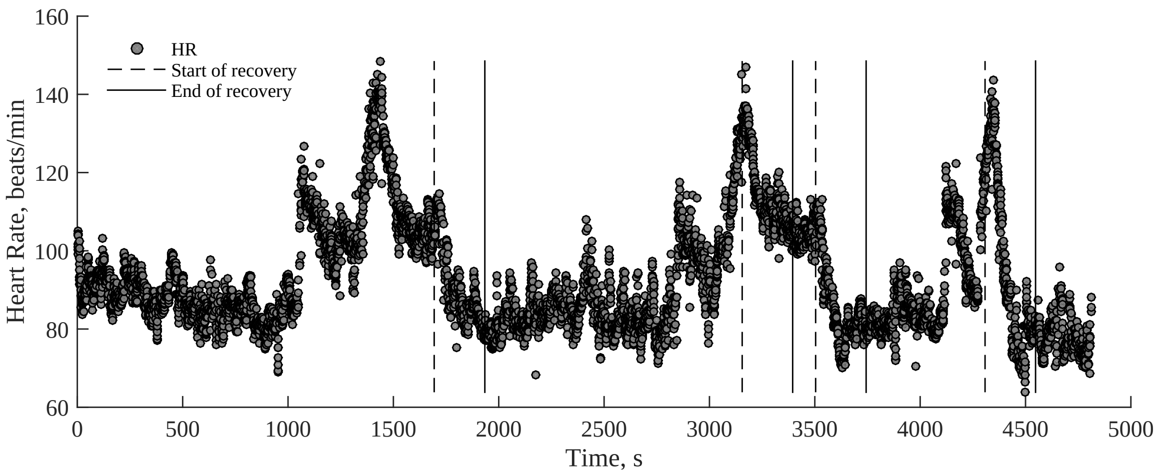

Figure 2.20 Extraction of exact HRR intervals

After possible recovery periods has been identified each segment can be analyzed individually. The analysis include the same parts as described in the previous section:

1. Correction of the start of recovery.
2. Window extraction.
3. Exponential fit application.
4. Estimation of HRR parameters.

Depending on the physical activity level of a person it is safe to assume that on average 3-4 episodes of HRR recovery can be identified during a normal day of usually highly sedentary office work.

3. RESULTS

PPG, ECG and Fitbit HR signals provide the same information, but with different accuracy, reliability. These methods of recording vary in many ways and are suitable in different situations. HRR parameters analyzed by an automated algorithm show the results of each recording.

3.1. Heart rate recovery variation

Heart rate decay varies for a person even at the same conditions at repeated experiments. Parameters of HRR_{30}, HRR_{60} and HRR_{120} represent the HR decay after certain period of time. A comparison of three consecutive tests of climbing stairs at 96 steps per minute shows the distribution of parameters (Fig. 3.1,3.2,3.3).

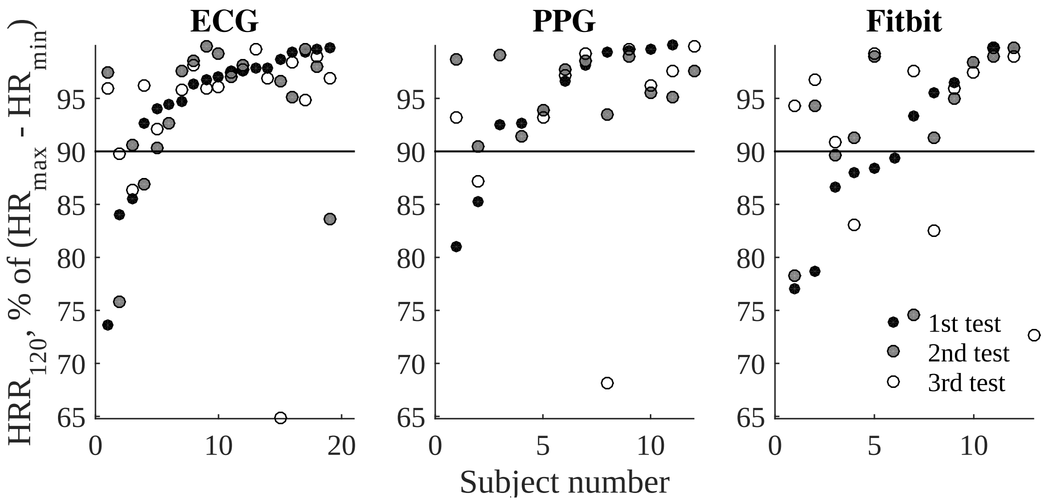

Figure 3.1 HRR_{120} of consecutive 96 step/min tests

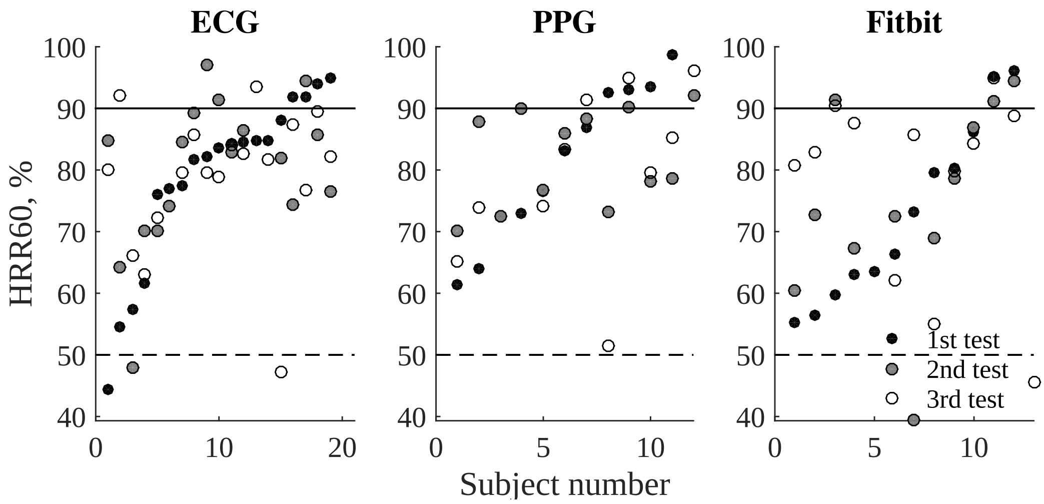

Figure 3.2 HRR_{60} of consecutive 96 step/min tests

HRR_{30} parameter show an average of 50% HR recovery, HRR_{60} average recovery is increased up to about 80% and at 120 seconds mark an average recovery is nearly over for most of tested subjects (about 97%). For easier comparison the 50% and 90% marks are highlighted.

