Informatics for Health & Social Care
September–December 2010; 35(3–4): 144–156

informa
healthcare

Supporting rehabilitation training of COPD patients through multivariate sensor-based monitoring and autonomous control using a Bayesian network: prototype and results of a feasibility study

MAREIKE SCHULZE[1], BIANYING SONG[1], MATTHIAS GIETZELT[1], KLAUS-HENDRIK WOLF[1], RIANA KAYSER[2], UWE TEGTBUR[2] & MICHAEL MARSCHOLLEK[1]

[1]*Peter L. Reichertz Institute for Medical Informatics, University of Braunschweig - Institute of Technology and Hannover Medical School, Mühlenpfordtstr. 23, D-38106 Braunschweig and Carl-Neuberg-Str. 1, Hannover, Germany and* [2]*Medical School Hannover, Institute of Sports Medicine, Carl-Neuberg-Strasse 1, Hannover, Germany*

Abstract
Repeated endurance training – supervised by an expert – is one of the most effective rehabilitation methods for patients with chronic obstructive pulmonary disease (COPD) to improve physical function. Monitoring of vital signs in combination with an automatic intelligent training control and emergency detection facilitates supervised training without the physical presence of an expert as well as training optimisation through individualisation. The aim of this study is the development of a suitable analysis and control method for this purpose. Healthy volunteers and patients with COPD were equipped with body sensors during ergometer training to enable measuring their vital signs continuously. Depending on these values, the exercise load of the ergometer was controlled automatically using a Bayesian network. The network, trained with expert knowledge and training data, is embedded in our system by using Java application programming interface. Extensive tests in a laboratory setting have proved safe usage of our prototype. In a case study, evaluation during training sessions with patients with COPD took place. Due to the automatic control the patients' vital signs ranged inside the predefined optimal thresholds for at least 95% of the time. Furthermore, our results suggest an increase of the training efficiency compared with the conventional method (constant exercise load).

Keywords: *COPD, monitoring, training control, decision support system, Bayesian network, health care*

1. Introduction

Chronic obstructive pulmonary disease (COPD) affects a patient's pulmonary system by means of a chronic inflammatory process, thus leading to an airway obstruction in the bronchi which in turn leads to a decreased capability for ventilation and gas exchange. This slowly progressive process ultimately leads to a destruction of healthy lung tissue [1].

Correspondence: Mareike Schulze, Peter L. Reichertz Institute for Medical Informatics, University of Braunschweig – Institute of Technology and Hannover Medical School, Carl-Neuberg-Str. 1, Hannover D-30625, Germany. E-mail: mareike.schulze@plri.de

ISSN 1753-8157 print/ISSN 1753-8165 online
DOI: 10.3109/17538157.2010.528659

COPD is the fourth leading cause of death (and counting) and the fifth leading cause of disability worldwide [2,3]. The global prevalence of COPD is estimated to be 8.5% among the population aged over 40 [4]. Current treatment regimes include medication therapy to reduce the symptoms, but full recovery often stays out of reach. Physical training therapy including endurance exercises is one of the main pillars to moderate COPD effects [5]. The established training method for these patients is endurance training, especially using a bicycle ergometer [6]. Due to the often significantly reduced endurance exercise capacity of patients with COPD, which is sometimes as low as 20 W of power, it becomes essential to control these exercise sessions strictly. If the exercise load is too high, the patients will be quickly exhausted and will stop the session, if it is too low the patient will not benefit optimally from the training. It has been shown that supervision during ergometer practice makes the training more effective compared with unsupervised training [7]. Nevertheless, frequent sessions are indicated (three to five times a week) and, due to limited resources, not all patients with COPD can be trained by a personal expert supervisor [8]. The usage of information and communication technology is an important resource in this field [9]. Continuous sensor-based monitoring to supervise and control physical training may support to optimise this important therapy option, thus alleviating the harmful effects of COPD as one of the most important societal diseases of the future [10].

Our prototype gives an example of how physical training of patients with COPD can be supported by sensor-based monitoring and autonomous control based on a Bayesian network. Telemonitoring and teletraining are indispensible parts of pervasive health already [11], and in view of the future demographic development and its consequences for health care – considering home training and monitoring – autonomous supervision may soon be necessary in rehabilitation care.

2. Objectives

The aims of this study are to examine a new method based on a decision support system that supports physical (here: ergometer) training of patients with COPD in the therapy process and to test its feasibility in clinical practice.

For this purpose, multivariate sensor data have to be monitored and analysed considering existing medical patient data and automatic control of the target load must take place on this basis. It is essential that all decisions made by the system are transparent and understandable for the supervising clinical staff. The prototype developed should furthermore reliably generate alarm signals in order to ask for attention and help in case of need. That is important because applied in clinical practice the developed system should support the clinical staff in supervising the patients. Afterwards, the recorded data should be compatible with the data recorded by the current procedure of medical documentation in clinical routine with respect to the rehabilitation training process.

