FITPIT – FITNESS COCKPIT: INFORMATION SYSTEM TO OPTIMIZE TRAINING SCHEDULES IN REHABILITATION

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Abstract

Optimal healthcare supply today requires the extensive usage of information and communication technologies (ICT) to reduce the emerging costs and to ensure high quality standards. With FitPit – The Fitness Cockpit we are investigating concepts, methods and algorithms to implement an information system which will cope with the increasing problems in rehabilitation. Caused by the demographic change there is a growing number of patients with a need for rehabilitation. However, the success of a rehabilitative treatment depends mostly on the knowledge of the physiotherapist who prepares the training schedule. Caused by the increasing market demand, more unskilled staff will be employed. Therefore, FitPit will combine Machine Learning (ML), Data Mining (DM) and Complex Event Processing (CEP) technologies to enable an automated generation of optimal training schedules, based upon former knowledge as well as on methods to monitor the patients’ health status. Using FitPit a rehabilitation centre will be capable to ensure high quality treatment. Within this paper we’ll give a broad architectural overview with a brief description of the used technologies.

Keywords: IS, Telemedicine, CEP, Machine Learning, Data Mining, HL7.
1 Introduction

The usage of information and communication technologies (ICT) like electronic health records plays an important role to improve healthcare supply by optimizing the communication between the stakeholders of the public health sector. Lack of adequate information could lead to inefficient medical treatment or to erroneous decisions (Koch & Rotaru 2010). Most of the discussion related to healthcare supply and its anticipators as well as existing solutions are focussed on the therapy process. One should bear in mind that also prevention and rehabilitation plays an important role to improve the health status of a patient. While the therapy is mostly led by physicians, rehabilitation and prevention is realized by physiotherapists, certified sports scientists or other stakeholders, hereinafter also called trainer. Based upon their knowledge and medical (diagnosis etc.) as well as demographic (age etc.) parameters they create patient specific therapy plans, in terms of a training schedule.

Within the following years the demographic change will cause two major problems:

- The demographic change causes a shift within the age structure. The increase of the amount of the elderly amplifies the need for personalized concepts within rehabilitation and prevention (European Commission 2011).
- The increased demand can only be satisfied by expanding the staff (Landry et al. 2008).

The quality of preventative and rehabilitative measures extensively relies on the knowledge and experience of the leading stakeholder. Putting the two major problems mentioned above together, it is obvious that the need for those measures will increase, while in relation expert know how will decrease. To meet the need, preventive and rehabilitative institutions have to compensate the missing resources by deploying unskilled staff. It would make costs explode to use senior experts only. The missing knowledge and experience of unskilled staff could negatively affect the quality of healthcare supply and endanger the health status and thus also the success of the therapy. Therefore we propose the investigation of an information system that supports the knowledge management for rehabilitation and prevention measures, called FitPit – The Fitness-Cockpit.

FitPit acts upon two types of information – a training schedule and vital signs. The first basic information object within FitPit is a training schedule. Such a schedule provides structured information about demographic parameters of the patient, the diagnosis, the sequence of exercises and its parameters as well as training goals. Today it is originated by a trainer who is experienced in arranging exercises based upon the diagnosis. The success of a training schedule is directly related to the rehabilitative progression. A good training schedule will challenge the patient and support him to maximize the rehabilitative success as fast as possible. To get an objective overview of the patients’ health status that significantly influences the success of training, FitPit uses a second basic information object in terms of vital signs, e.g. blood pressure, pulse or weight. We support two different ways to communicate vital sign values: real-time (high frequency) and periodic (low frequency). The first way is especially used during training to detect critical situations, like raised pulse, as fast as possible. The second way is used for a long-term, periodical documentation of the progression of vital signs. The values are stored related to the actual training schedule.

Now, how can FitPit support the process of creating a training schedule and thus ensure a high quality of preventive and rehabilitative measures? FitPit will use a combination of technologies from the research areas of Data Mining (DM), Machine Learning (ML) and Complex Event Processing (CEP) and bring them together in one information system. The processing is structured according to the PDCA (plan–do–check–adjust) cycle. The training schedules created by experienced staff are transformed into a Hidden Markov Model (HMM) in which the nodes represent the exercises. The transition probability is influenced by different parameters, like performance tests, feedback about the success and the subjective well-being as well as vital signs, documented during the training. Using DM, similarities between different training schedules will be calculated and related to the success of
the schedule. At last upon the foresaid step and ML the HMM will be adjusted. Each iteration of the PDCA upon the HMM will enhance the quality of decision support for an optimal training schedule.