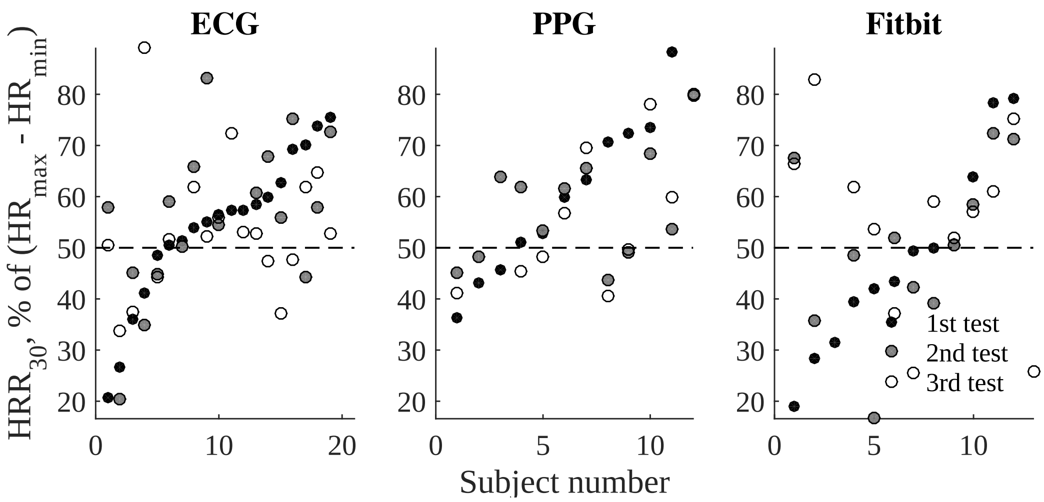

Figure 3.3 HRR$_{30}$ of consecutive 96 step/min tests

To estimate the natural variation of HR recovery for each experiment standard deviation is calculated. The value taken is difference of maximum and absolute value at each mark. Then the mean of all standard deviation values are calculated.

$$\sigma_{30} = \frac{\sum_{n=1}^{N} \sigma_n}{N} \tag{3.1}$$

In equation above σ represents the scattering of HR values between all three experiments. σ_{30} is the mean of standard deviation for all subjects at designated mark of 30, 60 and 120 seconds.

Table 3.1. Standard deviation of each parameter, ECG

Parameter	HRR$_{30}$	HRR$_{60}$	HRR$_{120}$
SD	4.83	4.65	4.12

The results show that variation of HR is highest at the start of recovery.

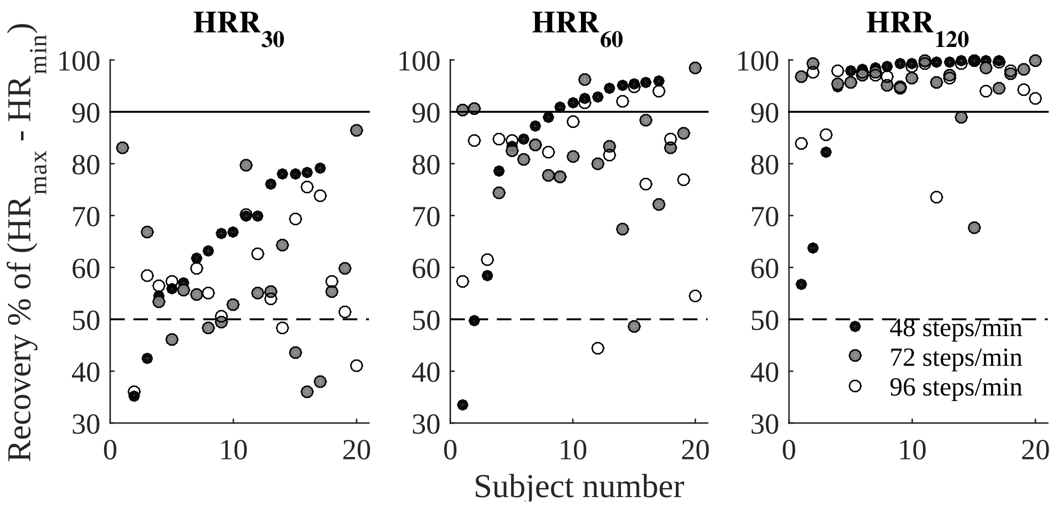

Figure 3.4 Recovery percentage between different physical activity levels of parameters HRR$_{30}$, HRR$_{60}$ and HRR$_{120}$

In the case of Parameter values at different exercise types the values are scattered and any distinction is hard to notice (Fig. 3.4). Different physical activity intensity levels highly influence recovery speed. This change in recovery rate is exceptionally obvious in case of HRR_{30} parameter. Percentage of recovery at 30 seconds mark is higher in nearly all cases of excessive with 48 steps per minute speed.

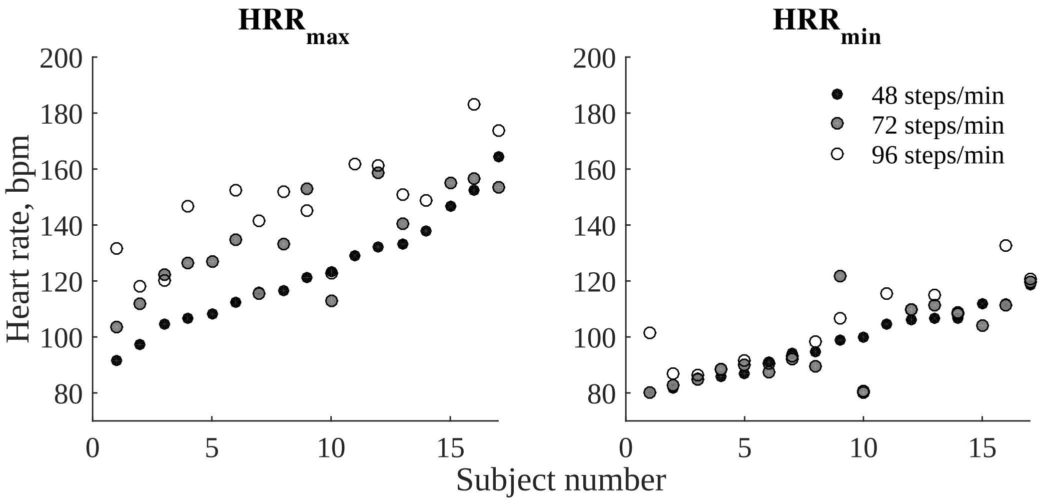

Figure 3.5 HR_{max} and HR_{min} of each experiment

Maximum heart rate that is reached after experiment varies for different physical activity intensities (Fig. 3.5). Maximum reached heart rate depends on the natural minimum heart rate as well. Subject who have higher difference between HR_{max} reached at different PA intensities show higher fitness level. It is safe to assume that heart should be working with less force while body is doing less work.

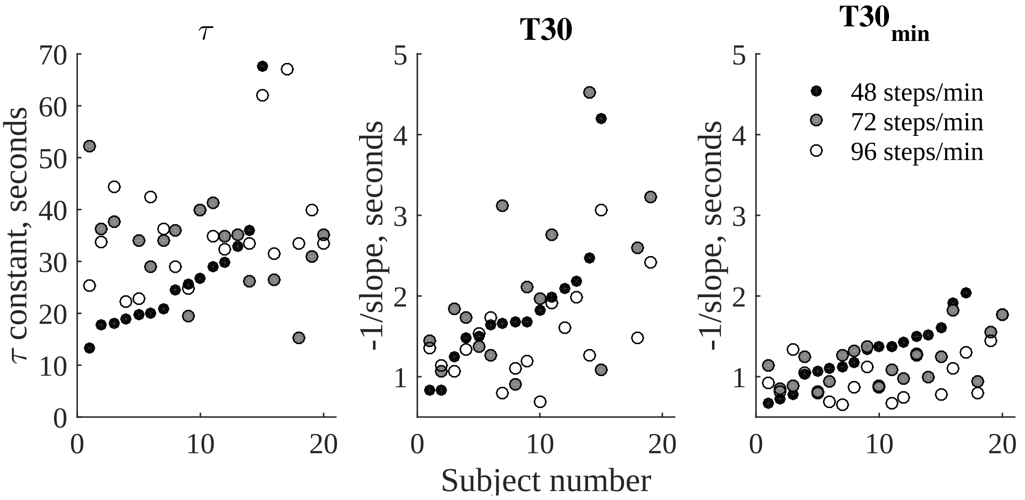

Figure 3.6 τ constant, T30 and $T30_{min}$ of each experiment

Parameters τ, T30 and $T30_{min}$ on different physical activity intensities show various results (Fig. 3.6). τ constant is unpredictable and varies between 20 and 40 seconds with no separation from PA level. In case of T30 and $T30_{min}$ parameters, there is a big difference in variation. As expected $T30_{min}$ shows greater stability and repeatability.

