A HEART RATE PREDICTION MODEL FOR THE TELEREHABILITATION TRAINING OF CARDIOPULMONARY PATIENTS

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Abstract: Chronic obstructive pulmonary disease (COPD) and coronary artery disease are severe diseases with increasing prevalence. They cause dyspnoea, physical inactivity, skeletal muscle atrophy and are associated with high costs in health systems worldwide. Physical training has many positive effects on the health state and quality of life of these patients. Heart Rate (HR) is an important parameter that helps physicians and (tele-) rehabilitation systems to assess and control exercise training intensity and to ensure the patients' safety during the training. On the basis of 668 training sessions (325 F, 343 M), demographic information and weather data, we created a model that predicts the training HR for these patients. To allow prediction in different use cases, we designed five application scenarios. We used a stepwise regression to build a linear model and performed a cross validation on the resulting model. The results show that age, load, gender and former HR values are important predictors, whereas weather data and blood pressure just have minor influence. The prediction accuracy varies with a median root mean square error (RMSE) of ≈11 in scenario one up to ≈3.2 in scenario four and should therefore be precise enough for the application scenarios mentioned above.

1 INTRODUCTION

1.1 Background

Patients with chronic obstructive pulmonary disease (COPD) are suffering from the consequences of a chronic inflammation of their pulmonary system. This leads to an obstruction of the bronchi that causes airflow limitation and shortness of breath. Often, immobility and social isolation are the consequences, which in turn reinforce the degeneration of muscle mass and aggravate the symptoms. The Global Initiative for Chronic Obstructive Lung Disease (GOLD) summarizes: "COPD is the fourth leading cause of death in the world and further increases in its prevalence and mortality can be predicted in the coming decades" (Rodriguez-Roisin and Vestbo, 2009). Just the direct medical costs attributable to COPD were estimated at $49.5 billion in the US (Lung Institute, 2009) and €38.6 billion in the European Union (Simon et al., 1990) for 2010.

Beside the pharmacological treatment, an important part of therapy is regular endurance training. Pulmonary rehabilitation training improves physical capacity, reduces breathlessness, reduces the number of hospitalizations and increases the quality of life (Rodriguez-Roisin and Vestbo, 2009).

1.2 Related Work

Achten and Jeukendrup summarized current research achievements in the field of heart rate monitoring in 2003 and state: "…the most important application of

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HR monitoring is to evaluate the intensity of the exercise performed” (Achten and Jeukendrup, 2003). They conclude that the important influence factors on HR are age, gender, environmental temperature, hydration and altitude. They estimated the day-to-day variance under controlled conditions to be 2-4 beats per minute (bpm).

Velikic et al. used data from an accelerometer for a comparison of different models (linear, non-linear, Kalman filter) for HR prediction of healthy subjects and such with congestive heart failure (Velikic et al., 2010). The two linear models delivered the best results for a short term prediction of 20 minutes. Su et al. introduced a model to control HR during treadmill exercise (Su et al., 2006). Further approaches for the same application were provided by Cheng et al. (Cheng et al., 2008) and Mazenc et al. (Mazenc et al., 2010). Neither have any of these models been checked for their applicability to cardiopulmonary patients nor do specialized HR models exist for these.

1.3 Aim and Scope

Heart rate is an important vital parameter and thereby an important indicator of a patients physical state during rehabilitation trainings (Song et al., 2010). The knowledge about factors that have an influence on the exercise physiology might help physicians to take this information into account when deciding how much load a patient can undergo during a training session. Hence it could be used to support creation and optimization of training schedules and during the current training session itself to derive the future course.

A difference between the predicted trend of a normal training and a measured heart rate may give a hint on a potentially abnormal development and thereby help to detect critical states before they occur. This is especially important in tele-rehabilitation settings, when patient’s train under unsupervised conditions at home (see (Helmer et al., 2010); (Lipprandt et al., 2009)). Integrating predictive models in systems for the planning and execution of individualized trainings has the potential to increase patient’s security during rehabilitation.

