Inclusion of Data from the Domestic Domain in the Process of Clinical Decision Making using the Example of a Comprehensive Ambient Energy Expenditure Determination for COPD Patients

Axel Helmer, Frerk Müller, Okko Lohmann, Andreas Thiel, Marco Eichelberg and Andreas Hein
R&D Division Health, OFFIS Institute for Information Technology, Escherweg 2, D-26121 Oldenburg, Germany

Keywords: Telemedicine, Physiological Modelling, Knowledge Management, Electronic Health Records.

Abstract: Patients suffering from COPD benefit from the performance of any kind of physical activity. The 3D layer context (3DLC) model characterizes data from different domains in relation to their relevance for the clinical decision making process. We have used this model to show how data from an ambient activity system in the domestic environment can be used to provide better diagnoses and prognoses for COPD patients. As a proof of concept an experiment has been conducted to provide an individual intensity relation between household activities and telerehabilitation training on a bicycle ergometer. We have extracted features from the power data of the activities ironing and vacuuming to calculate the energy expenditure for the performance of these activities.

1 INTRODUCTION

1.1 Background

Chronic Obstructive Pulmonary Disease (COPD) is a collective term for different diseases affecting the respiratory system. The World Health Organization estimates that COPD affects 210 million people worldwide (Bousquet and Khaltaev, 2007). The illness is the third leading cause of death in the United States, where the yearly direct / indirect costs are estimated with 29.9 / 49.5 billion USD.

National and international clinical guidelines, which summarize large randomized controlled trials (RCT), show that the performance of rehabilitation training with relative high intensity provides many benefits for COPD patients e.g. an improved exercise tolerance, less exacerbations and an improvement in the quality of life (Abholz et al., 2010), (Rodriguez-Roisin and Vestbo, 2011). Typically, a patient will begin the rehabilitation after he/she had an exacerbation, which often leads to a stationary hospital stay. After the patient has been stabilized, a number of clinical assessments such as a physical exercise tolerance test will be performed to determine the individual functional capacity. This data is the basis for the medical staff to create a training schedule, which is then used to perform a supervised ambulatory or inpatient training in a rehabilitation clinic.

The current versions of the relevant clinical guidelines emphasize that the training has to be continued at home to preserve the positive effects of the clinical rehabilitation. Several systems were developed to implement a supervised or automatically controlled COPD related telerehabilitation training at home (Busch et al., 2009); (Lipprandt et al., 2009).

The goal of the clinical or home-based rehabilitation training is that the patient performs a specific amount of physical activity over time. This amount is defined by frequency, duration, and intensity of performed activities and can be measured as energy expenditure. However, the rehabilitation training with its high intensity is only one specific activity of many that a patient will perform in his/her everyday life. Studies show that also activities with moderate intensity like walking or household activities are able to preserve the benefits that were reached during the clinical rehabilitation (Grams et al., 2011). This data could also be relevant for follow-up examinations. For example, a trend that shows a reduction in the performance of physical activity could indicate that the health state of a patient becomes worse. This could be a hint towards an upcoming exacerbation or

Helmer A., Müller F., Lohmann O., Thiel A., Eichelberg M. and Hein A..
Inclusion of Data from the Domestic Domain in the Process of Clinical Decision Making using the Example of a Comprehensive Ambient Energy Expenditure Determination for COPD Patients.
DOI: 10.5220/0004223800420051
In *Proceedings of the International Conference on Health Informatics* (HEALTHINF-2013), pages 42-51
ISBN: 978-989-8565-37-2