After same PA intensity $T30_{min}$ have again performed with the best repeatability (Fig. 3.7). τ constant values are less sporadic after higher intensity stress.

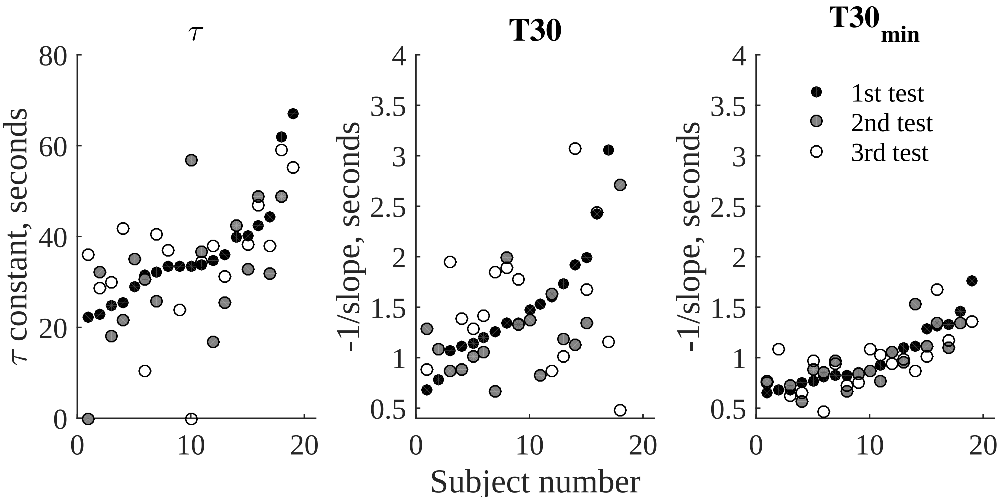

Figure 3.7 τ constant, T30 and T30$_{min}$ on three consecutive 96 steps/min experiments

Variation in three consecutive stair climbing tests, performed on the same participant under nearly identical conditions, was assessed using the repeatability coefficient which is defined,

$$r = 1.96 \cdot \sqrt{2} \cdot \sigma \tag{3.2}$$

where σ is an estimate of the within subject standard deviation, obtained by fitting a one-way analysis of variance (ANOVA) model to the repeated HRR parameter data (Bartlett et al. 2008). Repeatability coefficients are presented in the following table:

Table 3.2. Repeatability of parameters

Parameter	ECG	PPG	Fitbit
HRR $_{max}$, bpm	10.4	14.1	13.5
HRR $_{30}$, bpm	21	39.3	40.1
HRR$_{60}$, bpm	13.5	23.3	36.5
HRR$_{120}$, bpm	4.2	14.6	14.9
HRR$_{\tau}$, bpm	6.5	8.8	8.5
τ, s	33.2	44.3	52.1
T30, -1/slope	0.9	1.1	0.2
T30$_{min}$, -1/slope	0.4	0.4	0.3

Repeatability study demonstrate that HRR parameter values are highly variable for most of the participants despite that the stair climbing test is performed under nearly identical conditions. This finding suggests that physiological factors, such as previously experienced physical activity, may play important role on the HRR. When comparing the PPG-based devices, the wrist-worn device shows better repeatability than the consumer smart wristband for τ and HRR60 parameters.

3.2. Comparison between methods

PPG, ECG and Fitbit HR signals provide same information, but in different accuracy and reliability. These method of recording vary in many ways and are suitable in different situations. HRR parameters analyzed by an automated algorithm show the results of each recording.

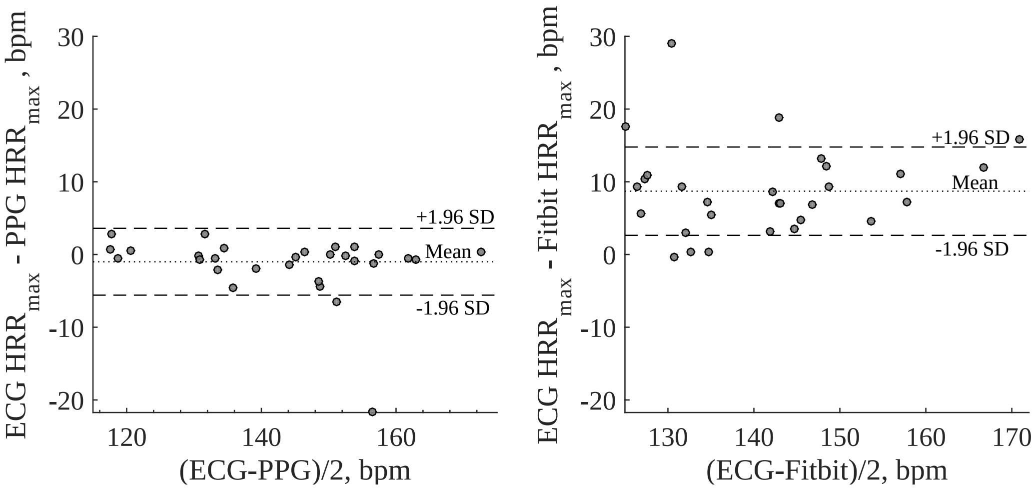

Figure 3.8 Bland-Altman diagrams for Fitbit and ECG HRR_{max}

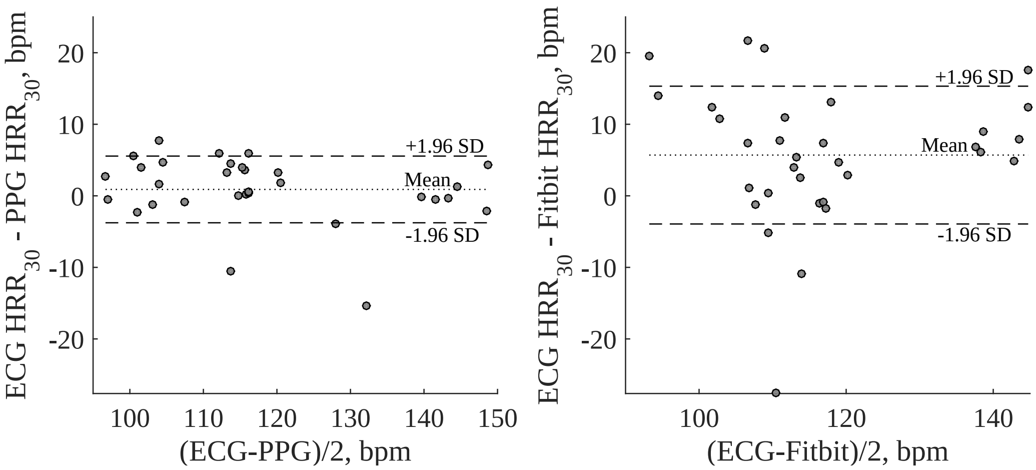

Figure 3.9 Bland-Altman diagrams for Fitbit and ECG HRR_{30}

Algorithms performance and adaptability is tested working with different devices by comparing results of ECG, Fitbit and PPG signal based results. The compared parameters are HRR_{30}, HRR_{60}, HRR_{120}, HRR_{max}, HRR_{τ}. Parameters are measured after consecutive 96/min stair climbing experiments. Bland-Altman method is used to compare the scattering of values and find out the underlying differences of both HRR estimation methods.