Subsequently, reliable usage of this prototype should be evaluated in field test. Potentialities for integration into established systems and involvement in clinical processes should be revealed to consider generic feasibility in clinical routine at a later time.

3. Methods

To achieve these aims, we firstly designed the required system architecture using the *Three-Layer Graph-Based Meta Model* (3LGM^2) [12]. It allows modelling the architecture – in terms of functions, entities and relationships – of a health information system on the distinct layers: the domain layer, the logical tool layer and the physical tool layer. The 3LGM^2-method is

widely used in the domain of health information system architecture design and provides an in-depth view of our system.

Our system architecture designed by this model is shown in Figure 1. The physical tool layer describes the hardware (electronic and paper-based) we used. Our software (termed 'CAT-Bayesia'; CAT stands for 'COPD patients' Assistant for physical Training') and data elements are shown in the logical tool layer, and the domain layer on top specifies the tasks fulfilled by our system.

3.1. Preparation

We conducted a literature review to identify similar solutions. A rule-based decision support system for rehabilitation training developed at our institute has been described in detail in [13]. To the authors' knowledge, concerning patients with COPD there are no other articles containing the use of a decision support system in rehabilitation training. With regard to our objective of multivariate online vital signs data analysis, we decided to use Bayesian networks (BNs), primarily because of their ability to deal with uncertain knowledge (medical knowledge often is uncertain knowledge; we cannot know by sure how a treatment will have effect on every single patient) and incomplete data (not every single possible case in medicine is accessible; we are just able to acquire knowledge about cases that have occurred). For this purpose, BNs provide the facility to use the so-called a-priori probabilities for initialisation (probabilities pre-estimated through clinical knowledge) [14] along with

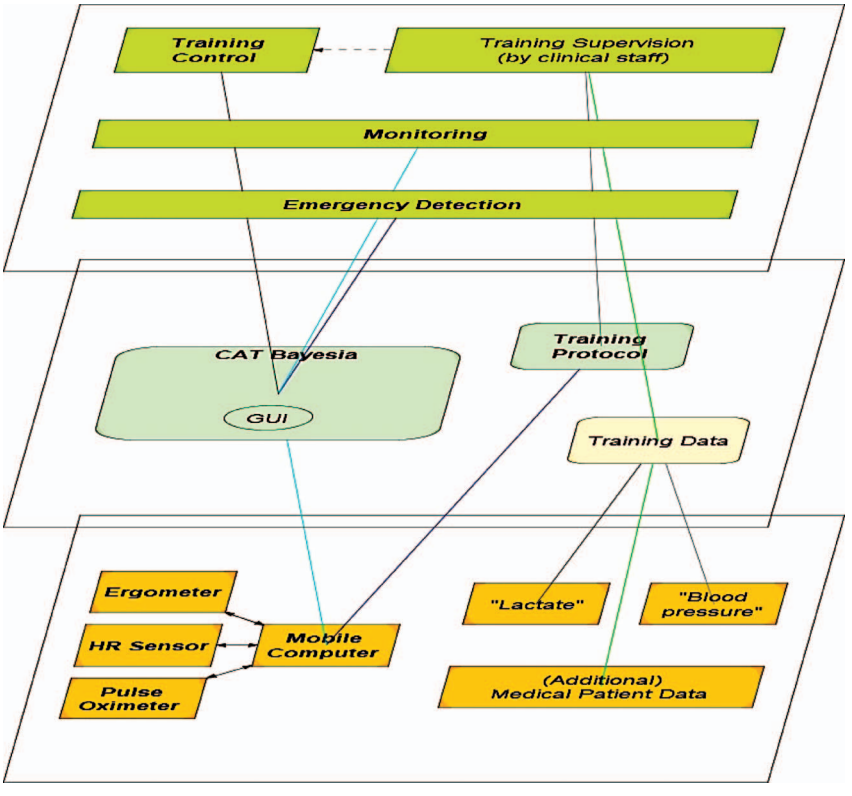

Figure 1. 3LGM^2 Model of our system.

unsupervised learning (probabilities recalculated autonomically by the machine). The demand for a qualitative structure as much as for a high degree of transparency and replicability can also be satisfied in this manner.

In addition to the results of our literature analysis, expert interviews have been conducted to identify relevant rules for ergometer-based exercise training [13]. These rules served as a basis for the construction of our BN. Furthermore, additional expert insights acquired by interviewing clinicians from the Institute of Sports Medicine at Hannover Medical School about their practical knowledge concerning patients with COPD in ergometer training could be used to define the a-priori probabilities of the network.