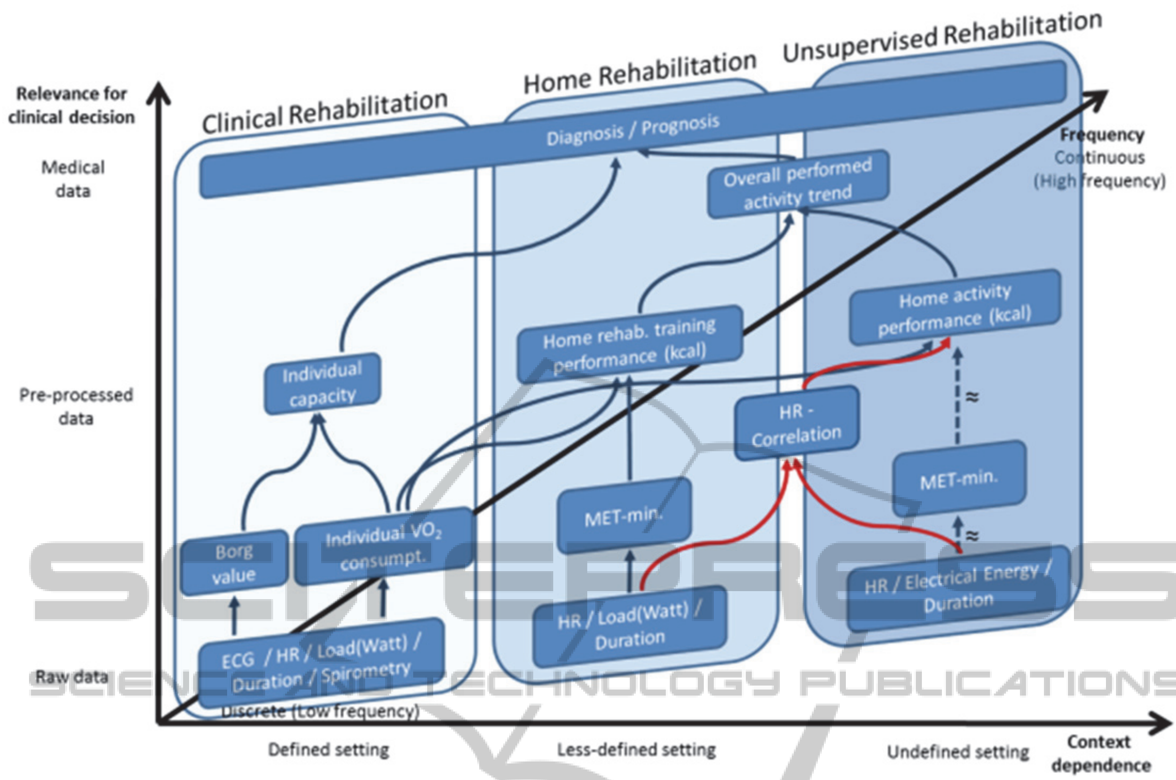

Figure 1: The three dimensional layer context (3DLC) model.

indicate the need of a medication change.

The detection of household activities for COPD patients is a good example that shows how data from the domestic domain can be used by clinicians to derive more informed and potentially better diagnoses or prognoses. One general problem that prevents the usage of this information is the difficulty to decide which of this collectable information is of real relevance to the clinical decision making process.

The currently increasing number of assistive systems at home and approaches to connect user-centered IT systems like Personal Health Records (PHRs) with professional Electronic Health Records (EHRs) reinforces the need for a structured approach to clarify this question.

1.2 Related Work

The professional and the domestic domain have been strictly separated in the past when it comes to data sharing. Little research has been done concerning the combination of data from both domains. Most of the work concentrates on the clinical decision making process and data quality in the professional environment e. g. for clinical trials, but does not regard measurements that were obtained by the patient him/herself (Pauker and Kassirer, 1980); (Kuperman et al., 2007),; (Williams, 2006); (Carson et al., 1998). Electronic and Personal Health Records are IT systems where the professional and the domestic domains meet. Häyrinen et al. have conducted a systematic review on the definition, structure, content use and impact of EHRs. They state that further studies on the EHR content are needed; especially on patient self-documentation (Haeyrinen et al., 2008). Tang et al. discussed the dependence of patient generated PHR content and clinical decision making in (Tang et al., 2006). They recognized the problem and put it in a nutshell as follows:

> "*The reliability of patient-entered data depends on the nature of the information per se, the patient's general and health literacy, and the specific motivations for recording the data.*"

However, the nature of patient-entered data and the relation to clinical decision making were not further characterized.

The field of activity detection can be divided into approaches based on body-worn sensors like accelerometers or heart rate sensors and ambient sensors like cameras or motion sensors. Activity detection with body-worn sensors is well

Figure 2: Training modalities: a) ironing, b) vacuuming, c) telerehabilitation ergometer training and system components: d) mobile vital parameter recording, e) monitoring and training control, f) ergometer training view.

researched; commercial products are available, used in many studies and showing satisfying results (Mattila et al., 2009), (Chen et al., 2008), (Bauldoff et al., 2007). However, obvious problems with these sensors are that patients constantly have to wear an electrical device, remember to put it on and to charge the batteries (Scanaill et al., 2006). Systems for activity detection with ambient sensors are currently under research in the field of ambient intelligence. They use statically installed motion sensors (Barger et al., 2005), (Virone et al., 2002); (Virone et al., 2008), microphones (Chen et al., 2005), light sensors (Monekosso and Remagnino, 2007), and cameras. The main disadvantage for most of these systems is that they can be intrusive and depend on a lot of sensors that have to be installed in the user's environment. This probably leads to acceptance problems and high installation costs. Frenken et al. introduced a system that detects activities of daily living (Frenken et al., 2010). They use one single sensor that measures the power consumption of electrical devices that are used during these activities.