Most of the tested parameters showed better performance results for PPG based parameters. The biggest difference is observed between mean value of Bland-Altman diagrams. Parameters HRR_{max}, HRR_{min}, HRR_{30}, HRR_{60}, HRR_{120} and HRR_{τ} have insignificant mean scattering from reference ECG based values (Fig. 3.8,3.9,3.10,3.11). In the case of Fitbit a constant higher mean value is observed for most parameters except T30 and $T30_{min}$. τ constant distribution scattering is

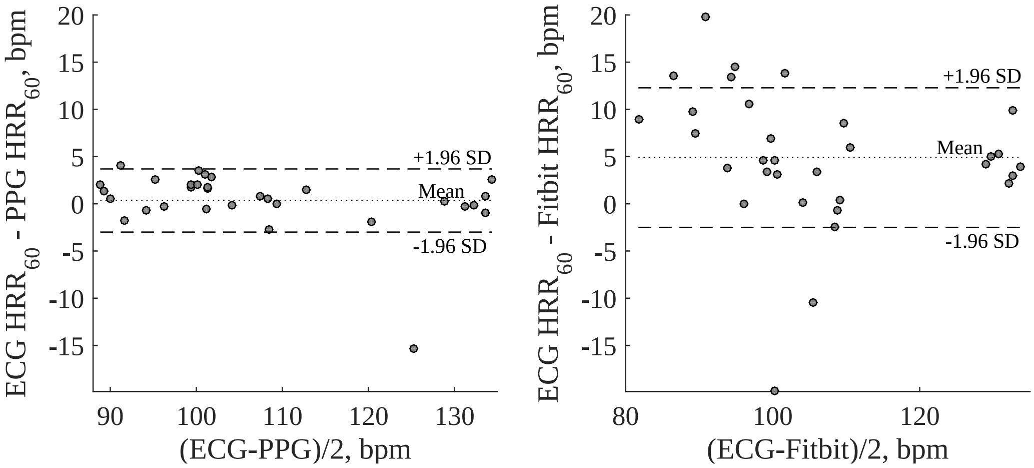

Figure 3.10 Bland-Altman diagrams for Fitbit and ECG HRR_{60}

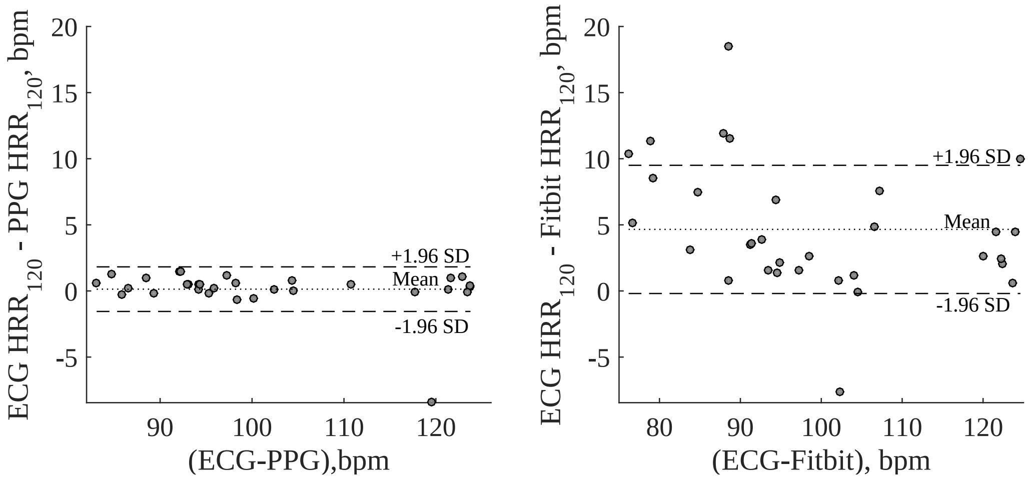

Figure 3.11 Bland-Altman diagrams for Fitbit and ECG HRR_{120}

similar to ECG for both methods. Fitbit signal has lower variability and takes time to reach true value of heart rate, thats why there is greater variation of exponential decay.

Table 3.3. Agreement between ECG, PPG and Fitbit

Parameter	ECG-PPG	ECG-Fitbit
HRR $_{max}$	-0.11(±3.31)	8.6(±6.01)
HRR $_{min}$	0.11(±3.88)	5.51(±6.0)
HRR $_{30}$	-0.18(±5.01)	7.39(±7.88)
HRR_{60}	0.66(±4.05)	4.82(±4.62)
HRR_{120}	0.55(±2.23)	5.43(±6.35)
HRR_{τ}	0.94(±3.71)	6.76(±4.6)
τ	1.83(±7.89)	5.95(±10.93)
T30	-0.12(±0.61)	0.054(±0.67)
$T30_{min}$	0.066(±0.158)	-0.179(±0.227)

3.3. Exponential fit quality evaluation

The most sensitive part of the algorithm is an exponential fitting of HR series. The accuracy of applied fit does greatly affect the outcome of most calculated parameters. To examine quality of exponential fit we will apply a statistical measure R^2 which evaluates how close the fitted line represents the real data.

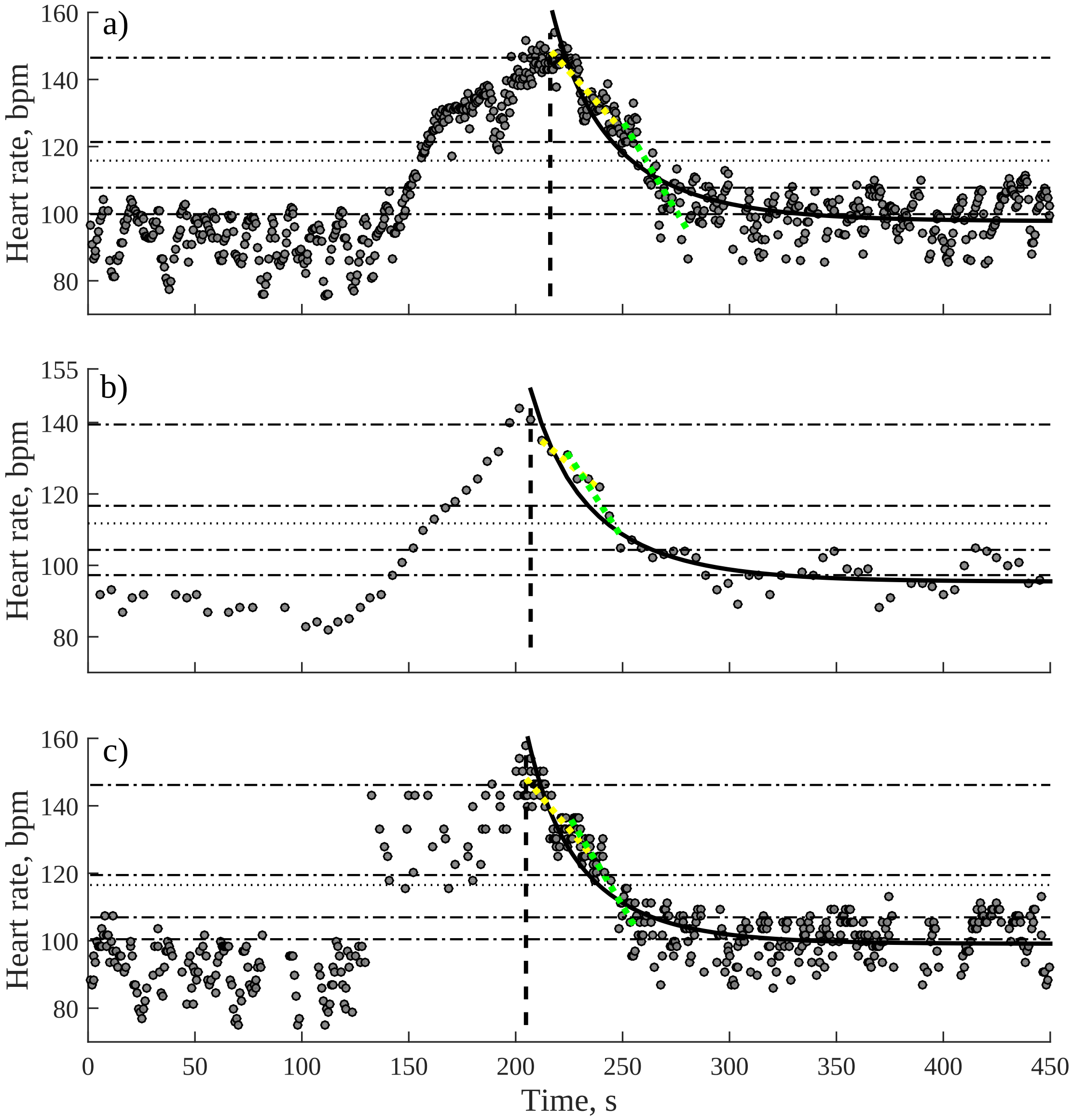

Figure 3.12 HRR parameters detection for: ECG(a), PPG (b), Fitbit (c). Note that yellow dotted line represent T30 parameter and green line represent $T30_{min}$ parameter

