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A System for the Model Based Emergency Detection and Communication for the Telerehabilitation Training of Cardiopulmonary Patients

Axel Helmer[1], Friedrich Kretschmer[2], Riana Deparade[3], Bianying Song[4], Markus Meis[5], Andreas Hein[6], Michael Marschollek[4], Uwe Tegtbur[3]

Abstract— **Cardiopulmonary diseases affect millions of people and cause high costs in health care systems worldwide. Patients should perform regular endurance exercises to stabilize their health state and prevent further impairment. However, patients are often uncertain about the level of intensity they should exercise in their current condition.**

The cost of continuous monitoring for these training sessions in clinics is high and additionally requires the patient to travel to a clinic for each single session. Performing the rehabilitation training at home can raise compliance and reduce costs.

To ensure safe telerehabilitation training and to enable patients to control their performance and health state, detection of abnormal events during training is a critical prerequisite. Therefore, we created a model that predicts the heart rate of cardiopulmonary patients and that can be used to detect and avoid abnormal health states.

To enable external feedback and an immediate reaction in case of a critical situation, the patient should have the possibility to configure the system to communicate warnings and emergency events to clinical and non-clinical actors. To fulfill this task, we coupled a personal health record (PHR) with a new component that extends the classic home emergency systems. The PHR is also used for a training schedule definition that makes use of the predictive HR model.

We used statistical methods to evaluate the prediction model and found that our prediction error of 3.2 heart beats per minute is precise enough to enable a detection of critical states. The concept for the communication of alerts was evaluated through focus group interviews with domain experts who judged that it fulfills the needs of potential users.

I. INTRODUCTION

Cardiovascular and pulmonary diseases are the major causes of death worldwide. The Word Health Organization estimated that the only the Chronic Obstructive Pulmonary Disease (COPD), which is a pulmonary disease that is often associated with other cardiovascular diseases, affects 210 million people worldwide [1]. The indirect costs for the treatment were estimated at 49.5 billion Dollars, only in the USA [2].

[1]Axel Helmer is with the OFFIS-Institute for Information Technology, Escherweg 2, 26121 Oldenburg, Germany. Corresponding author phone: +49-441-9722-293; e-mail: axel.helmer@offis.de

[2]Computational Neuroscience, University of Oldenburg, Carl-von-Ossietzky-Straße 9-11, 26129 Oldenburg, Germany

[3]Institute of Sports Medicine, Medical School Hannover, Carl-Neuberg-Str. 1, 30625 Hannover, Germany

[4]Peter L. Reichertz Institute of Technology, Carl-Neuberg-Str. 1, 30625 Hannover, Germany

[5]Hoerzentrum Oldenburg, Marie-Curie-Strae 2, 26129 Oldenburg

[6]OFFIS-Institute for Information Technology, Escherweg 2, 26121 Oldenburg, Germany

COPD causes an inflammation of the lung tissue that slowly reduces the patient's ability to breath. As a consequence affected patients reduce their physical activity, which causes a degeneration of the muscle mass and worsens the symptoms. This cyclic reinforcement of symptoms has a severe negative impact on the patient's health state.

Studies show that pulmonary rehabilitation training improves physical capacity, reduces breathlessness, reduces the number of hospitalizations and increases the quality of life [3]. Typically, training takes place when the patient has recovered after having had an incident that led to hospitalization. The rehabilitation training is monitored by physicians, who design individualized training schedules and adapt the training load manually when it is considered too high or too low for the patient.

After the patient has been discharged, the training should be continued at home, but COPD-patients live with the constant fear of getting a respiratory crisis and are thus unsure how much training load they can undergo. As a consequence they often train at a suboptimal level that is too low in intensity.

Telerehabilitation systems like the OSAMI-System [4] trying to close the gap by providing a telesupervised training that is remotely monitored. Vital signs are recorded and streamed to a computer where they can be evaluated by physicians. A drawback of this approach is that a physician has to be present for the whole time period of the training session and an internet connection must be available. This weakness is compensated by offline training modes using autonomous training control algorithms (e.g. [5]).