None of the mentioned ambient systems is able to derive the intensity or the energy expenditure of the performed activities.

1.3 Aim and Scope

The combination of clinical data with patient obtained information from the domestic environment is a general but well-known problem for clinicians. The emerging use of new health-related systems in patient's homes adds a new technical dimension to this problem. This complicates the decision making process, but also holds the potential to make more informed and better decisions.

The aim of this work is to show how new assistive systems can be included in the practice of medical decision making. We applied our prior developed three dimensional layer context (3DLC) model to the data of the COPD rehabilitation process. The model gives a structured approach for the combination of clinical and domestic data. As a proof of concept we combined data from home based telerehabilitation trainings for COPD patients with an activity detection system based on the power consumption of electrical devices. We used this detection system in an experiment to develop a comprehensive method to estimate the energy expenditure for household activities.

2 METHODS

2.1 Three Dimensional Layer Context Model (3DLC)

The 3DLC model was first published in (Helmer et

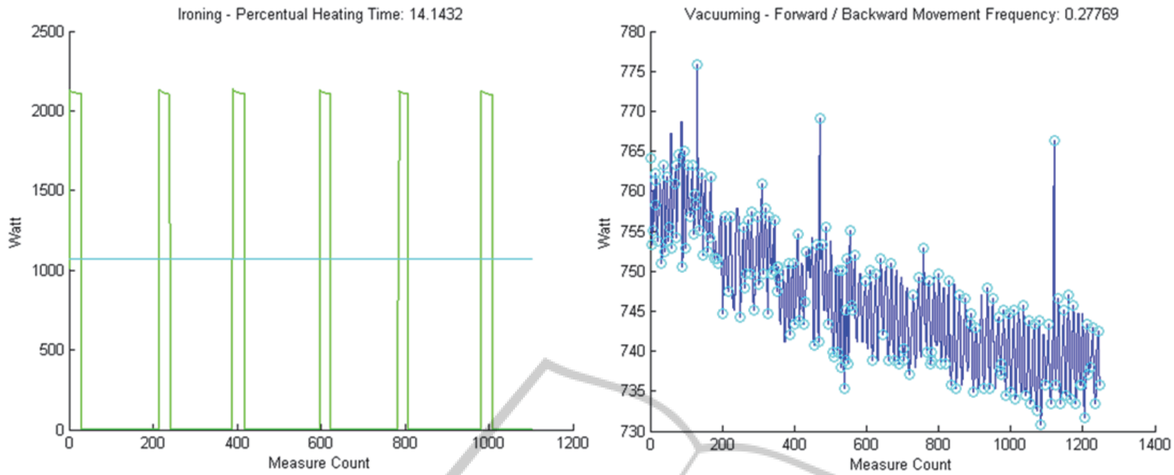

Figure 3: Intensity feature extraction (cyan) from the power curve of an iron (left) and a vacuum cleaner (right).

al., 2011). It distinguishes among three continuous dimensions (*frequency, context dependence*, and *relevance to clinical decision making*) to characterize data from different domains (see Figure 1). These three dimensions will be described in more detailed in the following paragraphs.

The *context dependence* dimension reflects the influence of the environment on the data acquisition. A laboratory is used to minimize or stabilize influences of the environment that could have a possible impact on the acquired data. Such a very well-understood and controlled setting is termed a *defined setting* in the *context dependence* dimension of the 3DLC. If a normalized clinical test / protocol is performed outside of a laboratory then this is termed a *less-defined setting*. The rest of our everyday activity, which is possibly performed without the intention of capturing medical data, is termed a *undefined setting* in 3DLC.

Frequency reflects the occurrence in which one test or dataset is being performed or received. A higher (ideally: *continuous*) frequency is desirable in most situations, to gain a more fine-grained picture of the observed item. However, many tests in the medical domain (e. g. x-ray) can only be performed punctually (*discrete*).

Relevance to clinical decision making separates the abstraction and importance of data into three layers. The most valuable data to make decisions in the medical domain e. g. for diagnoses is other medical facts in form of *clinical knowledge*. When this knowledge is not sufficient to make a diagnosis the clinician has to perform further tests and is normally interested in the results in form of a trend or some other kind of *pre-processed data*. This information is based on *raw data* that often represents a physical measurement and is typically not directly relevant for the decision making process.

