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Biosignal Processing Methods to Guide Cardiac Patients to Perform Safe and Beneficial Exercise for Rehabilitation

Hilkka Runtti[a], Anita Honka[a], Ioanna Chouvarda[b], Emmanouil Michail[b], Athina Kokonozi[b], Juho Merilahti[a], Juha Pärkkä[a], Mark van Gils[a]
[a]*VTT Technical Research Centre of Finland, Tampere, Finland*
[b]*Lab of Medical Informatics, Aristotle University of Thessaloniki, Thessaloniki, Greece*

Correspondence: H Runtti, VTT Technical Research Centre of Finland, P.O. Box 1300, FIN-33101 Tampere, Finland. E-mail: hilkka.runtti@vtt.fi, phone +358 40 152 6627, fax +358 20 722 3499

Abstract. This paper describes biosignal interpretation methods in an application to support a CAD (Coronary Artery Disease) patient during rehabilitation. The methods use physiological signals from a wearable device (embedded in a shirt) to guide the patient through safe and beneficial exercise. The paper describes the different design considerations of the processing chain: signal quality verification; on-line analysis and feedback; recovery analysis and exercise summary analysis. The system components have been validated: differences in heart rate between the device and the reference were small, electrocardiograph (ECG) signal quality estimation algorithm had high sensitivity and specificity, and the on-line feedback algorithms perform well enough for use during exercise in practice. A study regarding the clinical usefulness of the overall system is carried in 2012 in the context of the EU project Heartcycle.

Keywords: Coronary Artery Disease; Exercise Monitoring; Rehabilitation, Wearable Biosignal Processing

1. Introduction

One of the application areas of telemedicine can be found in guiding patients at home during rehabilitation. A concrete example is providing support to CAD (Coronary Artery Disease) patients to regularly carry out physical exercise in a safe and beneficial manner after hospitalization. This enables the patient to become cardiovascularly fit again, and to maintain this fitness level in the long term during daily life. Additionally, it helps the healthcare professional to monitor the patient's progress and compliance and allow early intervention if necessary. The work described in this paper is carried out in the context of the EU FP7 project Heartcycle [Maglaveras and Reiter, 2011] that has as aim to improve compliance and effectiveness in heart failure and coronary artery disease closed-loop management.

The system to guide exercise is based on an overall exercise plan agreed upon by the healthcare professional and the patient. It comprises a schedule, covering weeks or months, of physical exercises at the right intensity that the patient is able and willing to do. Different exercises can be done, according to the patient's personal preferences (e.g., cycling or jogging). The patient's progress is followed by the system using recorded physiological signals, and the exercise plan may be updated accordingly. During exercise, vital body signs are monitored with a wearable biosignal-interpretation and feedback set-up to ensure that the exercise is done at the right level: beneficial and safe.

The overall system contains many different components: information processing methods to define and adapt the exercise plan, methods that are used during the actual exercise session, and methods that help to evaluate how the patient has been adhering to the overall plan. This paper focuses on the biosignal processing methods that are central to guidance during the actual exercise, describing their design considerations and validation with test persons. The clinical assessment of the overall system commences during mid 2012.

2. Material and Methods

2.1. Guided Exercise System Components

The approach to guide the CAD patient to a desired fitness level, and maintain that level, contains many components. We will concentrate on those that center on physiological signal processing during exercise, but for an overall understanding of the system, all components are here briefly introduced. Technically, the system contains three main components.

The professional station (residing on a PC), allows the healthcare professional, amongst others, to perform patient management, create and personalize a physical exercise plan (using intensity, frequency, and duration of exercise as basis), and generate summaries of performed exercises.

The patient station (implemented also on a PC) provides the main interface between the patient and the Guided Exercise (GEx) system. It provides the link between the professional station and the portable station (that will be used during the exercise) – allowing for synchronization of exercise plans and upload of monitored exercise data to the professional station. Additionally, it includes a tool to motivate and educate patients by showing them how their actually performed exercise relates to the plans.