It should be mentioned that a training schedule appropriate to the level of fitness of every single patient with COPD is derived from a so-called level test and an endurance test. Depending on the maximum heart rate (HRmax) achieved herein, the following training intensities (which are defined for patients with coronary artery disease) also apply for COPD rehabilitation training:

- A: low intensity [65–72% (of HRmax)]
- B: extensive intensity [72–80% (of HRmax)]
- C: intensive intensity [80–86% (of HRmax)]
- D: high intensity [86–97% (of HRmax)]

The level test and endurance test as well as their impacts are described in detail in [15]. During training, the heart rate (and the oxygen saturation as well) should be kept steadily within the target individual thresholds ($x\% - y\%$ of HRmax; $x\% = \text{min\_threshold}$ and $y\% = \text{max\_threshold}$) applying automatic control of the exercise load.

Due to a training effect over time, the maximum heart rate changes. Ascertainable by lactate values and under the influence of the daily condition, the estimation of the optimal heart rate especially requires wide practical experience in training patients with COPD.

Therefore, the consequent optimal maximum heart rate and recommended training intensity along with the oxygen saturation (OS, an important parameter for an assessment of the respiratory function) serve as command variables for the training control. The manipulated variable of the emerging controlling circuit is determined by the exercise load. The underlying controlling circuit is shown in Figure 2.

The training sessions of the patients with COPD within the scope of physical training therapy using ergometer training take 20 min each (shown in Figure 3). Two minutes at the beginning as a so-called *warm-up* with a moderate constant exercise load is followed by a doubling of this load to the recommended training intensity. After another 1 min for

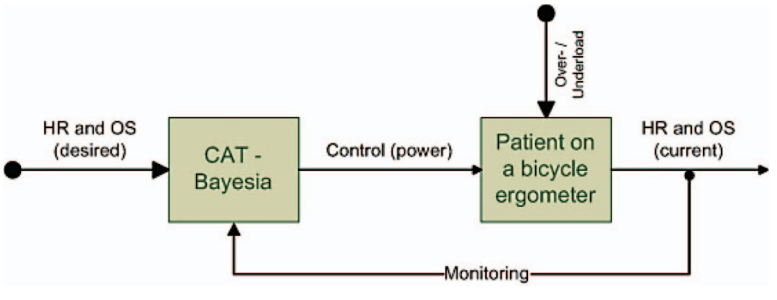

Figure 2. Underlying controlling circuit.

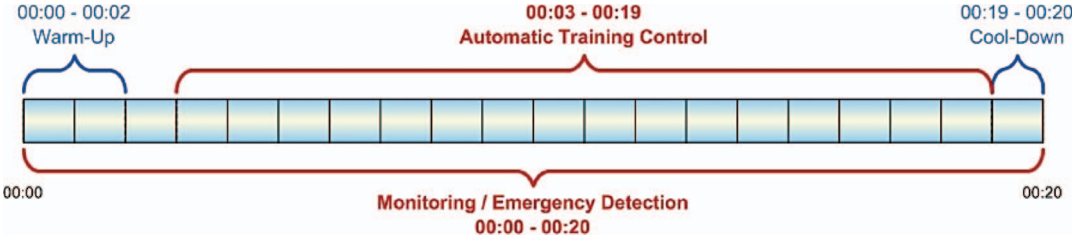

Figure 3. Time table of a training session.

physiologic adaption to the increase the automatic control of the training takes place until the end of the 19th min. A so-called *cool-down* with a halving of the current exercise load helps the patient to come to rest. This time schedule has been defined by clinicians from the Institute of Sports Medicine at the Hannover Medical School and is also applied in their conventional training method.

3.2. Implementation

The system is built upon the following three components, namely *real-time monitoring*, *emergency detection* and *training control*.

To begin with, a BN has to be designed on the basis of expert domain knowledge, and our final model developed with the software tool BayesiaLab© [16] is shown in Figure 4. It considers the recommended vital signs *heart rate* and *oxygen saturation*, measured by non-invasive body-sensors each second.

Our BN consists of seven nodes including five value nodes plus one decision and one utility node. The value nodes coded in green colour (*Pulse_before* and *Pulse_after*) represent the heart rate values at two consecutive points in time; the red-coded value nodes (SaO_2*_before* and SaO_2*_after*) represent the corresponding oxygen saturation. Among these two points in time the automatic control of the exercise load takes place, represented by the blue-coded decision node (*Control Watts/Power*). In order to work out which of the alternatives given is qualified most in every single matter at hand, a utility node is needed. The violet-coded node (*Rating*) in our network gets support from its direct ancestor natural node (*Evaluation*).