The aim of our research, which is presented in this paper, is to introduce a model which predicts the patients HR on the basis of given information about the patient and the environment.

2 METHODS

2.1 Population, Data Acquisition and Preparation

The data was obtained during outpatient rehabilitation from cardiopulmonary patients with NYHA 1-2 and COPD level 2-3. The only exclusion criterion was the inability to perform training.

We started with an original dataset of 164 patients (82 W, 82 M) and 1201 training sessions, which were collected between July and September 2009 in the exercise training center of the Medical School Hannover in addition to regular ambulatory training sessions. Patients performed their sessions twice a week, whereas in mean each patient performed ~8 training sessions (± 7.7). HR was obtained on the basis of electrocardiogram (ECG) data. The following additional data were available:

- *Patient demographics*: age, sex
- *Training data*: date and time, duration, load
- *Vital signs data*: resting HR before training, recovery HR after training, blood pressure (BP) (rest, load, recovery – systolic and diastolic), Borg value (Borg, 1970) (used scale 6-20), HR during the whole training (sample rate ≈ 1 Hz.).

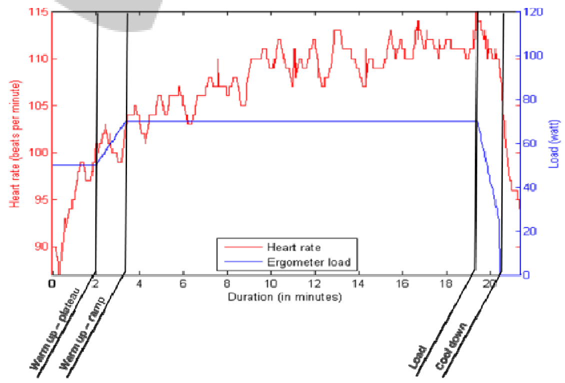

Figure 1: Sample training session with heart rate, training load and distinction into the four training phases.

We also included environmental variables, which could have a possible influence. For this purpose we procured data from the German weather service that was recorded by a weather station in Hannover (station id: 2014), where the training took place. We chose temperature, humidity and air pressure as main descriptors for weather and added them to the training data.

Only fully completed training sessions with a specific phase and full duration and a typical load course showing the characteristics of a successful four-phase rehabilitation training (see figure 1) were included into the dataset. The first phase (warm up) consists of a load plateau at a certain level. This load increases stepwise over time in the second phase. The third phase (load phase) shows a constant load for at least 10 minutes. In the fourth phase (cool down) the load is reduced stepwise until it reaches null. We also excluded sessions, where a monitoring physician interfered by de- or increasing the training load, because the reasons of such changes were not documented in our data. This could also be an indicator for training under suboptimal conditions, e.g. the training load was too high or low for the patient due to an inadequately adapted training schedule.

To automatically and robustly extract the sessions from the dataset matching the previously mentioned criteria, we calculated the difference derivate of the load values over time to detect whether the load was in- or decreasing during a training session. Additionally, a session had to last from 12 to 26 minutes in total. After discarding all training sessions not fulfilling these criteria, we reduced the above mentioned number of 1201 to 668 (325 F, 343 M) training sessions from 115 patients (in mean 5.8± 4.5 trainings per patient).

2.2 Model Creation

For the integration of the predictive model into existing training systems the set of potential predictors (input variables which explain a significant part of the response variable) varies depending on the point in time and the use case.

We designed five different scenarios with expanding/extending datasets, which take place in settings of telerehabilitation training and during live training in clinics. The first scenario describes a situation before training when the schedule is created, but no reliable weather forecast is available (approximately three days before the training day). The second scenario includes the weather forecast. In the third scenario the patient already wears the sensors, but the training has not yet been started. The fourth scenario depicts an ongoing training and the prediction includes data that was gathered during previous completed training phases. To provide an example, the average heart rate of the warm up plateau phase can be included into the dataset for the load phase. The fifth scenario describes the situation after the training and does also include data like the subjective perceived exertion of the patient expressed on the Borg scale.