Finally, ***the portable station*** is used for carrying out the actual exercise. It includes sensor components to acquire vital signs as well as a portable device (PDA, mobile phone) that interacts with the patient during exercise. On the data acquisition side, there is an IMAGE sensor (CSEM, Switzerland [Correvon et al., 2010]) that is able to record electrocardiograph (ECG) signals (fs = 250 Hz), respiration via impedance (fs = 25 Hz), and 3D-acceleration signals (fs = 25 Hz). It is fixed to a special shirt (Clothing+, Finland) that positions the sensors correctly on the upper chest. The raw signals are additionally summarized to features by the IMAGE sensor. Features include RR-intervals, Heart Rate (HR, fs = 1/5.5 Hz), Breathing Rate (BR, fs = 1/15 Hz), and Activity Level (AL, fs = 1/2 Hz). Exercise sessions are executed on a MS Windows Mobile based PDA (worn on the upper arm).It obtains physiological data from the IMAGE sensor via Bluetooth and provides real-time feedback to the patient regarding the measured signals, provides instructions for performing the exercise, and gives motivational messages.

2.2. Exercise Session – Biosignal Processing Methods used

An exercise involves stages in which different methods are being used to process physiological signals. An exercise session has the following phases:

Before exercise – the system is checked for its functionality (battery level, communication, ECG signal quality etc.) and the patient's baseline HR and blood pressure are measured. The quality of the ECG signal is checked by evaluating the morphology of an ECG segment of 5-15 seconds. Reasons to reject the ECG signal as being 'normal' (and thus require further checking of the system) are: 1) saturation (>10% of the data exceeds 95% of the maximum digital range), 2) flatness (a large amount of signal values have a first derivative close to zero), and 3) abnormal morphology. This latter point is verified by correlating the high-passed filtered (fc = 0.5 Hz) signal to QRS-templates. If the correlation coefficient is below a threshold (obtained via an independent development set) the morphology is deemed too far from a typical ECG. Similar signal quality verification procedures have been suggested in [Redmond et al., 2008].

During exercise – live guidance algorithms guide the patient to exercise in the beneficial HR zone during the warm-up and core phases of the exercise session. The algorithms are based on the analysis of AL, HR and BR. For walking and running activities, HR and AL values are required as inputs for the algorithms. For cycling, only HR is used. The algorithms use the running average HR over the two latest samples, as well as the trend (increasing, decreasing, stable) of the AL (walking, running) or HR (cycling) obtained via linear regression in a sliding window.

Guidance is based on comparing the mean HR to given limits in combination with the trend information. The HR limits of the warm-up and the core phase of the exercise session are shown in Fig. 1. As an output, the algorithms provide 5 different suggestions. In Table 1, few examples of different scenarios and the guidance provided by the algorithms are presented.

Ninety-second trend values of BR are used for detection of abnormalities (e.g., arrhythmias). If HR is increasing abruptly and BR is not increasing the patient is guided to stop the exercise. The patient is also advised to stop exercising if two consecutive HR values are above the upper unsafe HR limit (limit F in Fig. 1).

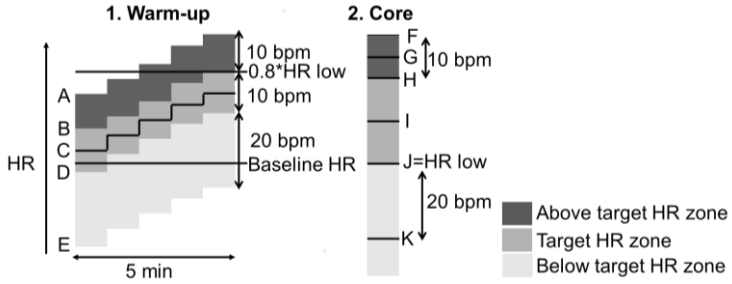

Figure 1. *Heart rate (HR) limits used by the guidance algorithms. Limits J=HR low and H are the lower and upper limits of the target HR zone, respectively, and they are defined by the healthcare professional. Limit F is the upper safety limit. Rest of the limits (A, B, C, D, E, G, K) are defined in relation to the limits J, H, F, and baseline HR.*