Heart rate (HR) is an important vital parameter and thereby an important indicator of a patient's physical state [5]. Different variables influence the patients HR during training. Considering these factors can be of major use for physicians and automated systems when deciding how much load a patient can undergo during a training session. The information could also be used to support the creation and optimization of training schedules and during the current training session itself to derive the future development of the patient's health state [6]. Deviances from the predicted trend during a normal training session may also give a hint on potentially abnormal development and hence allow detection of critical states before they occur. This may also lower the patient's fear of getting in an unstable health state.

After a potential negative trend was detected the patient and/or external users have to be informed. Classic home emergency systems, which are often used by elderly people, are not suitable for the communication of events, which were generated by autonomous systems. Typically, classic alert communication systems have two different states: “alarm” and “not-alarm”. These two states are not adequate to differentiate between warnings and critical situations. Also, they cannot include any supplementary information like the reason that lead to an emergency. False alerts cannot be avoided when relying on autonomous systems. Hence, such systems should only contact an official emergency department when a situation is detected that requires immediate action. In most cases it is more appropriate to involve a notification of other people as neighbors or nearby living relatives. Only if none of these actors responds, the responsible emergency department should be involved. Classic emergency communication systems are not flexible enough to reflect such an emergency chain, which depends on the detected situation.

The aim of our research is to improve the patient’s safety during rehabilitation training. The alert detection that works on the basis of our prediction model is not in the focus of this paper, but we planning to use an extended version of a former published system that uses expert knowledge to control the training intensity and to raise alarms [5].

We created and integrated a model that predicts the patients HR in training situations on basis of a given training schedule, demographic information about the patient and weather data. This information is stored in a Personal Health Record (PHR) and can be shared with physicians by the empowered patient. Training results can thus be evaluated and a continuous and time-independent adoption of the training schedule is possible. If an alarm is detected during training, the system manages the communication of warnings and alerts to the patient, relatives, and professionals who are participating in the treatment.

II. RELATED WORK

Achten and Jeukendrup identified age, gender, environmental temperature, hydration, altitude and anti hypertensive medication such as beta blockers [7] as important influence factors for the training HR [8]. For an effective and safe training it is not only important to know the optimal and maximum HR at which a patient should train, but also how HR will develop over time to predict and prevent critical states and to plan an optimal training schedule taking into account as many of the influencing variables as possible. For this purpose several models have been developed. Velikic et al. compared Kalman filters to linear and non-linear models for the prediction of HR of patients with congestive heart failure (see [9]). They used a pedometer to measure the subject’s activity and found that linear models delivered the best results for a short term prediction. Their work also shows that physical activity in everyday life has an influence on HR. Other approaches modeled the HR response to provide a better training control [10], [11], [12]. Neither have these models been checked for their applicability on cardiopulmonary patients nor do specialized HR models exist for these patients.

Most commercially available emergency systems[1] are based on similar functional principles. The user can operate a mechanical button, which activates the alarm and uses the land line telephone of the user to dial a predefined number, which belongs to a service center and/or caregiver. After the call was accepted by a service employee the verification of the alarms takes place by direct communication with the patient through a connected microphone and speaker. Other systems use an opt-out approach, where the user has to press a button inside a predefined time schedule to avoid an automated raise of the alarm.

We conducted a survey of 48 existing third-party PHRs in [13]. Some of these products enable the user to enter emergency contacts, but none of them combines this functionality with a communication system for alerts that uses other channels such as email.

III. METHODS

A. Heart Rate Model Creation

Our Data were recorded during the outpatient rehabilitation from cardiopulmonary patients with NYHA 1-2 and COPD level 2-3 (see [14]). The datasets were collected during training sessions performed from July to September 2009 in the exercise training center of the Medical School Hannover and include the following information:

- 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 with systolic and diastolic values), Borg value [15], HR during the whole training derived from Electrocardiogram (ECG) data

Because weather can influence the training, we also included data from the German weather service, which were recorded by a weather station in Hannover (station ID: 2014) and included temperature, air pressure, and humidity.