2.2 Experiment Design

The Experiment aimed to show how data from the domestic domain can be useful for medical decisions. Therefore, we wanted to obtain the individual relation between the rehabilitation training at home and two different household activities.

As COPD patients were not available and the experiment is a proof of concept for the applicability of the 3DLC method, it was conducted with healthy test persons. The participants performed two household activities (ironing, see Figure 2a., and vacuuming, see Figure 2b) and one step test on a bicycle ergometer (see Figure 2c) in the home lab of the OFFIS institute. Both household activities were performed for five minutes with low intensity and for five minutes with high intensity. The participants rested for 3 minutes between the two intensities to recover themselves. The step test on the bicycle ergometer consisted of four steps with a length of 7:30 minutes each. The starting load was 30 watt and increased each step by 40 watts, so that the overall length of the training was 30 minutes with a maximum load of 150 watt.

To perform the tests and to collect the data, three software components were developed: The first

component runs on an Android mobile phone (see Figure 2d) and collects the vital sign measurements during the household activity tests. The second component system was used to create training plans and to monitor the training with the bicycle ergometer (see Figure 2e). The third component was mainly developed during

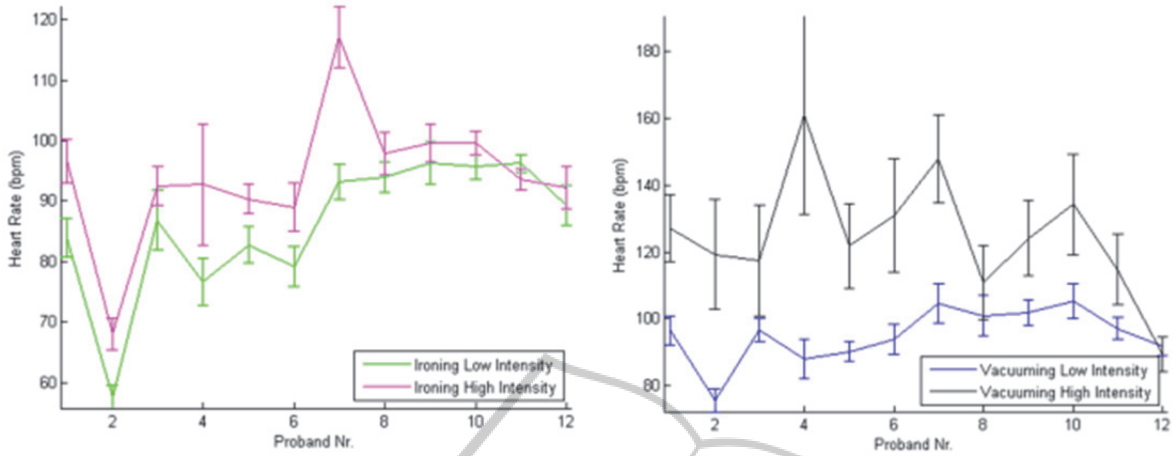

Figure 4: Heart rate and standard deviation during the performance of household activities per test person.

OSAmI project (Lipprandt et al., 2009). It runs on the training device for bicycle ergometer training and controls the load of the device depending on training plan (see Figure 2f).

All systems have an integrated user management to allow multi-user access and are capable of using several vital sign sensors. For this experiment the Polar Wearlink+ was chosen. A video was recorded during household activities to synchronize the data from the different systems in time before analysis.

2.3 Feature Extraction

We use the individual energy consumption of the iron and the vacuum cleaner to extract features that can be used to determine the intensity of the performed activity.

Figure 3 shows the power curve of the iron (left) and the vacuum cleaner (right) during the use in the experiment. The periods where the iron heats up can be clearly recognized. If a test person performs ironing with higher intensity the iron has to heat up more of the material (e. g. a shirt) that is intended be freed from wrinkles. This results in longer heating periods over the time of the trial. Therefore, we calculated the duration of the heating periods in which the power consumption lied above a certain threshold (cyan line in left in Figure 3).

The power consumption of the vacuum cleaner changes, with the load of its motor, which depends on how much air is drawn into the opening. This amount differs during the forward and backward movements of the suction head over the floor. So, the flickering of the power curve of the vacuum cleaner at the right of Figure 3 reflects these movements, which was validated with help of the video that was taken during the experiment. We determine the frequency of the forward and backward movements by counting the peaks of the power curve (cyan circles on the right of Figure 3).