As expected greater match of exponential fit is observed for recovery periods after higher intensity of PA, 96 steps/min. In the case of higher level PA natural variability of HR makes less impact and recovery period lasts longer. Highest R^2 values are observed on Fitbit based signals. Fitbit device have integrated filters which makes beat values less sporadic and with smaller sampling rate. However Fitbit provided higher number of erroneous signals unsuitable for analysis.

Table 3.4. R^2 values and signal usefulness

Experiment type	48 steps/min	72 steps/min	96 steps/min	all signals
mean R^2, ECG	0.46	0.62	0.69	0.65
% of useful signals	76.5	88.2	90.2	87.1
mean R^2, Fitbit	0.7	0.65	0.81	0.77
% of useful signals	47.1	58.8	68.6	62.4
mean R^2, PPG	0.4	0.56	0.68	0.63
% of useful signals	67.7	75.6	78.8	76.3

ECG signal had best signal usefulness of 87%. Signal usefulness also improved with higher PA intensity.

Figure (3.12) display results of ECG, PPG and Fitbit analysis of HRR. Note the differences of each recording method. Because of drastic differences in sampling rate of PPG and Fitbit parameters like T30 and $T30_{min}$ vary a lot. There is no clear favorite between PPG and Fitbit considering T30 and $T30_{min}$ parameters (Table. 3.3).

3.4. Discussion

In this study, we proposed an algorithm for recovery onset detection which can be implemented in wearable smart devices. Furthermore, we tested algorithms capability of analyzing three different kinds of signals: ECG, wrist based PPG and a Fitbit pulse rate signal. This study allow us to compare each methods given proficiency to extract main parameters that determine HRR.

Analyzed parameters include HRR_{max}, HRR $_{30}$, HRR $_{60}$, HRR $_{120}$, HRR $_{\tau}$, τ time-constant, T30 and $T30_{min}$. These parameters are commonly used in clinical studies, therefore, results can be compared with the work done by other researchers. However, this study included subjects of relatively young age (25 years on average) and good health. This makes study more focused on general fitness of a person and less about cardiac problems detection.

PPG based HRR analysis showed better accuracy to the results given by a reference ECG signal in all of our tested parameters (Table 1). The inaccuracies of both compared methods are understandable, because of different sampling rates of the recording methods. HRR_{60} and HRR_{τ} parameters of Fitbit based signal have constant difference from the reference ECG which can only be explained by a delay of Fitbit signal. Fitbit based pulse rate signals performed better at exponential fit quality due to lower variability. However the amount of artifacts made many of the recorded signals not available for analysis.

PPG was also recorded from the wrist part of the hand, but signal quality provided is unsuitable for analysis. These technological problems are bound to be solved in the future.

Study demonstrates that a smart wristband with a PPG sensor can replicate a full ECG based HRR analysis during less physical activity intensive periods of time. Moreover, an analysis of raw PPG signal do perform better than pulse rate given by a commercial Fitbit smart wristband. In

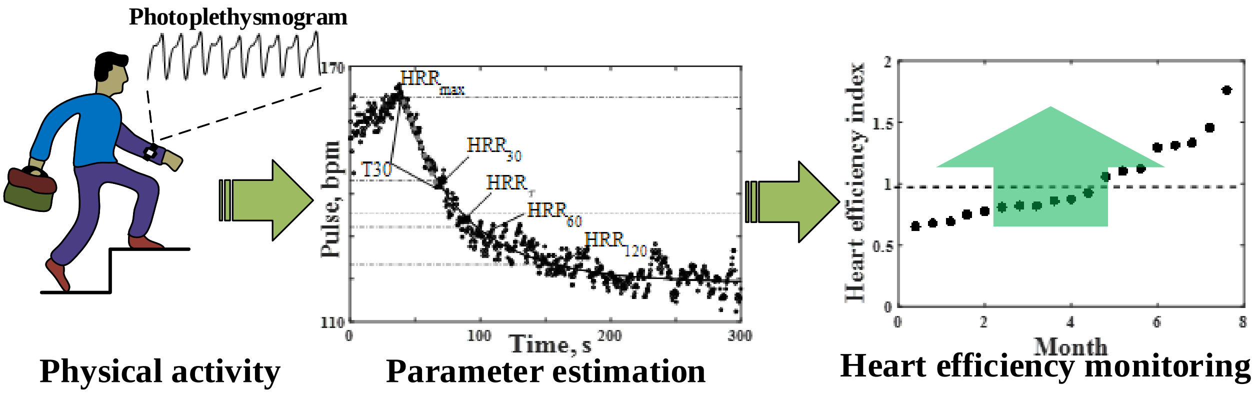

Figure 3.13 Structure of the system

addition, the study introduces a method of heart rate recovery parameters estimation that is well suited for integration to smart wearable devices.

Estimation of physical activity level is an important factor for mentioned representation of HRR. However, maximum reached heart rate HR_{max} is a value that represents physical activity level proportionally. It is seen in (Fig. 3.5) that HR_{max} changes under different physical activity levels.

Considering all acquired parameters it is hard to estimate cardiac health and hearts ability to recover as a whole. As a parameter for estimating cardiac health it is better to use index which include all available parameters. Each parameter value roughly represents the ability of heart to recover itself. By evaluating each parameter individually, it is easy to produce incorrect conclusions because of possible errors of estimation. Synthesis of parameters that represent the same property has a higher chance of correctly assess the desired result.

In the future the plan is to solve technological problems of PPG recording off wrist. These advancements will allow more effectively adapt developed algorithm with three stages of system all integrated in smart device (Fig. 3.13).

CONCLUSIONS AND SUGGESTIONS

1. Clinical significance of heart rate recovery as a biomarker of heart rate efficiency has been proved in previous studies. As a result many methods for heart rate recovery assessment have been proposed. However, previous research show that the complexity of heart rate recovery during free-living activities makes adapting this system for integrated use challenging.

2. A novel method for heart rate recovery assessment during free-living activities has been developed. This method uses efficient mathematical operations to detect heart recovery episodes and estimate parameters. That makes it suitable for integration to wearable devices. Algorithm have proved to be functional during uncontrolled situations for longer periods of time (1-2 hours).

3. For analysis of heart rate recovery process a database of signals has been collected. Each person have been asked to perform walking, climbing stairs and step-test exercises, heart rate signal was recorded during and 5 minutes after the experiment. Stair climbing test was performed 5 times, once with 48 and with 72 steps per minute speed and three time with 96 steps per minute speed. PPG, ECG and Fitbit signals have been recorded simultaneously.