The following node states are defined in the particular nodes:

- *Heart rate values (pulse before/after)*: Nine discrete ordinal values depending on the individual maximum heart rate and recommended training intensity (both determined by previous clinical tests and the clinical staff)

1. >10% above max_threshold
2. >05% above max_threshold
3. >max_threshold
4. top quartile of the threshold
5. middle quartiles of threshold
6. bottom quartile of the threshold
7. <min_threshold
8. >05% below min_threshold
9. >10% below min_threshold

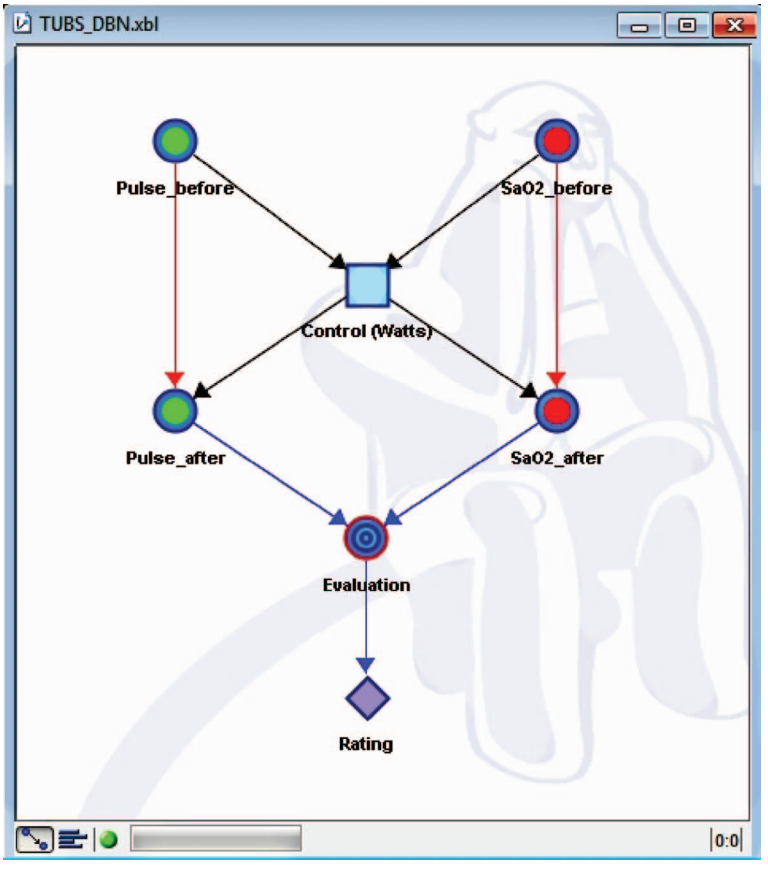

Figure 4. Our Bayesian Network, designed with the software tool *BayesiaLab*.

- Oxygen saturation (SaO_2 before/after): Four discrete ordinal values depending on the individual oxygen saturation at rest (determined before each training session)

1. $>96\%$ of SaO_2 at rest
2. $>94\%$ and $\leq 96\%$ of SaO_2 at rest
3. $>92\%$ and $\leq 94\%$ of SaO_2 at rest
4. $\leq 92\%$ of SaO_2 at rest

- *Control options (control power)*: Increase/decrease of the exercise load (five steps in each case) and no change
- *Evaluation/rating*: Evaluation of the particular alternatives of regulating with the aim to reach the target heart rate and oxygen saturation (on an interval scale, based on the probable outcomes predicted by the BN)

The heart rate and oxygen saturation (at any given time t) are determined by their values directly preceding them (at the time $t - 1$) as well as the control of the exercise load (shortly after $t - 1$). The use of an ordinal scale here instead of an interval scale is based on the resulting amount of potential states in relation to feasibility and efficiency.

Embedded in a Java programme (accomplished by an API called BayesiaEngines© [16]), our developed Bayesian network can be applied to control the exercise load during the rehabilitation training. The graphical user interface (GUI) at runtime of our newly developed programme CAT-Bayesia is shown in Figure 5. By means of this graphic display, our system gives a feedback to the physicians and the accompanying clinical staff about the patients' actual vital signs, the training status and the decisions made by our system.