3 RESULTS

3.1 Inclusion of Data from the Domestic Domain in the Medical Decision Making Process

The target of physicians in our COPD example scenario is to make a decision or prognosis (see top of Figure 1) for a patient that is as good as it can be. The typical process for the COPD rehabilitation with three different stations was described in section 1.1. These domains (*clinical rehabilitation, home rehabilitation, and unsupervised rehabilitation*) are reflected in the 3DLC model (see three blue framed boxes in Figure 1) where they span along the three dimensions.

Clinical rehabilitation is the most defined setting, where a patient is strongly supervised and external influences are avoided as much as possible during the data acquisition. The frequency is very low because the patient cannot perform tests in the clinic more than once or twice a year due to the effort that this would take from her/him and the medical staff and also for cost reasons. The *home rehabiliation* can (and should) be perfomed with a higher frequency, but the setting is less defined than in the clinic. The patient performs a normalized training that is defined by a clinician and may also be supervised. *Unsupervised rehabilitation* takes place in the patient’s everyday life and reflects her/his normal behaviour, which can be a very active or passive lifestyle. It is clear that these activities are being performed with high frequency.

The contents of the dark blue box in the lower left of Figure 1 display the raw data that is being obtained during the physical exercise tolerance test, when that functional capacity of the patient is estimated. Typically this is done by a stepwise increase of the training load e. g. on a bicycle ergometer. Parts of the data that can be recorded during this test are the *heart rate* during the test, *load* of the training modality and *duration* of the different test-steps. Further rather complex sensors like *electrocardiography* and *spirometry* may be used in the clinical setting. The spirometry data is very important in case of COPD because it reflects the oxygen consumption (VO_2) under different loads, which is different for each patient. The VO_2 value can used to precisely compute energy expenditure during physical activities. The *Borg value* (Borg, 1970) is provided by the patient and expresses the individual perceived exertion of a physical activity. Physicians use VO_2 and Borg to estimate the *individual capacity* (lower and centre left in Figure 1) and finally create an individual training plan for one patient.

The partially normalized home rehabilitation uses such a training plan to perform training in the domestic environment by using a device (also typically a bicycle ergometer) for telerehabilitation. Typically such a system provides a subset of the data that is also measured during the physical exercise test (see bottom in centre frame in Figure 1), but without the complicated and expensive sensors like the ones used for the spirometry. Load and duration are known for the specific activity of ergometer training. This information can be used to calculate the so called *MET minutes* (see bottom in centre and middle frame in Figure 1). MET stands for Metabolic Equivalent of Task which is a measure to express the energy cost of physical activities. It is based on the oxygen consumption of the muscles and expresses the energy consumption as a factor of the mean resting metabolic rate for a specific activity. This data can be used over a longer time period and a number of trainings by an appropriate IT system like a PHR to calculate a *home rehabilitation training performance trend* for a patient.

The third domain summarizes unstructured activity in an undefined (domestic) setting, where unsupervised rehabilitation takes place. Currently, the typical method to estimate activities in this domain is a patient diary, where performed activities are documented. We use an *electrical power consumption* sensor to detect performed activities, their duration and their intensity at home (bottom in right frame in Figure 1). The corresponding MET values can be looked up in a catalogue and can then be used to estimate the energy expenditure and for the calculation of the *home activity performance* of a patient (centre in right frame in Figure 1). This estimation of the energy expenditure for household activities only with the activity and duration is imprecise (dashed line right in Figure 1) because the MET concept does not take any individual or physical parameters into account, except of gender and weight.

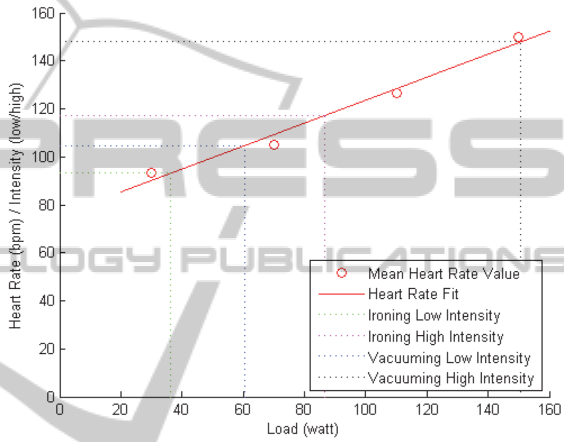

Figure 5: Relation of the household activities ironing and vacuuming with low and high intensity to the fitted load values of a step test on an bicycle ergometer.