4. PPG and Fitbit based HR recording were compared with a reference ECG based heart rate signal. PPG showed better repeatability and lower scattering than Fitbit based recordings. Fitbit recordings have a bias when compared with ECG on all tested parameters except T30 and T30min. More intensive exercises produce more reliable heart rate recovery parameters. Higher intensity exercise resulted into more signals suitable for analysis than lower intensity exercise - 79% for 96 steps/min and 67% for 48 steps/min respectively. Study of repeatability demonstrates that HRR parameter values vary highly for most of the participants despite that the stair climbing tests are performed under almost identical conditions. This finding suggests that physiological factors, such as previously experienced physical activity, may play important role on the HRR. When comparing the PPG-based devices, the custom PPG device shows significantly better repeatability than the consumer smart wristband for τ and HRR_{60} parameters. Better results of parameters repeatability has been observed in the second half of the recovery period (after 1^{st} minute). Standard deviation of parameter HRR_{120} is lower than HRR_{30}, 4.12 bpm and 4.83 bpm respectively. The proposed signal analysis based bio-markers have the potential to be used for both, fitness monitoring and rehabilitation monitoring after diseases like heart failure and myocardial infarction.

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Appendix No. 1. Poster for "Technorama 2018"

Veiklos nevaržanti širdies efektyvumo stebėsena naudojant išmaniąją apyrankę

ktu 1922

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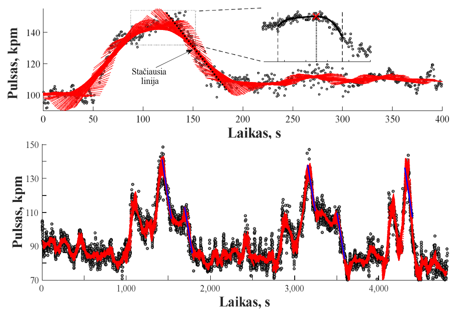
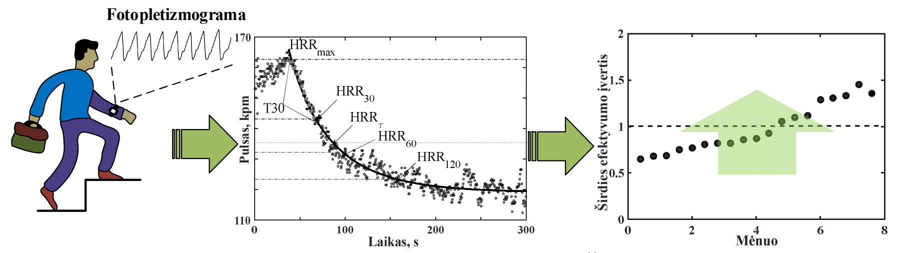
1 Problema ir motyvacija

- Augant išmaniųjų dėvimų įrenginių rinkos konkurencijai, didėja šių įrenginių funkcionalumas. Naudotojams nebepakanka sekti fizinį aktyvumą ir širdies ritmą.
- Pristatomas vartotojo veiksmų laisvės nevaržantis širdies efektyvumo stebėsenos metodas, pagrįstas ritmo atsistatymo laiko po fizinio krūvio automatizuotu vertinimu.
- Atliktos klinikinės studijos įrodė, kad širdies ritmo atsistatymo greitis yra susijęs su širdies efektyvumu. Iki šiol šis širdies efektyvumo įvertinimo metodas buvo taikomas tik **kontroliuojamų** tyrimų metu.
- Šio metodo integracija į išmaniuosius dėvimus įrenginius leis naudotojo **laisvės nevaržančiomis** priemonėmis stebėti širdies efektyvumo pokyčius ilgajame laikotarpyje.

2 Siūlomas metodas



3 Širdies efektyvumo stebėsena ilgajame laikotarpyje



4 Širdies ritmo atsistatymas

- Išmaniosios apyrankės puikiai tinka stebėti širdies ritmo atsistatymą visiškai nevaržydamos įprastinės kasdieninės veiklos. Įprastinė fizinė veikla, tokia, kaip lipimas laiptais ar ėjimas reikalauja nemažai energijos, sukelia širdžiai stresą ir padidina širdies ritmą.
- Dienos bėgyje automatiniu būdu aptinkami fizinio aktyvumo epizodai. Apskaičiuojami pagrindiniai atsistatymo kreivės parametrai, įvertinantys trijų minučių pulso sekos kitimą įvairiose atsistatymo fazėse. Parametrai apjungiami į atskirą indeksą, įvertinantį širdies efektyvumą ir gebėjimą atsigauti nuo fizinio krūvio sukelto streso.
- Žmogui dėvint apyrankę galima stebėti šio įverčio kitimą bėgant laikui. Tokiu būdu galima indekso vertę sieti su fizinės būklės pokyčiais.
- Metodas gali būti naudingas tiek įprastiems apyrankių naudotojams, tiek vertinant reabilitacijos programų efektyvumą sergant širdies ligomis.

5 Padėka

Darbas atliktas vykdant projektą „Personalizuotos dėvimos technologijos gyvybei pavojingoms sveikatos būsenoms įvertinti lėtine inkstų liga sergantiems pacientams - KidneyLife" (Nr. K-718-0130F)."

KIDNEY LIFE

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Photoplethysmography-based estimation of heart rate recovery after climbing stairs

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***Abstract*—Pulse rate estimation from photoplethysmogram (PPG) signals has led to a breakthrough in a smart wristband technology. Thus far, pulse rate is mostly used for self-monitoring purposes, however, there is a growing interest to extend the capabilities of smart wristbands, which prompts the need for novel approaches of pulse rate parametrization. This study introduces a method for estimation of heart rate recovery (HRR) after climbing stairs using a developed wrist-worn device, capable of acquiring instantaneous pulse rate. The feasibility to estimate HRR parameters using the wrist-worn device was assessed by comparing to the reference electrocardiogram-based method, as well as to a consumer smart wristband, which provides pulse rate at intervals of 5 s or longer. Three HRR parameters were studied on pulse rate data, obtained from 22 healthy participants, instructed to perform standardized stair climbing test. The HRR parameters, estimated using the developed wrist-worn device, are associated with twice as low absolute error compared to the consumer smart wristband, suggesting that instantaneous pulse rate is essential to ensure a sufficient accuracy.**

I. INTRODUCTION

A breakthrough in a smart wristband technology is attributed to the capability to acquire pulse rate from photoplethysmogram (PPG) signals. Thus far, pulse rate-derived parameters, such as time spent in specific pulse rate zone, are being used for self-monitoring and performance feedback, however, there is a growing interest to take a further substantial step towards providing a more comprehensive information about the health status (Steinhubl et al. 2016).

Heart rate recovery (HRR) after the standardized physical workload is a widely used parameter to assess the status of the heart in clinical practice. Slower post-exercise HRR is associated with aging, decreased physical fitness, cardiovascular diseases, and is recognized as a predictor of an increased risk of death (Cole et al. 1999, Jouven et al. 2005, Peçanha et al. 2014). Estimation of HRR has been offered by several smart wristband manufacturers (e.g., Garmin, Apple), however is currently inconvenient due to manual switching on the device into a recovery mode. Given that climbing stairs is a common daily activity, which is usually followed by a rest period, this activity can be considered as a HRR test in free-living conditions. To the best of our knowledge, this study is among the first which addresses the question whether PPG-based device is suitable for estimating HRR parameters after climbing stairs without any user intervention.

II. MATERIALS AND METHODS

A. Study population and data acquisition

Twenty-two healthy participants (7 women), 25±4.8 years old, with a height of 178.5±10 cm, weight of 76.2±17.2 kg, and body mass index of 23.8±4.2 kg/m^2 were included in the study. Participants were asked to perform three consecutive stair climbing tests at a stepping rate of 96 steps per minute, resulting in 72 steps per single test. The participants had to rest three minutes before and five minutes after each test. The study was conducted in accordance to the ethical principles of the Declaration of Helsinki.