After filtering of implausible data, we had 668 (325 F, 343 M) training sessions left from 115 patients (in mean 5.8 ± 4.5 trainings per patient). We built the model using a stepwise regression analysis [16]. This statistical method performs a multivariate regression to determine a (local optimal) model that includes all relevant predictors from a given set of variables. We used this method to create 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 fig. 1).

To determine the quality of the overall model 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

[1]E.g. http://www.rescuealert.com/

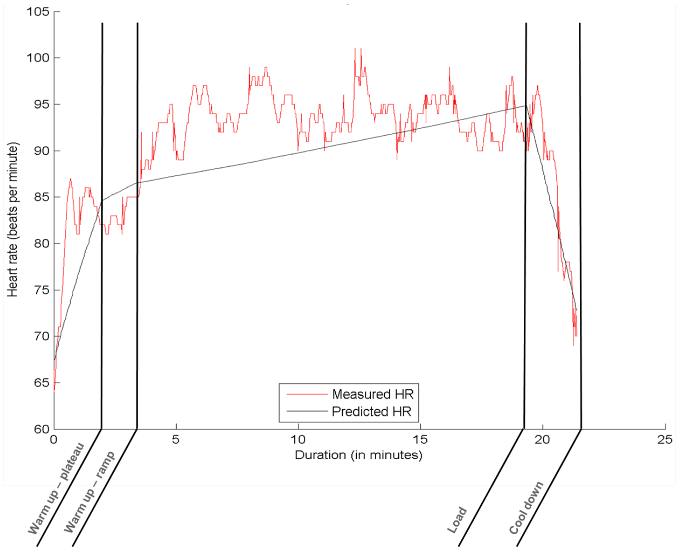

Fig. 1: Training session with curves for the measured HR and HR that was predicted by the four linear models.

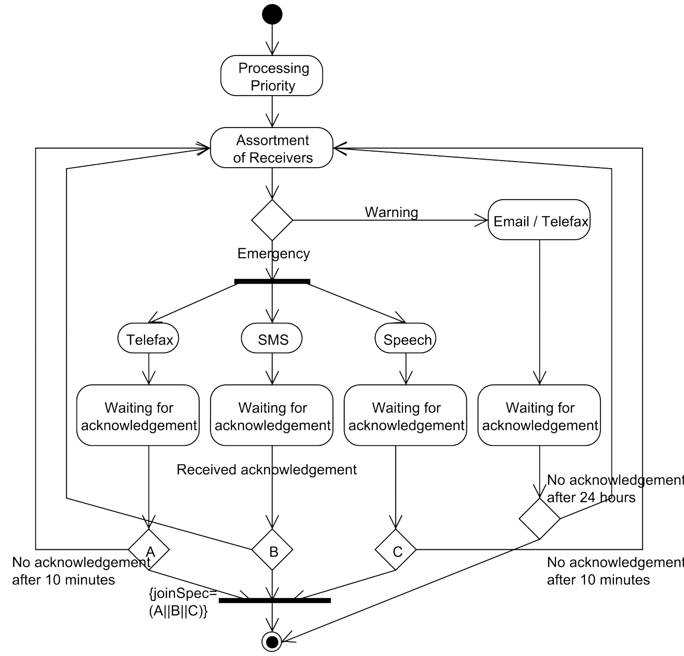

Fig. 2: Behavior of the alert communication system to process escalation chains in UML action diagram notation.

procedure vice versa. The error was quantified by root mean square error (RMSE) which represents the deviation between measured and predicted HR over a whole training.

B. Alert Communication System

The alert communication system distinguishes between two levels of alert: Warnings and emergencies. Warnings depict in situations where an event was detected that potentially affects the patient's health state in a negative way. Hints for an upcoming medical problem might include a continuous decrease of performance during a single rehabilitation training or a continuous increase of the average HR during a series of training sessions. Emergencies depict situations where immediate medical attention could be necessary. For example if the patient suffers a heart attack or a breathing crisis during training.