The energy expenditure estimation of rehabilitation training and household activities can be improved by including the individual VO_2 value of the formerly obtained exercise tolerance test. The two trends are being combined to an *overall performed activity trend* that is of high relevance for the clinical decision making process in which a physician estimates the health state of a patient. This trend can be compared with the former defined individual capacity to make better diagnoses and prognoses, e. g. to predict exacerbations before they occur.

The estimation of the energy expenditure for the detected household activities can be further improved by not only including the MET minutes and individual VO_2 but also the intensity of the performed activity.

In our proof of concept experiment, we calculate two individual correlations between the recorded heart rate (HR) and the energy expenditure during the rehabilitation training and during the household activities (bottom two red arrows in Figure 2). This enables us to relate the detected activity with their duration and intensity to the telerehabilitation training. Since HR reflects the impact of an activity on the metabolism, it can be used to estimate which specific amount of household activity substitutes one complete rehabilitation training session. In other words, the correlation with the rehabilitation training over HR can be used to estimate the energy expenditure of household activities.

3.2 Energy Expenditure Determination

12 healthy test persons aged between 27 and 39 years participated in the experiment that took place between August and September 2012 in the home and assessment labs of the OFFIS Institute in Oldenburg, Germany.

Figure 4 shows the standard deviation and mean HR of the test persons during the performance of the household activities ironing (left) and vacuuming (right). Except for one trial, HR was lower when the test persons were instructed to perform an activity with low intensity. Compared to the low intensities, the overall HR was 9.4% higher during ironing with high intensity (mean low int. 86.0 bpm ±11.2, mean high int. 94.1 bpm ±11.0) and 31.2% higher during vacuuming with high intensity (mean low int. 95.2 ±8.2, mean high int. 124.9 ±18.2). HR rises during the step test with each increment of the load in each of the four steps (mean HR in bpm of step 1: 97.19 ±7.1, step 2: 109.44 ±8.2, step 3: 126.1 ±13.4, step 4: 144.37 ±16.4).

To determine the intensity of ironing, the total heating time of the iron was extracted as feature from the power curve. Except for two trials, the heating time was lower when test persons where instructed to iron with low intensity. The iron heated in mean 16.02% of the time during trials with low intensity and 16.95% of the time when intensity was high, which corresponds to a difference between low and high of 6.53% in heating time.

To determine the intensity of vacuuming we extracted the frequency of forward/backward movements from the power curve. Except for one trial, the frequency was lower during trials that should be performed with low intensity. The frequency during trials with low intensity was 0.40 ±0.069 movements per second and for high intensity 0.65 ±0.124 movements per second, which corresponds to a 62.5% higher frequency.

The target of the next step was to calculate the energy (E) for household activities. Therefore, we first calculated for each household activity (h={*ironing, vacuuming*}) the linear correlation between the detected intensity ($I_h(E)$={*low, high*}) and the recorded heart rate (HR_h). This results in a simple linear model that enables us to calculate the heart rate for an activity and intensity:

$$R_h\big(I_h(E)\big) = HR_h = c_h + i * f_h \quad (1)$$

The same procedure was applied to the four intensities (l={30,70,110,150})) of the step test on the bicycle ergometer:

$$R_e(l) = HR_e = c_e + l * f_e \quad (2)$$

These formulas are then solved for *l*:

$$\begin{gathered} R_h\big(I_h(S)\big) = R_e(l) \\ l = (c_h + i * f_h - c_e)/f_e \end{gathered} \quad (3)$$

The principle of this linkage over the HR is shown in Figure 5, where the household activities have been set in relation with the bicycle ergometer load for one patient. With usage of the measured power data we can now estimate the corresponding load values for an activity and intensity. Ironing with low intensity corresponds to 36.39 watt (green dashed lines), ironing with high intensity to 86.58 watt (magenta dashed lines), vacuuming with low intensity to 60.36 watt (blue dashed lines) and vacuuming with high intensity to 150.8 watt (black dashed lines).

4 DISCUSSION

Since the 3DLC model characterizes data on a very abstract level, it is usable when new applications or technical improvements take place and data from different domains have to be merged. However, the model has to be used with concrete examples to show its worth. Our proof of concept experiment was conducted without real COPD patients, but is a detailed blueprint that shows how activity data from the domestic domain could be included in the clinical decision making process to improve medical diagnoses.