The developed wrist-worn device (Biomedical Engineering Institute, Kaunas University of Technology, Kaunas, Lithuania) is capable of synchronously acquiring PPG, 3-lead ECG, barometric pressure, and motion signals (Fig. 1). ECG and PPG are sampled at 500 Hz and 100 Hz, respectively. The developed device was compared to the consumer smart wristband Fitbit Charge 2 (Fitbit Inc., san Francisco, CA, USA), which provides minute-by-minute accumulated steps, as well as pulse rate at intervals of 5 s or longer, depending on PPG signal quality. In contrast to the developed wrist-worn device, the consumer smart wristband do not provide an instantaneous pulse rate for each heart contraction, but rather averaged values over the time interval.

B. Detection of recovery onset

Detection of HRR onset is a considerable problem since free-living activities may result in motion artefacts. Usually HR recovery sequence is filled with irregular heart rate variability and its quality highly depends on the intensity of physical activity. However, it has a distinct indication of falling heart rate episode that have an approximate duration of between 60 and 200 seconds. For each individual the time of full HR recovery is proportional to the level of physical activity performed beforehand.

The proposed method to detect the falling curve of HRR is to fit a 1^{st} degree polynomial curve and evaluate its parameters to determine slope and steepness of the function. Long duration heart rate signals or real-time integrated device computation require fast processing and efficient algorithms to provide results with as little processing power required.

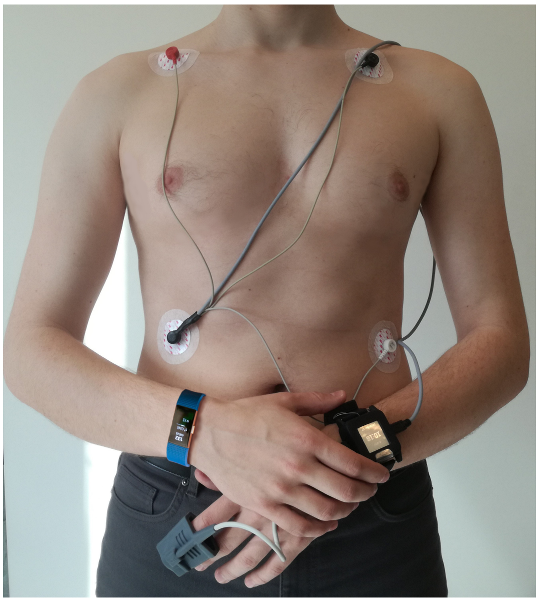

Fig. 1. The developed wrist-worn device for acquiring PPG and reference ECG (left arm). The pulse rate and minute-by-minute steps are obtained using the consumer smart wristband Fitbit Charge 2 (right arm).

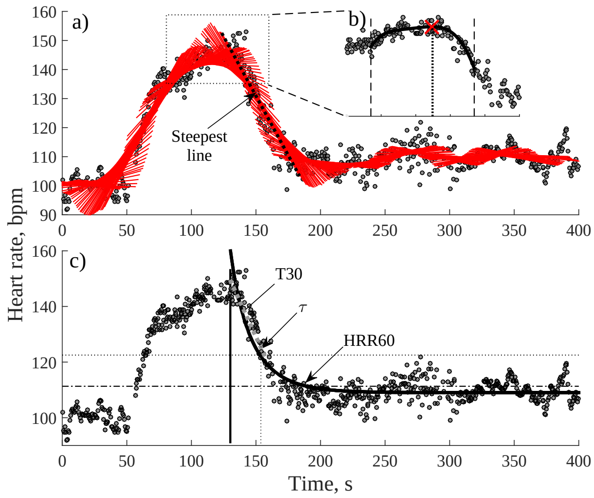

Fig. 2. a) Fitting of 1^{st} degree polynomial curves to the stairs climbing event, b) detection of HRR onset, and c) estimated HRR parameters.

1^{st} degree polynomial on its own is a simple mathematical operation and in this case it provides useful information about particular part of the signal. In order to detect the recovery episode, we cycle the signal with the step of one beat and apply a window of 60 seconds which is the effective minimum of HR recovery time. By cycling the signal, we acquire a series of polynomials which hold an information of its steepness. The representation of the cycled signal is presented in (Fig. 2). The polynomial which has the highest steepness and a falling slope direction has the highest probability of being the part of HR recovery.

Steepest slope extraction provide us an approximate position of the start of heart rate recovery. Start of the steepest polynomial function is the current start of the recovery phase. To more precisely locate instance of the start of the recovery a window of 50 seconds is adapted, with the aproximate start of recovery at the center. The start of recovery phase is a peak of heart rate after which the recovery process begins. The problem is that it might not be the highest peak nor the last in the defined window.

Firstly, a higher, 6^{th} order polynomial function is applied to the defined period of heart rate sequence. Secondly, the peaks that appear in the defined window are detected. Under normal conditions the last peak that appears in the interval is considered the start of the recovery.

C. *Estimation of heart rate recovery*

Exponential fit is applied to the period of 5 minutes, which is expected to be enough for full heart rate recovery after any level of physical activity. An important parameter of the fit is its quality of match with the original signal. A determination coefficient is estimated for each exponential fit applied and the values of R^2 that are over 0.5 are considered to be adequate for further analysis. If R^2 happened to be of lower value than 0.5 recovery interval can be adjusted and the process is repeated.

HR recovery period is usually separated into two parts, a primary-fast phase lasting up to 60 seconds and a secondary-slow phase that lasts up to 5 minutes. Fast phase and slow phase estimation reflects the rapid vagal reactivation and sympathetic withdrawal (Imai & Saito 1994).

Since smart wristbands provide synchronously recorded pulse and physical activity (e.g., steps or climbed floors), combination of this information can be used for estimating heart recovery time. It has been earlier shown that heart recovery can be modelled by a first-order exponential model (Bartels-Ferreira et al. 2015),

$$x_e(t) = x_0 + x_\Delta e^{\frac{t}{\tau}} \quad (1)$$

where x_0 is the interbeat interval immediatelly after the recovery period, x_Δ is the difference between the interbeat intervals at the end and at the beginning of the recovery period, and τ is the time-constant of exponential growth.

Using a model it is viable to estimate a time-constant of the curve τ which evaluate the HRR decay. τ has shown to be an index that reflect parasympathetic reactivation and sympathetic withdrawal (Pierpont & Stolpman 80).

HR decay is notably important during the first minute of heart recovery. First degree polynomial function fitted on recovery part of heart rate provides a line. Steepness of this line quantifies the change over time which is a reliable index. T30 parameter estimates the slope during first 30 seconds of recovery and $T30_{min}$ estimates the 30 second duration interval which exhibits the greatest steepness during the first minute of recovery. T30 parameter values are often impaired by unexpected HRR behaviour at the start of recovery therefore $T30_{min}$ has higher reproducibility.

A simple method to assess HR recovery rate of the fast phase is to estimate the HR that dropped from the peak to the 60 s mark. The difference can be shown in the percentage of HR decline as related to the peak value. Studies has shown HRR60 parameter to highly reflect parasympathetic reactivation (Peçanha et al. 2017). A lower HRR60 measured can be a predictor of mortality (Nanas & Anastasiou 2006).

Exponential time constant τ, $T30_{min}$ and HRR60 are the main parameters that will be disscussed in this study.

D. Performance evaluation

Bland–Altman plots were used to evaluate and display the agreement between the HHR parameters, estimated using PPG-based device and the reference ECG method.