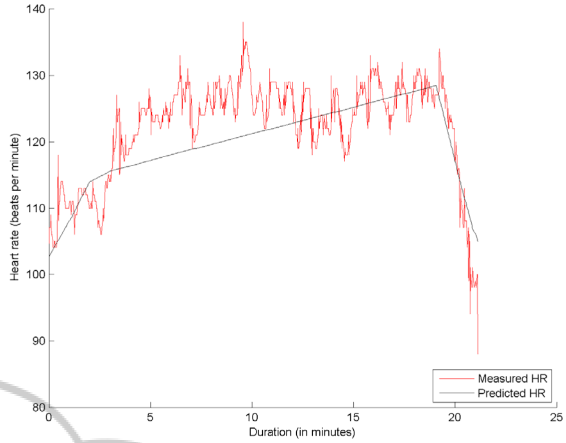

Figure 2: Sample training session for scenario four with measured and predicted heart rate. The RMSE is calculated for the four training phases.

The following list is sorted in ascending order by the number of predictors available and the time in relation to the training session. Each scenario expands the predictor set of the previous one:

- *Scenario S1 (training plan creation)*: patient demographics and training plan data (load, duration of each phase)
- *Scenario S2 (training plan creation few days before the training day):* weather data
- *Scenario S3 (at the beginning of the training)*: resting HR, resting BP
- *Scenario S4 (during the training)*: average HR of the former phase, HR at the end of the former phase, BP during the load phase (phase three)
- *Scenario S5 (after the training)*: average HR of current training phase, average HR of load phase, average HR of all phases, recovery pulse, recovery BP, average of all BP values, Borg value

The final list of predictors for scenario five included 24 items (see table 1).

To build a hypothesis about which values have a relevant influence on the HR, we used a stepwise regression analysis (Hair et al., 2006). This algorithmic approach performs a multilinear regression and determines a model, by adding or removing the variable with the highest or lowest correlation of the model’s F-statistics stepwisely.

So the variable with the highest chance of explaining the variance of the given normally distributed data set is added to the model, when the correlation is big enough to reject the null hypothesis. This is done until all variables with significant influence (predictors) have been added and all variables with non-significant influence have been removed from the final model. We used the standard entrance and exit tolerances of $p \leq 0.05$ and $p \geq 0.10$ for the model. Additionally, we performed chi-square tests to confirm the normal distribution of the HR dataset.

The stepwise regression determines a set of coefficients (B_i) and an intercept (also called constant term) (c) as result. Together with a number of given predictor values (X_i) it yields a linear combination of the following form to calculate the response variable (Y):

$$Y = c + b_1 x_1 + b_2 x_2 ... + b_i x_i \quad (1)$$

We created such a submodel for each training phase (warm up plateau, warm up ramp, training and cool down) to reflect the different physiological targets. These four submodels were then concatenated to a complete model for one training session (see figure 2). This also simplified the comparison to the real HR of the training sessions used for validation.

2.3 Model Evaluation

To determine the quality of our model and to prevent overfitting, we performed a 2-fold cross-validation. We divided the dataset into two parts d_0 and d_1. Both parts were of the same size and contained randomly selected training sessions (n=334) from the dataset. First, we used d_0 to train the model and validated it against the d_1 dataset then we performed this procedure vice versa.

We calculated the root mean square error (RMSE) which quantifies the deviation between measured and predicted heart rate over a whole training.

It is not easy to determine, which predictor of the resulting model explains which part of the response variable, as each added predictor depends on the former one. To make a statement about the influence of the predictors, we measured the percental improvement of the RMSE when a predictor is added to the model in relation to the former one.

3 RESULTS

We modeled the four stages of a training session (one for each training phase) for the five different scenarios and determined the weighted RMSE to quantify the error of each model (see figure 2).

Table 1 shows the contribution of different predictors to the model and their effect on the RMSE. Because of their naturally high correlation (also known as multicollinearity) it is no surprise

Table 1: Mean contribution of the predictors on the scenario (S1-S5) model. All values represent the improvement of the former RMSE in percent by addition of a predictor during stepwise regression. The "-" symbol denotes that a predictor is not available in the given scenario. The calculated average influence of a predictor is shown in column "Overall". The order of these values is additionally illustrated by a rank order in the last column.