The GUI comprises the following four components:

- Input parameters: The initial exercise load, maximum exercise load, maximum heart rate, oxygen saturation at rest, recommended training intensity
- Primary display parameters: The timer, exercise load, colour-coded current heart rate, colour-coded current oxygen saturation
- Secondary display parameters: The pedal frequency, short explanation of the regulations occurred, heart rate threshold (favoured heart rate), exercise load on average
- Control options: The following manual interventions; abort training, commence cool-down, set exercise load manually, switch on/off [default is on] automatic control

Due to the input parameters it is possible to adjust the training programme to the individual actual circumstances of particular patients. The primary display parameters act as indicators for automatic control as well as for monitoring vital signs. The secondary display parameters provide transparency with regard to the decisions made and the resultant regulations of the exercise load apart from giving information about the training intensity. The automatic control can be switched off manually (and switched on again) at any time when required and the exercise load can be set manually by physicians. Furthermore, the training session can be aborted at each point in time (either with or without cool-down); the reason will be recorded in the output files. The on-screen display of the programme gets updated every second and the automatic control takes effect every 15 s, thus allowing for an adequate period of time for the patient's physiological parameters to adjust to the changed exercise load.

During training aggregated information is documented in two separate CSV (comma-separated values) files for further interpretation by physicians (e.g. concerning training performance and trends). One of these logs the vital signs every second in association with the

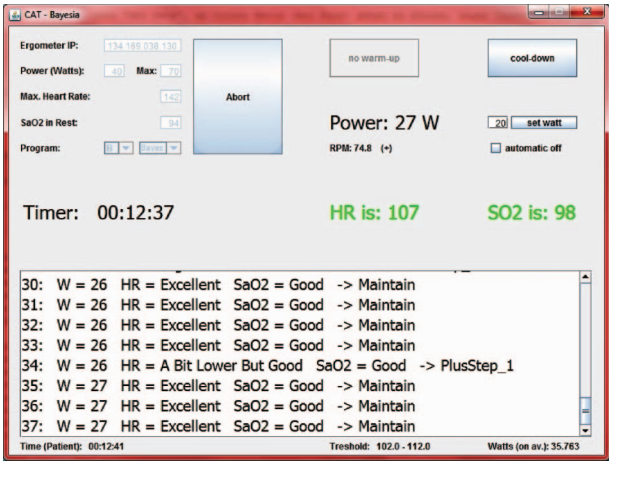

Figure 5. GUI of our software tool.

input parameters and the resultant training parameters. This file is important to trace the vital signs of the patients during training in order to estimate quality of the automatic control. In addition to this, the training schedules can also be adapted based on this information. The second file is updated every 15 s subsequent to the control of the exercise load and records this process for replicability and continuous improvement. All relevant information concerning every single decision making process is stored here. The user interventions done as well as the contemporary status report of the programme are logged further in both files.

To ensure safety for the patients, it is important to handle potential adverse incidents. Our programme perceives – apart from human exhaustion (on the basis of the vital signs considering the input parameters) – a loss of connection to every sensor or the ergometer itself. Furthermore, the cessation of pedalling is detected. In all these cases an acoustic alarm signal is given and, if there is no response within a given time the training will be stopped and the exercise load will be regulated down to the minimum. Nevertheless, the monitoring of the (remaining) vital signs continues for safety reasons. Those alarm signals function predominantly as an advice for the clinical staff because an aborted training must not pass unnoticed and definitely has to be analysed.

3.3. Practice

Our system was developed at the Peter L. Reichertz Institute (PLRI) for Medical Informatics at the University of Braunschweig – Institute of Technology. All relevant data for our feasibility study were collected during regular exercise training of patients with COPD in the Institute of Sports Medicine at Hannover Medical School between August 2009 and November 2009. The voluntary participants among these patients with COPD had to outperform a target initial exercise load of 40 W (doubling from 20 to 40 W after the second training minute) because our ergometer provided (Daum Electronics Premium 8, variable in one-watt steps) was not able to manage a lower exercise load than 20 W.

First of all, proper functioning of our system has been confirmed by numerous test runs with healthy volunteers (students and staff members between 22 and 38 years of either sex) in the laboratory of the PLRI only. The programme was only used on real patients once its efficacy could be pre-estimated using the example of the healthy volunteers, and highest possible safe application could be guaranteed by proving reliable problem handling in practice-oriented laboratory tests. In the next step, members of the target group of patients with COPD were involved in the test process in order to facilitate adaptation of circumstances and to ascertain user acceptance among the patients in practical use. It had to be counter-checked if the challenges presented in the forehand prove themselves in practice. Not only must advances in technology be a key factor in the design and implementation of our system but also the actual needs of the patients (and physicians as well) make significant contributions to the final outcome [17]. Due to the findings gained the intervals for automatic control as well as their intensity could be improved once more. Using at first the a-priori possibilities of the Bayesian network for automatic control, the outcomes provide a basis for unsupervised Bayesian learning. Finally the trained Bayesian network was used in field tests with four COPD patients (only two of them underwent training consistently, so we could merely use their data for evaluation). These two patients are listed in Table I.