To contact different actors, related to the cardiopulmonary patient, the alert communication system extends the concept of classic emergency chains. The system attempts to establish a connection with one or more participants, who need to acknowledge the receipt of a message. To provide a reliable communication that fulfills the needs of this heterogeneous group of actors, it combines different physical communication channels with different communication media.

Beside the preferably low acquisition costs, the potential criticality requires a very high availability. To meet these challenges our system combines different widely available communication channels. The first prototype was developed for the usage in Germany and uses the standard ISDN (Integrated Service Digital Network[2]), which is mainly used in Germany, UK, Austria and Canada. The system can also use the standard GSM / UMTS mobile network (see [17]). The hardware as well as the functionality for accessing and switching between these networks is integrated in many current internet routers.

Both communication channels permit to transmit data to the internet as well as speech to other landline or mobile phones. The system currently supports transmission of speech via ISDN or GMS standard. Short Message Service (SMS) data can be transferred via internet and telefax data via ISDN. The connection details of possible communication participants can be defined by the patient himself in his PHR and are stored in an XML-data format (see fig. 4). The system receives the alert priority that is defined through the predictive model and an (yet unimplemented) error detection component and chooses the list of contacts either for warnings or emergencies (see fig. 2) accordingly.

If the message to be delivered is an emergency, the system uses telefax, SMS and speech as communication media in parallel to inform either one or more persons. The system assigns a priority to each person and starts with the person(s) with the highest assigned priority. After the message was sent the system waits a predefined time (default 10 minutes) for an acknowledgement.

This manual acknowledgement is necessary for two reasons: firstly, to detect that the message could not be delivered e.g. because an answering machine or a different person accepted the call, the storage space for SMS on a mobile phone is full, the telefax has a paper jam or a mail was falsely recognized as spam. Secondly, it could be important for legal reasons to know, which of the contacted persons provided the acknowledgement.

The acknowledgement can be provided either directly while the incoming call is received by entering a unique id (which was previously assigned to the communication

[2] `http://www.itu.int/rec/T-REC-I/e`

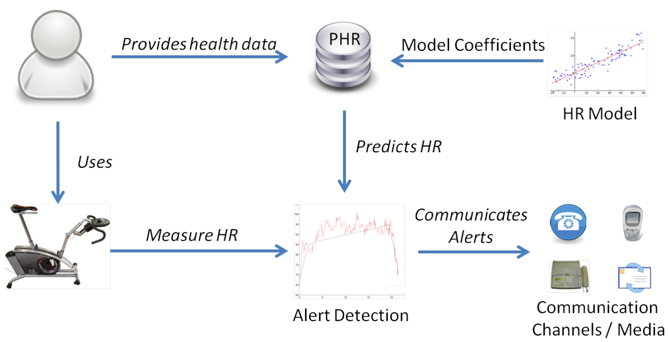

Fig. 3: Components of the model based emergency detection system.

Fig. 4: Screenshots of the PHR: a) Contact details for the alert system, b) Training schedule creation supported by the model for the prediction of the patient's heart rate.

participant) with the push-buttons of the receiving phone. If the person missed the call the id can also be provided through a call back to the phone of the patient, where an announcement is played that requests the id.

The ISDN standard provides two speech channels that can be used simultaneously. The system uses one channel to perform an outgoing call and the other channel to process incoming acknowledgments. When no acknowledgement is received after a predefined time, the system tries to contact the person(s) on the list with the next lower priority. In case that the message is a warning the system uses email and telefax as asynchronous communication channels and a longer waiting period for the acknowledgement (default 24 hours). Emails can also be acknowledged by selection of a link provided in the email.

The system is built on open source components. Incoming and outgoing calls are handled by vBox3[3] as well as the Dual-Tone Multi Frequency Signaling (DTMF) detection. A Jetty webserver[4] handles the email acknowledgments and forwards them to our software. A Fritz! Card (AVM, Berlin, Germany) has been used to provide communication channels and the Common ISDN Application Programming Interface (CAPI) provides support for sending fax messages from within the Linux operating system on which the system runs.