Predictor	S1	S2	S3	S4	S5	Overall	Rank
Age	11.032	11.032	11.1115	9.002	8.018	10.0391	3
Gender	0.754	0.754	0.745	0.1555	0	0.4817	8
Load	0.368	0.368	5.5555	0.646	0.0775	1.403	6
Overall training duration	0.0645	0.0645	0	0	0	0.0258	12
Duration of current training phase	0.0395	0.0395	0.015	0.019	0.0105	0.0247	13
Air pressure	-	0.0265	0.0125	0.141	0.1355	0.078875	11
Temperature	-	0	0	0	0	0	-
Humidity	-	0	0	0.0585	0	0.014625	14
Resting HR	-	-	40.9895	7.1535	5.268	17.8036667	2
Resting BP systolic	-	-	0.494	0.118	0.119	0.24366667	9
Resting BP diastolic	-	-	0	0	0.0855	0.0285	11
Average HR of former phase	-	-	-	57.0635	54.3	55.68175	1
Load phase BP systolic	-	-	-	0	0.005	0.0025	16
HR at the end of former phase	-	-	-	0	0.0265	0.01325	15
Load phase BP diastolic	-	-	-	0	0	0	-
Average HR of current phase	-	-	-	-	5.648	5.648	4
Average HR of load phase	-	-	-	-	3.5475	3.548	5
Recovery pulse	-	-	-	-	0.6825	0.683	7
Recovery BP diastolic	-	-	-	-	0.122	0.122	10
Borg value	-	-	-	-	0	0	-
Average HR of all phases	-	-	-	-	0	0	-
Average of all BP values systolic	-	-	-	-	0	0	-
Average of all BP values diastolic	-	-	-	-	0	0	-
Recovery BP systolic	-	-	-	-	0	0	-
Total number of predictors	5	8	11	15	24		

that four of the first five predictors have a high impact on the model. Important other predictors are age and load (Overall>1.4). The only predictor from the weather data is the air pressure with just a very small influence of ≈0.08%. Most of the different blood pressure values and the Borg value have no impact on the model.

Table 2 shows the accuracy of the prediction. For the calculation of average and median over the complete training the phases are weighted by their duration.

The RMSE for scenario S1 and S2 is similar (mean ≈12.3 and median ≈11.1). This also shows that the available weather data has nearly no effect on HR prediction. With an average HR of ≈98.4 bpm over all training sessions, this is equivalent to a relative mean error of ≈12.5%. The third scenario shows an average and median error of ≈8.5 and ≈6.1 which corresponds to a relative mean error of ≈8.6%. The difference between the average and mean error suggests that there are some outlier trainings that have a strong influence on the average error.

Due to the additional predictors in S3, the median error is almost reduced to 50% compared to S2. The main reason for this strong improvement is one dominating predictor: the resting heart rate (see table 1). The overall ranking of this predictor is dominated by its S3 value of ≈41%. This strongly increases the average value where the values are much lower in S4 (≈7.2%) and S5 (≈5.3%). This might be caused by the dependence between resting HR and the average HR of the former phase. The latter seems to be the better predictor.

S3 is also the scenario in which the training load has by far the highest influence (≈5.6%) with a distance of 5% to the next smaller value in S4 (≈0.6%). A plausible explanation for this value might be that training sessions with cardiopulmonary patients are generally conducted at a very low load of ≈35 watt on cycle ergometers. Therefore the leg movement might have a stronger influence on the real training load, than the selected load of the bicycle ergometer.

S4 / S5 are further increasing the precision of the prediction (mean ≈4.7 / ≈4.9, median ≈3.2 / ≈3.5 in table 2) with an average relative error of ≈4.8% / ≈5%. This is mainly caused by time-near HR-based values (average HR of former ≈55.7% and current phase ≈5.6%).