Variation in three consecutive stair climbing tests, performed on the same participant under nearly identical conditions, was assessed using the repeatability coefficient which is defined,

$$r = 1.96 \cdot \sqrt{2} \cdot \sigma, \quad (2)$$

where σ is an estimate of the within subject standard deviation, obtained by fitting a one-way analysis of variance (ANOVA) model to the repeated HRR parameter data (Bartlett & Frost 2008).

III. Results

An exponential fitting to stair climbing event in the pulse rate series is a crucial part of the estimation of HRR parameters. Table I presents the proportion of useful signals and the corresponding average R^2 values for the reference ECG, the developed wrist-worn device and the consumer smart wristband. The results show that nearly 10% of the heart rate series were of insufficient quality for successful exponential fitting for the reference ECG; the numbers are much higher for both PPG-based devices, being 18.4% and 31.4% for the wrist-worn device and the consumer smart wristband, respectively. When analysing R^2 values, the best average fit (R^2 = 0.81±0.16) is obtained using the consumer smart wristband, whereas similar, however, much lower R^2 values are obtained for the reference ECG and the wrist-worn device. This finding can be explained by the reduced pulse rate variability in the pulse rate series of the consumer smart wristband, which is a direct consequence of the embedded pulse rate averaging.

TABLE I

THE PROPORTION OF USEFUL SIGNALS FOR AN EXPONENTIAL FITTING AND THE CORRESPONDING R^2 VALUES.

	Proportion of useful signals, %	R^2
ECG	90.20	0.69±0.22
PPG	81.59	0.68±0.20
Fitbit	68.63	0.81±0.16

Figure 2 shows Bland-Altman plots of HRR parameters, estimated from the reference ECG and the PPG-based device. The HRR parameters, estimated from the instantaneous pulse rate obtained using the wrist-worn device show much smaller bias and twice narrower limits of agreement compared to the consumer smart wristband. Considerably larger error obtained using the consumer smart wristband can be explained by the distorted and shifted onset of pulse rate recovery, which is due to insufficient pulse rate update interval and undisclosed signal processing algorithms used to process the data.

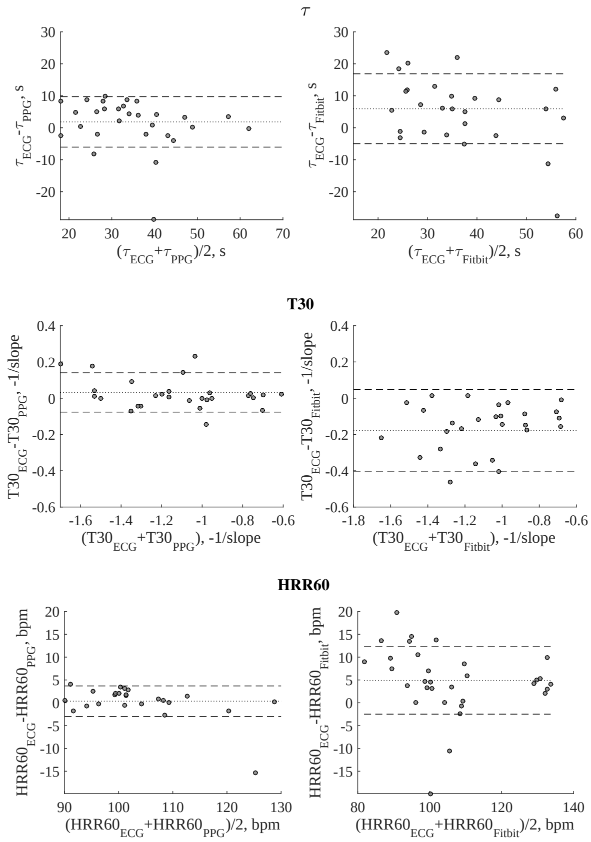

Fig. 3. Comparison of HRR parameters computed using the developed wrist-worn device and consumer smart wristband with respect to the reference ECG.

Figure 4 shows the repeatability of the HRR estimates for the three consecutive stair clinging tests. Repeatability study demonstrate that HRR parameter values are highly variable for most of the participants despite that the stair climbing test is performed under nearly identical conditions. This finding suggests that physiological factors, such as previously experienced physical activity, may play important role on the HRR. When comparing the PPG-based devices, the wrist-worn device shows better repeatability than the consumer smart wristband for τ and $HRR60$ parameters.

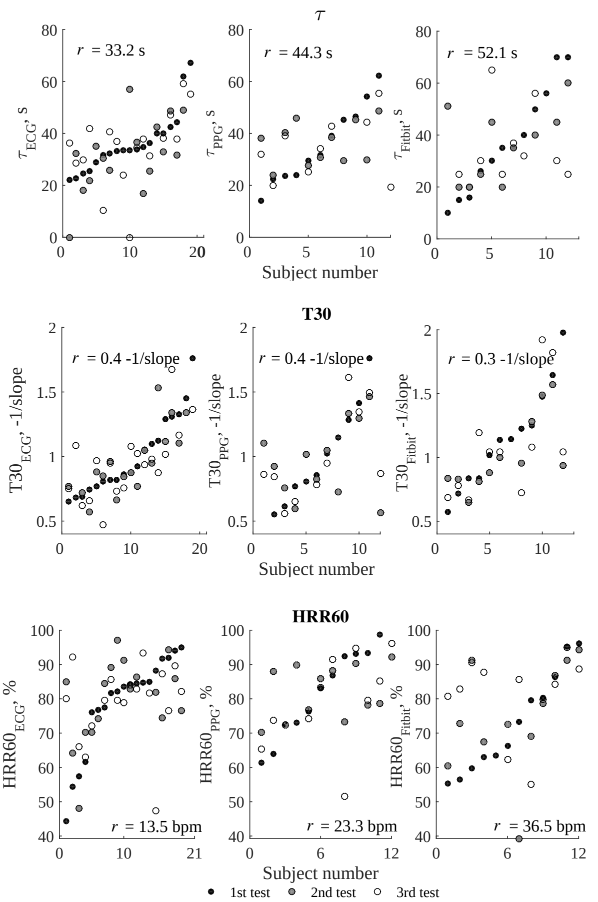

Fig. 4. Repeatability of HRR parameters obtained for three consecutive stair climbing tests. The HRR parameter values are sorted with respect to the first stair climbing test. Note that only the HRR parameter values for $R^2 > 0.5$ are shown, resulting in 16 subjects for the reference ECG, 9 for the wrist-worn device, and 11 for the consumer smart wristband.

IV. Discussion

The goal of the study was investigate the feasibility of the smart wristband to be used for computing HRR parameters after climbing stairs. In this study we proposed an algorithm for recovery onset detection which can be implemented to integrated smart devices. Furthermore we tested algorithms capability of analyzing three different kinds of signals: ECG, wrist based PPG and a Fitbit pulse rate signal. This study will allow us to compare each methods given proficiency to extract main parameters that determine HRR.

PPG based HRR analysis showed better accuracy to the results given by a reference ECG signal in all of our tested parameters. The inaccuracies of both compared methods are understandable, because of different sampling rate and recording method. HRR60 and τ parameters of Fitbit based signal have constant difference from the reference ECG which can only be explained by a delay of Fitbit signal. Fitbit based pulse rate signals performed better at exponential fit quality due to lower variability. However the ammount of artefacts made many of the recorded signals not available for analysis.

V. Conclusion

This study demonstrates that heart rate recovery estimation after climbing stairs using PPG-based device is feasible. Comparison of the developed device with the consumer smart wristband show that instantaneous pulse rate is necessary to insure tolerable accuracy of parameter estimation. The proposed method is expected to have clinical relevance when assessing the status of the heart during home-based cardiac rehabilitation after major cardiovascular diseases.

Acknowledgment

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