A Movement-Artefact-Free Heart-Rate Prediction System

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Abstract

Continuous automatic heart rate (HR) monitoring plays a crucial role in timely intervention for postoperative patients. However, for effective alarm management, patients' activities of daily living need to be considered as they influence HR. This explorative study aimed to develop a heart-rate prediction system while performing six activities. An experiment with fourteen participants was conducted to gather data to build a system. This system consisted of a support-vector machine classifier for activity recognition and a k-Nearest Neighbors regressor for HR prediction. The R-squared (a goodness-of-fit measure) of the HR predictor is 79% on average. Given the heterogeneity of different populations, the system will be further tested and developed using patient datasets in future towards clinical-practice applications.

1. Introduction

Clinical-adverse-event monitoring using continuous vital signs plays a crucial role in timely interventions for postoperative patients during their recovery period [1]. However, changes in vital signs, e.g. heart rate (HR), are not only effected by pathological conditions, but also by daily physical activity, stress, emotion, circadian rhythm, etc. [2]. An inaccurate monitoring system with reoccurring false alarms can lead to caretakers' alarm fatigue and even severe consequences. To accurately assess patients' health condition and support clinical decisions, a monitoring system should take these factors into account.

However, to our best knowledge, there is no previous studies that well considered the influence of the factors during the daily monitoring of patients' health condition. In this study, a HR prediction system was developed under the consideration of daily physical activity influence, and the physical activity was quantified by our developed human activity recognition (HAR) model. We also discussed the advantages and future works of the proposed HR prediction system here.

2. Method

2.1. Experiment

The experiment was ethically approved by the Ethics Committee Computer & Information Science of the University of Twente (reference number RP 2021-188). 14 healthy participants were included. The experiment was conducted in the eHealth House, a lab resembling a normal apartment. The lab is equipped with cameras and microphones to monitor and record experimental activities. The floor map of the eHealth House is shown in Figure 1.

The experiment protocol was designed according to Activities of Daily Living (ADL), similar studies [3], and activities that physiotherapists normally use at a hospital setting. Six main activity classes were executed: standing, sitting, lying, walking, climbing stairs, and cycling. The experiment was split up into three main parts: controlled movement, free movement, and cycling. The controlled part consisted of standing, sitting on the edge of the bed or on a chair, lying in a supine position, and 12-meter walking under a researcher's instructions at a fixed location. Walking was executed in a natural rhythm at three different speeds: self-selected slow, normal and fast. During the free movement tasks, participants were instructed to execute daily life tasks, like 'make a cup of tea' or 'fetch an object from another room', and climb stairs at three different self-selected speeds.

The experiment was ended by 10 minutes of cycling. The cycling consisted of three parts: three minutes of warming up at a moderate intensity, six minutes of cycling at a high power level, and one minute of cooling down at a low power level. HR of approximately 140 beats per minute (BPM) was used as the target for the high power part [4]. The researcher monitored the HR during cycling and adjusted the power level accordingly.

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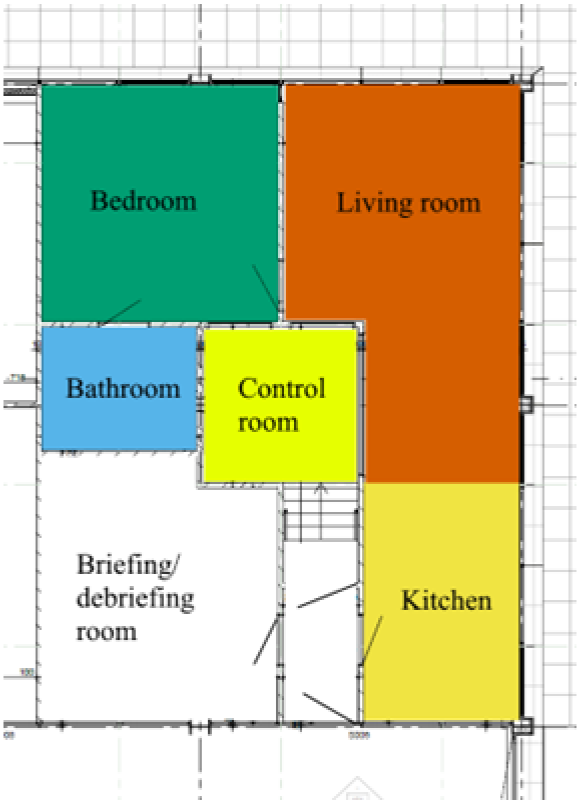