Although more predictors contribute to scenario S5 a higher prediction error is calculated compared to S4, whereas it was vice versa during the model building process (≈1.56 improvement for the mean and ≈0.93 for the median RMSE). This is an indicator for overfitting of the S5 model, which might occur due to the usage of too many explanatory variables.

4 DISCUSSION

The stepwise regression algorithm leads to a local optimum which is not necessarily the global optimum. A stepwise addition of variables decreases the models' RMSE. When using only the RMSE as an indicator for the degree of influence for each individual predictor this has the disadvantage, that a later added predictor may have less influence, because a part of his improvement is already explained by the previously added variable. Thereby the result depends on the order of the steps and could lead to a suboptimal model when applied to highly correlated variables (like systolic and diastolic BP).

Therefore a stepwise regression can never replace expert knowledge. On a statistical level, we want to improve the model by performing a factor analysis that will reduce the number of predictors and provide a better knowledge about their correlation to each other. This might also eliminate the potential overfitting of S5 and enable the transfer to other training modalities.

The accuracy of our model strongly depends on the scenario and the associated data items. The first scenario takes place during the training plan creation and the calculated model shows the highest error. This result might still be good enough to gain an impression about HR development of a common cardiopulmonary patient during training time. We believe that the error of this scenario can be improved by adding further predictors related to the

Table 2: Mean error of the prediction. All values refer to the RMSE of the model in relation to the real HR.

Scenario	Phase 1	Phase 2	Phase 3	Phase 4	Average	Median
S1	11.448	10.267	12.079	12.954	12.254	11.069
S2	11.443	10.267	12.079	12.986	12.260	11.084
S3	5.528	6.514	8.528	9.561	8.498	6.068
S4	4.347	3.636	4.637	6.572	4.733	3.266
S5	4.762	2.940	4.734	5.281	4.906	3.542

patients metabolic response like weight, medication and information about the current training state.

The available weather data only had a minor influence and lowers the precision of the model. This may reflect the fact that weather has no direct influence on the patient when he trains in a tempered environment. However, that does not mean that the direct environment has no influence at all. We want to examine this by the measurement of the conditions inside the training area. Furthermore we are going to examine if the weather indirectly affects the Borg value, another very important value to control the intensity of the rehabilitation training.

The influence of the resting HR at the beginning of a training in S3 leads to a good precision of the model during the training itself. This predictor is probably influenced by many other, hard to measure variables like medical treatment, stress, dehydration and coffee consumption, which might have a strong impact on the metabolic system. This leads to the unexpected observation that the given blood pressure values show only a very small effect on the HR. Blood pressure kinetics are in close relationship to HR, but not to absolute values, due to antihypertensive treatment in most patient's.

The prediction can be used to estimate the patient's physical state on the day of testing and thereby help to define an appropriate training intensity before the training starts.

The phase-wise prediction in S4 during the runtime of the training shows a relative error below 5%. This should be precise enough to robustly detect abnormal HR developments and calculate the optimal load for the next phase. In future we will focus on the analysis of other time dynamic predictors that might increase the model accuracy and also facilitate high refresh rates without the abstract distinction between training phases.

5 CONCLUSIONS

We created a statistical model to predict HR as an important vital parameter for the rehabilitation training of cardiopulmonary patients. We considered demographic data, training plan information, other vital parameters and weather information as potential predictors and classified them into five aim-specific scenarios. The validation of the model revealed that weather and the measured blood pressure have nearly no direct influence on HR. Age and previously measured HR based variables like the resting HR strongly influence the responding HR.

The model exhibits an overall low error of ≈11 bpm in median, when used for the creation of a training schedule (scenario 1). The error is reduced by about 50%, when the model is used for prediction at the beginning of a training session. The error decreases below a significance level when the model is used during a training to predict HR at the beginning of each of the four training phases. This makes it potentially suitable to detect critical situations before they appear.

The precision of the prediction might be improved by additionally including expert knowledge and further statistical methods, but it already serves as a good basis for the integration of HR predictive mechanisms into training related systems and might potentially increase the safety and efficiency during the rehabilitation training of cardiopulmonary patients.

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