Table 1. *Examples of scenarios and suggestions provided by the guidance algorithms.*

Scenario	*Guidance*
Warm-up	
Mean HR between D and E	
• Trend decreasing or stable	Speed up slightly
• Trend increasing	OK
Core phase	
Mean HR between H and G	
• Trend decreasing or stable	Slow down slightly
• Trend increasing	Slow down substantially

Recovery phase – the system provides fitness and cardiovascular risk assessments. HR recovery refers to the rate at which the HR declines after the (sub)maximal exercise performed in the core phase. It has been shown to have value as a predictor of mortality [Cole et al., 1999] and as an index of cardiovascular fitness [Jolly et al., 2011]. The values of the first 5 minutes of active or passive recovery are used, specifically:

1. Reduction in HR during the first minute after the exercise (<12 bpm for active recovery or <18 bpm for passive recovery in the supine position after a maximal exercise test represents an unfavorable prognostic index) [Watanabe et al., 2001; Cole et al., 1999].
2. $HRRS_{50\text{-}70}$ represents the derivative of the HR slope over the range 50-70 sec after the exercise [Hadley et al., 2008].
3. The HR in the 5th minute of recovery which should be less than an AlarmThreshold = HR_LastMinOfExercise - (HR_LastMinOfExercise-HR_Baseline)*0.5.

2.3. Design and Validation Approaches

To check the **performance of the HR from the IMAGE** sensor, its output has been compared to simultaneous recordings with the BioHarness-BT wearable sensing device (Zephyr Technologies, USA). Two datasets were collected: 1) 12 healthy volunteers, performing a treadmill stress test (BRUCE protocol) at the Aristotle University of Thessaloniki, and 2) 9 obese and hypertensive patients, performing a similar test at the 2nd Propedeutic Department of Internal Medicine of the Hippokration Hospital of Thessaloniki.

Before comparison between the sensors, signals were synchronized and HR from Bioharness-BT was downsampled from 250 Hz to the sampling frequency of the IMAGE sensor. The absolute difference between the simultaneous HR recordings was analyzed in terms of median and quartiles.

ECG signal quality check - Algorithms were tested with the data recorded in Rehaklinik An der Rosenquelle, Aachen, Germany, in which 8 cardiac patients performed a bicycle exercise test (Viasys-Jäger, Germany). ECG segments were selected manually from the recordings and classified as good or bad by visual examination. 43 ECG segments were selected from 8 cardiac patients and 73 ECG segments were selected from 14 healthy subjects measured in Tampere, Finland.

Live guidance – Outdoor data were collected during different activities with 11 healthy volunteers (age 24-39 yr) in Tampere, Finland. The protocol included 5 min standing, 10 min walking, 10 min running, and 10 min cycling. Indoor measurements were performed to tune and evaluate the sensitivity of the algorithms, i.e. to test how fast the algorithms react and whether it is practically feasible to follow the guidance in different situations. During the indoor measurements, different evaluation scenarios

were created by advising the volunteers to speed up, slow down or follow the guidance. The algorithms for walking and running were tested with 8 healthy volunteers (age 24-39 yr), who walked or ran on a treadmill (Daum Electronics, Germany). The algorithms for cycling were tested in the same manner with 4 subjects (age 25-39 yr) using an ergometer (Tunturi, Finland).

Recovery phase - Data recorded for the HR comparison studies were employed also for the validation of the recovery features, especially as regards their robustness in real life conditions.