Figure 1. Floor map of the eHealth House. More details can be found on the website: https://www.utwente.nl/en/techmed/facilities/htwb-labs/ehealth-house/

2.2. Data collection, processing & Analysis

Participants' age, sex, length, and weight were collected through a questionnaire at the end of the experiment. We applied inertial measurement units (IMUs) attached to the chest and upper leg for physical activity information according to our previous study [5] and prior knowledge about human movement analysis. The IMUs were of the type Xsens MTw Awinda [6] and measure six signals: linear accelerations (in m/s^2) in the x-, y- and z-axis and rotational velocities (in degree/s) around the x-, y- and z-axis. Dry ECG electrodes (Zephyr BioHarness [7]) were used for the one-lead electrocardiogram (ECG) recording at 250 Hz.

The video and collected signals were labelled by the researcher by watching back the recordings of the experiment using a customized labelling application. All labels were synchronized to both the IMU and ECG data by careful visual inspection of the ECG and IMU data for recognizable movement influence on the data and finding the corresponding activity label. The data was segmented by a 5-second sliding window with an overlap of 50% with the previous window. Each window was assigned the annotated physical-activity label. A linear interpolation was implemented when there were missing data caused by hardware connection issues.

According to our previous study [5] and human movement prior knowledge, 12 features were extracted from each IMU to describe average body component position due to gravity and physical activity dynamics. The features were the average value and the standard deviation of each IMU's six signals. All features were normalized to have zero mean and unit variance. The golden standard HR was extracted from the ECG signals using a modified version of the algorithm by Pan & Tompkins [8] verified with industry-standard ECG databases: the MIT-BIH Arrhythmia Database [9] and the European ST-T Database [10].

2.3. Machine Learning

2.3.1. Human Activity Recognition

Based on literature [11] and initial tests, a support vector machine (SVM) classifier was used and optimized to recognize the physical activity for each participant and for all combined participants' data, respectively. The classifier was trained based on the 24 features from the IMU data acquired from the chest and upper leg and transformed to be linearly separable using a Radial Basis Function (RBF) kernel. The labelled data was split into training and testing sets using a stratified five-fold splitter (5-fold cross validation method). The performance of the classifier was assessed using the f1-score, precision and recall. The final performances were given by the average score for the five different splits.

2.3.2. Heart Rate Prediction

The HR was predicted using a *k*-Nearest Neighbors regressor for each participant. The input data of the regressor were physical-activity intensities, durations, and labels. Activity intensity was defined as the average of all standard deviation values from the IMU data scaled to fit in a range from 0 to 1. Activity duration was the amount of consecutive data windows that the current activity has been going on for. The activity labels recognized by the HAR classifier was given as the physical-activity label input of the HR regressor. The regressor used the same five-second data window with 50% overlap as the HAR classifier. The 5-fold cross validation method was applied to train and test the HR regressor. The performance of the regressor was evaluated with the R^2-score that is a goodness-of-fit measure of a regression model. In addition, the median absolute error, mean absolute error and maximum error between the predicted HR and the ground truth HR were used to assess the performance of the regressor.

3. Results

3.1. Dataset

Nine of 14 experiment participants resulted in a usable dataset. One was excluded because of corrupted IMU data files. The other four participants were excluded because of unusable ECG data caused by a faulty sensor strap which produced excessive clipping artefacts during activity. One of the nine participants had around 30% less data available, as one of the sensor batteries died during cycling. The participants had a median age of 22 years, with a minimum of 19 years and a maximum 27 years. Length ranged from 159 cm to 193 cm with a median of 179 cm. Weight ranged from 45 kg to 93 kg with a median of 65. Five participants were female and four were male.

3.2. Human Activity Recognition

The HAR reached the mean sensitivity of $87\% \pm 3\%$, the mean precision of $88\% \pm 3\%$, and the mean f1-score of $87\% \pm 3\%$. For all-participant combined dataset, a confusion matrix (Figure 2) were generated to visualize the performance per activity class and shows that most misclassified events occurred between the activities “standing” and “walking”, and between that “stairs” and “walking”.