We used a qualitative approach for the evaluation of the alert communication component by conducting a focus group interview with three experts in the field. Two of them are employees of the Johanniter-Unfall-Hilfe e.V.[5] a non-profit organization operating 210 emergency centrals in Germany. One of the experts is the manager of an emergency central, the other one is the technical manager. The third expert has much experience in the sector of home care. The system was introduced to the experts and then discussed under technical and organizational aspects.

C. Technical Integration with the PHR

To substantiate the usefulness of our model we integrated it into a technical prototype for a PHR system, localized in the user's home environment (see fig. 3). An empowered user can enter and manage his own medical data and hence take an active role in the treatment process. The system stores and delivers health-related data for the telerehabilitation training and also provides standardized communication with professional IT-systems utilizing the IHE integration profiles Exchange of Personal Health Record Content (XPHR) [18] and Cross-enterprise Document Media Interchange (XDM [19]).

Platform components running inside an OSGi framework (see [20]). Beside component based development, the framework also provides standardized services including continuous remote updates of services during runtime by means of the initial provisioning specification. The model for the prediction of HR is expressed as a set of coefficients for each training phase in form of XML-files. The PHR uses these model data together with values, which were entered by the patient (e.g. age) and physicians (e.g. training load) to complete the linear combinations predicting HR during a training session.

IV. RESULTS

We started the integration of the HR prediction model with the training plan creation. Fig. 4 shows the creation of a training plan with usage of the model and the mask for the definition of contact details, which can be used by the system for alert communication. The blue line indicates the predicted HR for the patient. Values are changing on the fly, when the physician changes the load value or the training duration, or when the patient changes data relevant for the prediction in the PHR. The cross validation showed that our model is able to predict HR of cardiopulmonary patients during the training with a median error of 3.2 heart beats per minute.

We discussed with the experts in the focus group interview,

[3] http://www.malte-wetz.de/index.php?viewPage=vbox.html

[4] http://www.eclipse.org/jetty/

[5] http://www.johanniter.de/die-johanniter/johanniter-unfall-hilfe/

which persons should be informed by the alert communication system. They pointed out that this is a non-trivial task, because different factors like daytime and the type of emergency influencing the decision, which persons or institutions should be alerted. In every situation informing an emergency central would be of importance even although it is sometimes hard for the operators to decide if an incoming emergency demands an immediate reaction or not. Criteria are hard to define, because they are depending on the individual estimation of a patient's health state. The experts appreciate the inclusion of health information (e.g. the latest ECG data) in transmitted alert messages and stated that this would improve the estimation of a situations priority.

The experts also discussed the error-proneness of the communication channels intensively. They pointed out that most of the current available solutions using one communication channel (the landline). They judged the proposed concept of combining different communication channels as very robust.

V. Discussion and Conclusion

Our current HR model can still be improved in several aspects. First of all the predictors were limited to the data available for the study. Due to this limitation, e. g. medication could not be taken into account. Several other predictors will be examined and integrated as soon as further data becomes available. We hope to increase the precision of our model in this environment, as more predictors like e. g. blood pressure during the training are available.

Beside these improvements we think that the prediction during the training plan creation is already precise enough to give patients and physicians an impression about the normal development of HR and support them to define an appropriate training plan. The median error of 3.2 beats per minute is precise enough to work as a reliable reference for a system that detects critical health states during the training.

The concept of the alert communication component convinced experts and was rated as a suitable way to perform this task in a domestic environment. Mainly, the experts saw three main advantages compared with classical home emergency communication systems: firstly, the improvement of the robustness through the usage of multiple communication channels, secondly the compatibility with future alert detection systems and thirdly the inclusion of further information that allows human operators to make better decisions.

In our future work, we will integrate the PHR with its HR prediction model and the alert communication system with the OSAMI tele-rehabilitation system. The components will be used for training schedule planning and supervision of patients by using the alert detection and communication during training sessions.

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