For this purposes, the programme was executed on a portable computer (Samsung X65 Pro Bekumar II) connected to the ergometer by a network connection (direct link, TCP/IP protocol). The heart rate has been determined by a chest strap (Suunto Home Training Pack) and the oxygen saturation by a pulse oxymeter (Nonin 4100, data communication via Bluetooth). After each training session, every patient was asked to evaluate training intensity

Table I. The two patients involved in the evaluation of the final prototype version.

	Sex	Age	COPD stage (GOLD)
Patient 1	Male	46	III
Patient 2	Female	65	I

based on the so-called numeric Borg-scale [18]. These data are used to adapt training schedule for the next time. Figure 6 shows one of our test subjects during the field test. All of our volunteers were informed about the backgrounds of our research work and have given their consent. Our work with the patients was supervised at all times by physicians specialised in sports and rehabilitation medicine, who could abort each machine-controlled training session at any time.

3.4. Evaluation methods

To facilitate objective appraisal of our results, the goal criteria had to be defined before practical application. We decided to evaluate based on the following criteria (all of them referring to a training session):

1. Proportion of time the heart rate stayed within the specified threshold
2. Variance and standard deviation of the heart rate
3. Oxygen saturation kinetics
4. Average exercise load (in watt)

Unfortunately, an automatic evaluation of the blood pressure and lactate values with our system is hardly possible because those measurements are performed manually (blood pressure three times a training session and lactate values subsequent to a trainings session).

4. Results

In comparison to the conventional method, a higher workload without overstraining the patients (determined subjective by Borg scale and objective by vital signs) could be achieved. The target heart rate reached once could be held by automatic control for at least 95% of the time within the favoured threshold values (within a range of approximately 10 beats per minute), even though the exercise load was increased. Also, the oxygen saturation stayed always within the target range and never gave reason for concern.

The exercise load of an exemplary volunteer among the patients with COPD during conventional and automatic controlled training (considered except for warm-up and cool-down) is shown in Figure 7. On average, the load was increased from 59.95 W (conventional method) to 86.88 W (automatic control).

The corresponding heart rates to the exercise loads above are shown in Figure 8. Although the heart rate on average during automatic control was increased by approximately 10 beats per minute (from 109.14 to 119.30) compared to the conventional method, the variance (7.58 to 4.55) and standard deviation (2.75 to 2.13) after once reaching the threshold could be decreased. The target heart rate was kept for 99.36% of the time within the favoured thresholds (*here*: from 114 to 125 bpm).

Also, the reliable functionality of the programme with the new method has been shown during all the field tests. We have not encountered any severe problems or failures.

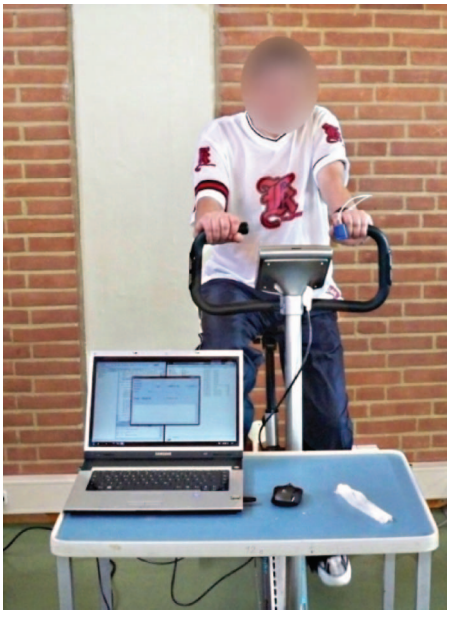

Figure 6. Field test with one of the COPD patients.

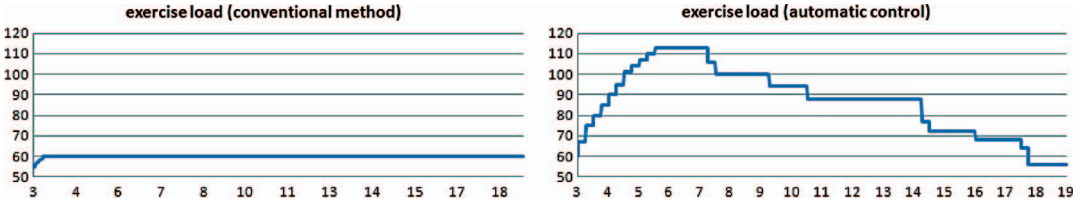

Figure 7. Performance curve (exercise load in watts over time, comparing both methods).

5. Discussion

Our application has fulfilled the requirements of efficient and safe training of patients with COPD. Furthermore, feasibility of our method developed for clinical rehabilitation training could be proved concerning reliable monitoring and automatic control of the exercise load. A training control, taking place every 15 s, is more than a physician (or other clinical staff) can manage during a training session with 20 patients exercising simultaneously.