3. Results

3.1. Comparison between IMAGE and Bioharness-BT

Technical problems (battery depletion, sensor detachment, serious artifacts) led to exclusion of 5 subjects from both groups. The median of the absolute HR difference in the healthy volunteers was 2.57 bpm (interquartile range, IQR: [1.14 11.57] bpm). Divergence can be traced to Bioharness-BT's failure during peak exercise in two subjects (Fig. 2). In hypertensives group, the median of HR differences was 1.0 bpm (IQR: [0 1.75] bpm).

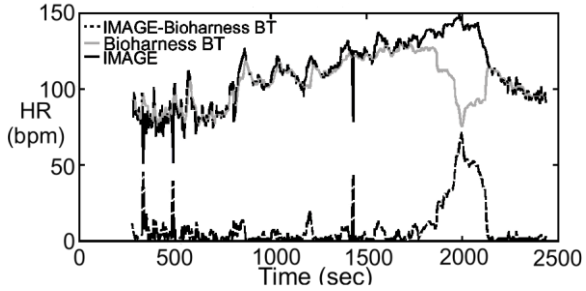

Figure 2. *Example case: IMAGE heart rate (HR, black solid line), Bioharness-BT HR (grey solid line) and their absolute difference (black dashed line). A divergence during peak exercise is caused by Bioharness-BT's failure.*

Wilcoxon Paired Signed-Rank Test showed that HR differences were significant in 4 out of 7 healthy subjects ($p<0.05$) and none in hypertensives group had significant differences ($p>0.05$). In general there was a high degree of similarity. It was observed that in cases of instantaneous detachment or bad conductivity, IMAGE produced short edges in the HR signal whereas, Bioharness-BT tended to produce a more persistent distortion.

3.2. ECG Signal Quality Check

Performance of the ECG quality check algorithm is shown in Table 2. Sensitivity refers to the ability to correctly recognize good quality ECG segments and specificity refers to the ability to correctly recognize bad quality ECG segments.

Table 2. *Performance of the ECG quality check algorithm*

	Dataset 1: Tampere	*Dataset 2: Aachen*
Length of ECG segment	10 sec	10 sec
Sensitivity	96.4%	100%
Specificity	91.1%	95.8%
Number of ECG segments	73	43

3.3. Live Guidance

An example of the output of the live guidance algorithms during the testing is presented in Fig. 3. As a summary, the guidance works satisfactory and it is possible to follow it in practical exercising. It is quite easy to increase HR to the target area and keep it there. During walking and running, when the subject speeds up heavily even though his HR is already in the target zone, HR increases quite easily above the upper unsafe limit. This is due to the small HR reserve between the limits F and H. However, this should not be a problem because the patient should have no reason to speed up heavily when his HR is already in the target HR zone.