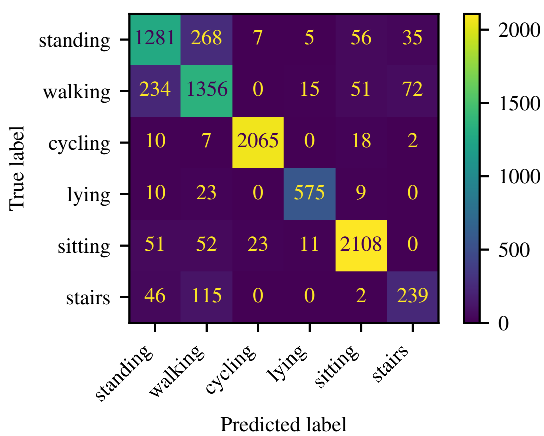

Figure 2. Confusion matrix for the combined dataset from all participants.

3.3. Heart rate prediction

The best performance of the regressor was achieved by using all input features: activity type, activity length and activity intensity. The R^2-scores ranged from 56% to 89% with a median of 81% and with the mean of $79\% \pm 9\%$. This was also reflected by the mean absolute error value of 6 ± 0.5 BPM, the median absolute error value of 4 ± 0.6 BPM, and the max error of 43 ± 14 BPM. We visualized the predicted HR of participant #11 in Figure 3 as an example that shows the predicted HR overlaid on the measured HR (golden standard).

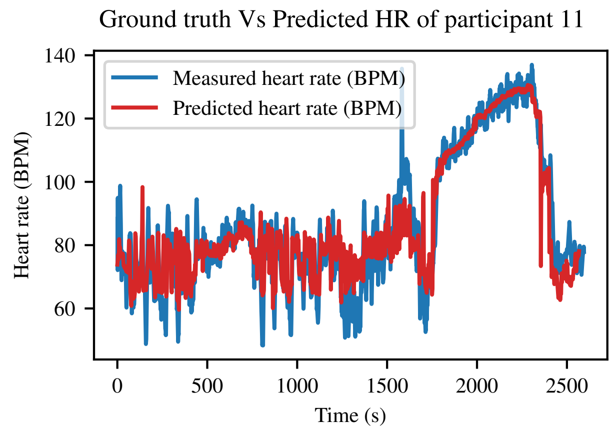

Figure 3. Predicted heart rate from the heart rate regressor model using recognized activity labels, overlaid on the measured heart rate for participant 11.

4. Discussion

This paper described the first study to develop a HR prediction system with the consideration of the influence of body movement described by IMU signals. The combination of features: activity type, activity length and activity intensity made the HR prediction system reach the best performance. The synergy between the human activity recognition system and the HR prediction system showed promising results with the mean R^2-scores of 79% for future patients’ automatic heart rate monitoring in clinical practice.

A data-driven model was developed in this study to predict the heart rate response to various daily life physical activity. According to our results, the features about activity type, length, and intensity play an essential role in the HR prediction. This precisely represents the homeostasis of the cardiovascular system: the heart rate changes along with the variation of the metabolic demands. A combination between a physiological-theory-driven model and a data-driven model would be recommend to be applied to increase the generalizability of the proposed HR prediction system in future work.

This study was initiated to increase the accuracy of heart rate monitoring of postoperative patients during their hospital stay. Moreover, the proposed system can be customized to estimate the heart rate response to daily life physical activity and gain valuable insight into people's health condition in their daily life for personalized disease management and interventions. For example, a broad population's heart rate and physical activity information collected by currently widely used wearable fitness trackers can be used as inputs to our proposed system. However, to apply our proposed method in different population in daily life, we need to further develop and validate the current system according to the target population. As the next steps, we will further develop our system using the data collected from in-hospital patients after surgeries and at-home patients with cardiovascular disease.

Even though our proposed HR prediction system reached good performances for general physical activity, the transient changes of HR are still hard to be predicted. This was probably caused by limited data available for activity transition. In future study, we can enlarge the dataset through focusing on the recognition of activity transition moments in daily life. A misclassified physical activity may also lead to the difficult transient HR prediction. For example, a sudden drop in the predicted HR was observed in Figure 3 around the 2400th second when the participant stopped cycling for a short period. The short cycling break was classified by the HAR classifier as "sitting", and the regressor did not consider the previous activity in predicting the HR. A time-series relevant regression model, such as, long short-term memory, can be applied in the future system to improve the performance of predicting transient HR changes.

5. Conclusion

This work has shown that healthy participants' heart rate can be predicted by physical activity types, intensity, and duration. The physical activity recognition system can be implemented and achieve high accuracy with two movement sensors and limited training data, and this HAR system output can be used to feed a data-driven regressor model to predict HR. We successfully established a synergy between physical activity recognition and heart rate prediction system for an movement-artefact free heart rate monitoring system for future clinical practice.

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