Due to the linking of our Bayesian network by using Java APIs from *Bayesia*, the network can be updated at any time without touching the Java programme. Compared to the rule-based system, our Bayesian network is adaptive and able to learn from previous training sessions. It must be mentioned here as well that most of the customary ergometer have an automatic training control programme (based on the heart rate only) itself, however those do not meet the particular requirements for clinical practice. Their weak points for the main part are – besides missing safety precautions and inadequate adaptability to the patients' needs – the insufficient accuracy and unavailable expandability concerning additional sensors.

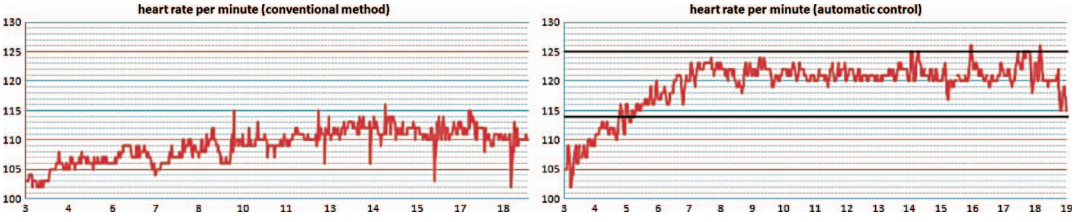

Figure 8. Heart rate curve (in bpm over time, comparing both methods).

In addition, our system has the potential to be enhanced further especially for future connections for measuring blood pressure and lactate values continuously. Nowadays, the sensors for these purposes are still expensive and obtrusive. Even among the sensors applied, we had to come to a compromise between patient's comfort (consequent acceptance) and signal quality [19]. In addition, our experience has shown that the measurement of the oxygen saturation via pulse oxymeter is error-prone. Furthermore, an access to the personal information from the electronic health records could help to personalise the training and to actively integrate every single patient in managing their health problems, thus helping to preserve self-dependence in everyday life [20].

With regard to the limitations of our work presented here, we cannot rule out a certain 'placebo' effect because all participants involved were informed about our approach and thus might have tried harder than usual. Our results, however, are based on the evaluation of objectively measured physiological and power outcome parameters. The implementation of a control group would be an option to preserve against these effects. Up to now, we only have compared control results from the same participants at the same time, within a time frame of a few days, with the conventional training method. Although an improvement of the training effectiveness through the use of a multivariate sensor-based monitoring and autonomous control using a Bayesian network could be noted among our participants, a further – prospective and randomised – controlled evaluation study with more patients has to be conducted.

6. Conclusion and future work

Based on our results, we may conclude that decisions based on a Bayesian network might obtain better results than static rules in this context. Nevertheless, the quality of our prototype in clinical routine still has to be evaluated on the basis of a prospective randomised controlled clinical trial. The next aim is to improve and integrate this method into daily clinical routine. Suggestions for improvement concerning the input values are for example to use the average over several samples to make the algorithm more robust and to show the real-time graphs in the GUI. Although decision support systems have a long tradition in isolated systems, integration into clinical information systems is still a challenge [21]. For this purpose, it has to be embedded in existing training monitoring software (in a setting as shown in Figure 9). This is the next step we will work on after conducting the above-mentioned clinical study. This integration contributes the long-term objective of a cooperative infrastructure of healthcare systems [22]. In general, the comprehensive pervasive healthcare approach evolves into a decentralised assistive approach with patient-centric continuous monitoring and sensors (reliable and wearable), which can also be used by non-professionals [23]. Embedded in a so-called smart home – defined by Demiris [24] as 'a residence equipped with technology that facilitates

Figure 9. Clinical training setting, Medical School Hannover, Institute of Sports Medicine.

monitoring of residents aiming to improve quality of life and promote independence' – our system could become a part of the residential infrastructure.

To look ahead the desired long-term objective will be the autonomous home-centred implementation (with clinical support).

Acknowledgements

We express our gratitude to the company *Bayesia* (http://www.bayesia.com) for their generous support regarding their modelling software '*BayesiaLab*' and application programme interface '*Bayesia Engines*', both of which have been made available for our research project. The work has been performed as part of the German Lower Saxony Research Network 'Design of Environments for Ageing' (www.altersgerechte-lebenswelten.de), which is supported by the Lower Saxony Ministry of Science and Culture through the 'Niedersächsisches Vorab' grant programme (VWZN 2420). Ethical approval for the clinical study was obtained from the ethics commission at Hannover Medical School.