The experiment results show that the heart rate correlates with the given instructions about the intensity with which an activity should be performed. This intensity is also reflected by the features that were extracted from the power sensor. It can be said that the difference in HR and feature values is expressed stronger during vacuuming in comparison to ironing. This can be explained with the kinetics of the movements, which demands or allows the use of the whole body during vacuuming, in comparison to ironing, where only the upper body is used. The smaller difference during the measured heating time of ironing reflects the smaller difference in HR. Even if the detection is not perfect, the data shows that the intensity (high/low) in which a household activity has been performed can be robustly detected by usage of an unobtrusive ambient power sensor.

The mapping between the intensities of household activities and the bicycle ergometer over heart rate is to our knowledge the first attempt to bring these different modalities together. The usage of a simple fit with one parameter as a model for energy expenditure is not sufficient for all practical needs. For example, the model would predict negative values when it extrapolates the energy expenditure under certain circumstances. The most important factor for a precise prediction of the energy expenditure is the individual oxygen consumption of a patient. To determine this value the patient has to perform a load test with a cost intensive breath by breath gas analysis. Hence, we are currently working on a more complex model that reflects the physiology of the human body in greater detail. It takes the individual VO_2 consumption and also environmental factors like temperature into account and should, thereby, enable a more precise prediction.

5 CONCLUSIONS

The use of the 3DLC model for the case study of an enhanced energy expenditure determination for COPD patients shows a way how data from the domestic domain could be used to improve the clinical decision making process. We substantiated this abstract path with an experiment that was conducted to create an intensity relation between the telerehabilitation training on a bicycle ergometer and the household activities ironing and vacuuming. We showed that intensities of the activities can be distinguished simply from the power consumption of electrical devices that are used during the performance of such an activity. We extracted heating time for ironing and the frequency of forward/backwards movements for vacuuming as features from the power curves. These features proved to be sufficient measures to distinguish between two intensities in which the activities were performed. Finally we used them for a correlation with the ergometer training to estimate the energy expenditure for household activities with an ambient power sensor.

ACKNOWLEDGEMENTS

This work was funded in part by the German Ministry of Education and Research within the research project “OSAMI-D” (grant 01 IS 08003) and in part by the Ministry for Science and Culture of Lower Saxony within the Research Network “Design of Environments for Ageing” (grant VWZN 2701).

REFERENCES

Abholz, H. H., Gillissen, A., Magnussen, H., Schott, G., Schultz, K., Ukena, D. and Worth, H., 2010. Nationale Versorgungsleitlinie - Chronisch Obstruktive Lungenerkrankung - COPD. In German. http://www.copd.versorgungsleitlinien.de/.

Barger, T. S., Brown, D. E. and Alwan, M., 2005. Health-status monitoring through analysis of behavioral patterns, *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans* 35(1), 22–27.

Bauldoff, G. S., Ryan-Wenger, N. A. and Diaz, P. T., 2007. Wrist actigraphy validation of exercise movement in copd, *Western Journal of Nursing Research* 29(7), 789–802. http://wjn.sagepub.com/content/29/7/789.abstract.

Borg, G., 1970. Perceived exertion as an indicator of somatic stress, *Scandinavian journal of Rehabilitation Medicine* 2(2), 92–98.

Bousquet, J. and Khaltaev, N., 2007. Global surveillance, prevention and control of Chronic Respiratory Diseases - A comprehensive approach, *Word Health Organization.*

Busch, C., Baumbach, C., Willemsen, D., Nee, O., Gorath, T., Hein, A. and Scheffold, T., 2009. Supervised training with wireless monitoring of ecg, blood pressure and oxygen-saturation in cardiac patients., *Journal of Telemedicine and Telecare* 15(3), 112–114. http://dx.doi.org/10.1258/jtt.2009.003002.

Carson, E., Cramp, D., Morgan, A. and Roudsari, A., 1998. Clinical decision support, systems methodology, and telemedicine: their role in the management of chronic disease, *Information Technology in Biomedicine, IEEE Transactions on* 2(2), 80 –88.

Chen, J., Zhang, J., Kam, A. H. and Shue, L., 2005. An automatic acoustic bathroom monitoring system, *in* ‘Proc. IEEE Int. Symp. Circuits and Systems ISCAS 2005’, pp. 1750–1753.