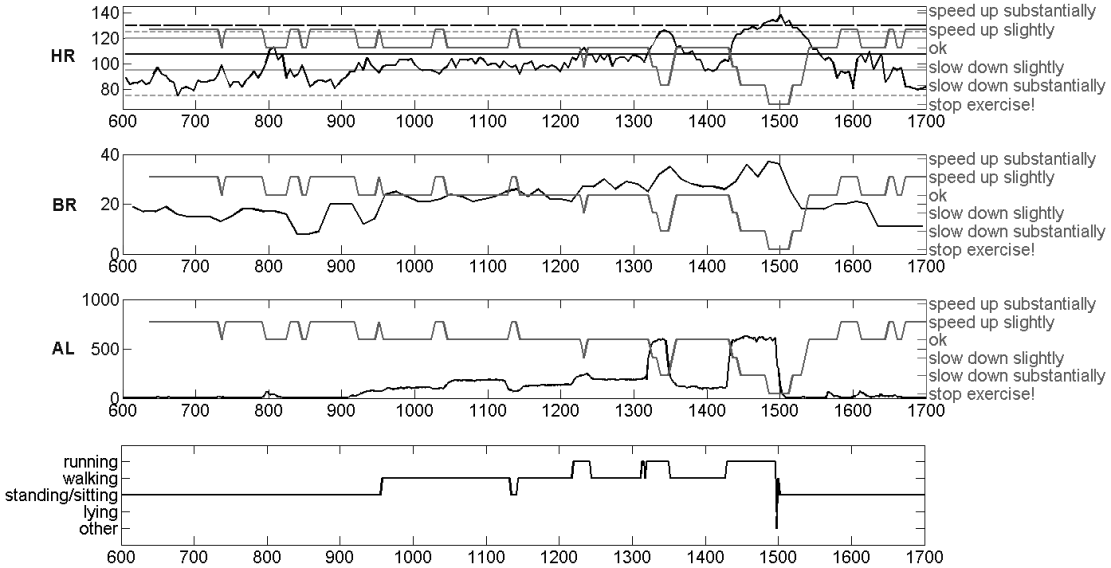

Figure 3. *An example of a recording during walking and running. The subject is creating different test scenarios by speeding up, slowing down and following the guidance. Panel 1 (top): heart rate (HR) in black line and the guidance in grey line. Horizontal lines are HR limits used by the guidance algorithms: black dashed line is the upper safety limit (F), grey dashed lines are limits G and K, grey solid lines define the target HR zone (limits J and H), and black solid line is limit I. Panel 2: breathing rate in black line and the guidance in grey line. Panel 3: activity level in black line and the guidance in grey line. Panel 4: activity classification as an output from the IMAGE sensor. The horizontal axis is time in seconds from the start of the recording.*

3.4. Recovery analysis

Table 3 contains results of the implementation of recovery features for the two different groups of subjects.

Table 3. *Results of recovery features (group: 1 = healthy, 2 = hypertensives). Results are reported as mean (standard deviation)*

Group	*HRpeak [bpm]*	*HRpeak-HR(1min) [bpm]*	*$HRRS_{50-70}$*	*HR (5min) [bpm]*
1	171.8 (18.2)	34.7 (6.0)	3.5 (2.5)	110.3 (9.6)
2	138.5 (23.8)	26.5 (8.7)	4.7 (5.2)	82.8 (18.2)

Healthy subjects achieved a higher peak HR during exercise and their standard deviation was slightly smaller than hypertensives had. They also had a higher HR decrease during the first minute of recovery. Specifically, the minimum value of this feature in healthy volunteers was 27.5, whereas in hypertensives it was 12.7. However, only for one hypertensive subject its value fell below the critical threshold of 18 bpm.

The index $HRRS_{50-70}$ was lower in the case of healthy subjects. This seems to be contradicting with the results of another long-term comparative study of cardiovascular patients and healthy volunteers [Hadley et al., 2008]. There, the mean $HRRS_{50-70}$ between subjects that died from cardiovascular reasons was 4.8 and the mean $HRRS_{50-70}$ between people that survived was 7.4. It has to be noted that this feature may be less robust to noisy HR estimates. Furthermore, it has not been widely used in clinical studies to safely produce normal ranges.

Finally, healthy subjects had higher HR values at the 5th minute of recovery with a smaller standard deviation. None of the subjects in this study had a HR value at the 5th minute above the alarm threshold, indicating a normal recovery in all subjects. However, one hypertensive subject had not sufficient recovery duration, in order to check this alarm.

4. Conclusions

A system for guiding cardiac patients using wearable sensors combined with biosignal processing methods for the different phases was developed, implemented and tested on its functionality. The system is being used in actual clinical trials to assess its effectiveness in management of patients in the

Heartcycle project. These clinical trials (performed in Germany, Spain, UK) will start in the spring of 2012. Further technical research is envisioned regarding the robustness in different setups and scenarios in a telemonitoring system with wearable sensors, in different exercise protocols, as well as the universality of the algorithm parameters employed.

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