Declaration of interest: The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

References

1. Fauci AS, Kasper DL, Longo DL, Braunwald E, Hauser SL, Jameson JL, Loscalzo J, editors. Harrison's principles of internal medicine. 17th ed. Mcgraw-Hill Professional; 2008. pp 1635–1642.
2. World Health Organisation. World Health Statistics 2008. WHO Press: Switzerland; 2008.
3. Murray CJL, Lopez AD. The global burden of disease: a comprehensive assessment of mortality and disability from diseases, injuries, and risk factors in 1990 and projected to 2020. Harvard University Press: Cambridge; 1996.

4. Fukuchi Y, Nishimura M, Ichinose M. COPD in Japan: the Nippon epidemiology study. Respirology 2004;9:458–465.
5. Chavannes N, Vollenberg JJH, van Schayck CP, Wouters EFM. Effects on physical activity in mild to moderate COPD: a systematic review. British Journal of General Practice 2002;52:532–534.
6. Murray JA, Waterman LA, Ward J, Baird JC, Mahler DA. Perceptual and physiological responses during treadmill and cycle exercise in patients with COPD. Chest 2009;135:384–390.
7. Janos V, Janos P, Krisztina B, Richard C, Attila S. Supervised high intensity continuous and interval training vs. self-paced training in COPD. Respiratory Medicine 2007;101:2297–2304.
8. Worth H, Meyer A, Folgering H, Kirsten D, Lecheler J, Magnussen H, Pleyer K, Schmidt S, Schmitz M, Taube K, Wettengel R. Empfehlungen der Deutschen Atemwegsliga zum Sport und körperlichen Training bei Patienten mit obstruktiven Atemwegserkrankungen. [Recommendations of t he German Airway League on sport and physical training in patients with obstructive airway diseases]. Pneumologie 2000;54:61–67.
9. Winter A. The future of medical informatics – some perspectives of intra- and inter-institutional information systems. Methods of Informative Medicine 2009;48:62–65.
10. Marschollek M, Wolf KH, Bott OJ, Howe J, Haux R. Predictions for epidemiologic indicators of age-related diseases and implications for the development of health-enabling technologies. In: Mühlhäuser MFA, Aitenbichler E, editors. Constructing Ambient Intelligence: AmI-07 Workshops Proceedings. Darmstadt: Springer; Communications in Computer and Information Science 2008;2:253–260.
11. Haux R, Howe J, Marschollek M, Plischke M, Wolf KH. Health-enabling technologies for pervasive health care: on services and ICT architecture paradigms. Informatics for Health and Social Care 2008;33:77–89.
12. Winter A, Brigl B, Wendt T. Modeling hospital information systems. I. The revised three-layer graph-based meta model 3LGM2. Methods of Informative Medicien 2003;42:544–551.
13. Song B, Wolf KH, Gietzelt M, Al Scharaa O, Tegtbur U, Haux R, Marschollek M. Decision support for teletraining of COPD patients. Methods of Informative Medicine 2010;49:96–102.
14. Basler H. Grundbegriffe der Wahrscheinlichkeitsrechnung und statistischen Methodenlehre. 11th ed. Physica Verlag Heidelberg; 2000.
15. Tegtbur U, Meyer H, Busse MW. Belastungsdiagnostische Kenngrößen und Katecholamie bei Koronarpatienten. [Stress diagnostic characteristics and catecholamines in coronary artery disease patients]. Zeitschrift für Kardiologie 2002;91:927–936.
16. Jouffe L, Munteanu P. Bayesia [Internet]. Laval: France. Available from: http://www.bayesia.com/ (accessed 9 August 2010).
17. Demiris G, Hensel BK. Technologies for an aging society: a systematic review of ''smart home'' applications. Yearb Medical Informatics 2008;3:33–40.
18. Borg G. Perceived Exertion as an indicator of somatic stress. Scandinavian Journal of Rehabilitation in Medicine 1970;2:92–98.
19. Arnrich B, Mayora O, Bardram J, Tröster G. Pervasive healthcare. Paving the way for a pervasive, user-centered and preventive healthcare model. Methods of Informative Medicine 2010;49:67–73.
20. Koch S, Marschollek M, Wolf KH, Plischke M, Haux R. On health-enabling and ambient-assistive technologies. Methods of Informative Medicine 2009;48:29–37.
21. Pfeiffer KP. Future development of medical informatics from the viewpoint of health telematics. Methods of Informative Medicine 2009;48:55–61.
22. Saranummi N, Wactlar H. Pervasive healthcare, editorial. Methods of Informative Medicine 2008;47:175–177.
23. Bardram JE. Pervasive healthcare as a scientific discipline. Methods of Informative Medicine 2008;47:178–185.
24. Demiris G. Smart homes and ambient assisted living in an aging society – new opportunities and challenges for biomedical informatics, editorial. Methods of Informative Medicine 2008;47:56–57.