Chen, Y.-P., Yang, J.-Y., Liou, S.-N., Lee, G.-Y. and Wang, J.-S., 2008. Online classifier construction algorithm for human activity detection using a tri-axial accelerometer, *Applied Mathematics and Computation* 205(2), 849 – 860. Special Issue on Advanced Intelligent Computing Theory and Methodology in Applied Mathematics and Computation. http://www.sciencedirect.com/science/article/pii/S009

6300308003640.
Frenken, T., Wilken, O. and Hein, A., 2010. Technical approaches to unobtrusive geriatric assessments in domestic environments, *in* '*Proceedings of the 5th Workshop on Behaviour Monitoring and Interpretation, BMI'10*, Karlsruhe, Germany, September 21, 2010'.
Grams, L., Tegtbur, U., Kueck, M., Guetzlaff, E., Marschollek, M. and Kerling, A., 2011. Energieumsatzmessungen unter kontrollierten Bedingungen - Vergleich von Accelerometer, Multisensorsystem und mobiler Spiroergometrie, *Deutsche Zeitschrift für Sportmedizin* 6, 160–165.
Haeyrinen, K., Saranto, K. and Nykaenen, P., 2008. Definition, structure, content, use and impacts of electronic health records: A review of the research literature, *International Journal of Medical Informatics* 77(5), 291 – 304. http://www.sciencedirect.com/science/article/pii/S1386505607001682.
Helmer, A., Lipprandt, M., Frenken, T., Eichelberg, M. and Hein, A., 2011. 3DLC: A Comprehensive Model for Personal Health Records Supporting New Types of Medical Applications, *Journal of Healthcare Engineering* 2, 321–336. ISSN 2030-2295 DOI 10.1260/2040-2295.2.3.321.
Kuperman, G. J., Bobb, A., Payne, T. H., Avery, A. J., Gandhi, T. K., Burns, G., Classen, D. C. and Bates, D. W., 2007. Medication-related clinical decision support in computerized provider order entry systems: A review, *Journal of the American Medical Informatics Association* 14(1), 29 – 40. http://www.sciencedirect.com/science/article/pii/S106750270600209X
Lipprandt, M., Eichelberg, M., Thronicke, W., Kruger, J., Druke, I., Willemsen, D., Busch, C., Fiehe, C., Zeeb, E. and Hein, A., 2009. Osami-d: An open service platform for healthcare monitoring applications, *in* 'Proc. 2nd Conference on Human System Interactions HSI '09', pp. 139–145.
Mattila, J., Ding, H., Mattila, E. and Sarela, A., 2009. Mobile tools for home-based cardiac rehabilitation based on heart rate and movement activity analysis, *Conf Proc IEEE Engineering in Medicine & Biology Society* 2009, 6448–6452.
Monekosso, D. N. and Remagnino, P., 2007. Monitoring behavior with an array of sensors, *Computational Intelligence* 23(4), 420–438. http://dx.doi.org/10.1111/j.1467-8640.2007.00314.x
Pauker, S. G. and Kassirer, J. P., 1980. The threshold approach to clinical decision making, *New England Journal of Medicine* 302(20), 1109–1117. http://www.nejm.org/doi/full/10.1056/NEJM198005153022003.
Rodriguez-Roisin, R. and Vestbo, J., 2011. Global strategy for the diagnosis, management, and prevention of chronic obstructive pulmonary disease, Report. http://www.goldcopd.org/uploads/users/files/GOLD_Report_2011_Feb21.pdf.
Scanaill, C. N., Carew, S., Barralon, P., Noury, N., Lyons, D. and Lyons, G. M., 2006. A review of approaches to mobility telemonitoring of the elderly in their living environment., *Annals of Biomedical Engineering* 34(4), 547–563. http://dx.doi.org/10.1007/s10439-005-9068-2.
Tang, P. C., Ash, J. S., Bates, D. W., Overhage, J. M. and

Sands, D. Z., 2006. Personal health records: definitions, benefits, and strategies for overcoming barriers to adoption., *Journal of the American Medical Informatics Association : JAMIA* 13(2), 121–126. http://dx.doi.org/10.1197/jamia.M2025.

Virone, G., Alwan, M., Dalal, S., Kell, S. W., Turner, B., Stankovic, J. A. and Felder, R., 2008. Behavioral patterns of older adults in assisted living, *Transactions on Information Technology in Biomedicine* 12(3), 387–398.

Virone, G., Noury, N. and Demongeot, J., 2002. A system for automatic measurement of circadian activity deviations in telemedicine, *Transactions on Biomedical Engineering* 49(12), 1463–1469.

Williams, G. W., 2006. The other side of clinical trial monitoring; assuring data quality and procedural adherence., *Journal of the Society for Clinical Trials* 3(6), 530–537. http://dx.doi.org/10.1177/174077450 6073104.