In the following we will describe a use case in which we are using FitPit and afterwards the architecture as well as the methods used and algorithms in detail. At the end we will give a brief overview of the on-going questions.

2 Motivating Use-Case

Cardiac diseases like cardiac insufficiency and hypertension are forthcoming all over the world (World Health Organization 2011). In Germany, more than 1.600.000 people suffer from cardiac insufficiency. Due to the aging society, this tendency is increasing. Hypertension (high blood pressure) is worldwide one of the most common chronic health conditions. The symptoms may include irregular heartbeat, tachycardia and water retention. The therapy today isn’t only focused on the prescription of drugs. Especially the prevention of further symptoms and rehabilitation is massively based upon the recovery and stabilization of the state of health by doing sports (Kahn et al. 2008). There are two types of information objects that significantly influence the effectiveness of a preventive or rehabilitative training:

2.1 Continuous Monitoring

In common parlance, cardiac insufficiency refers to a reduced pumping capacity as well as disturbed filling of the heart. Deficient therapy may lead to continuously reduction of the capacity of the cardiovascular system. Early and permanent medication is therefore essential for long life free of complaints. The choice and control of intensity of sports applied as intervention mechanism requires intensive monitoring of the following vital parameters

- Weight: Changes in weight is an important indicator for water retention in the lungs and limbs. Especially the weight is subject to fluctuations, which is caused amongst others by certain medicine (e.g. diuretics). Left ventricular insufficiency often causes pulmonary edema, while right ventricular insufficiency encourages water retention in the limbs.
- Blood pressure: A significantly increased blood pressure, especially in combination with weight gain can be a sign for an aggravating cardiac insufficiency.
- Pulse: Observing the pulse is also vital, especially when certain heart rate modulating drugs are prescribed. A simple, though little precise formula for determining the optimal pulse is: “180-Age”.

2.2 Training schedules

Training for patients with cardiac diseases was focused on endurance training until the end of the 90s. Within the last ten years there has been a recognizable change of thinking. On-going research shows that an optimal training for those patients should take endurance and strength training into account but there is still a lack of knowledge about the right training forms, intensities etc. (Delagardelle et al. 2002). To be able to select an optimal set of exercises from this two groups a trainer has to take many factors, like medication, into account (Levinger et al. 2005). Within this use-case we will propose 20 min endurance training, followed by 20 min of strength training for a training schedule.

3 Related Work

According to the two questions of vital sign processing and training schedule optimization, the research within FitPit can be divided as follows: On the one hand we take methods of CEP into account and on the other hand techniques of DM and ML.
To foster a fast, on-time processing of vital signs, we propose the usage of CEP. Basic definitions and concepts of CEP were developed and defined by Luckham, Chandy and Bates [9–11]. Citing them, an event is „…an object that is a record of an activity in a system“. A detailed overview about open questions and the current state of research in CEP is discussed in the Dagstuhl Seminar on „Event Processing“ in 2010 [12]. With Stride „The Stanford Translational Research Integrated Database“ of the Stanford University Lowe and Weber [13, 14] are presenting ongoing work to process health data using CEP upon the event processing engine Esper. One important aspect of on-time processing is the reduction of data by aggregating those to higher level information. Within FitPit we will build on concept of Charbonnier et al. (Charbonnier 2003; Horn et al. 1996; Haimowitz 1994) to dense data to relevant information in terms of trends.

The generation of optimal training schedules relies on techniques of DM and ML as well as sports science. Related work upon the conceptual design of schedules is highly related to a given diagnosis. Thus, there is no general definition but one can deduce that a training schedule is a set of exercises characterized by a training form, duration and intensity (Lavie et al. 2009; Delagardelle et al. 2002). Also demographic parameters such as weight, sex, number of exercises, and the athleticism of the patients selected exercise are important (Fröhlich et al. 2003). Most of the work on ICT for rehabilitation, is related upon the interpretation of vital signs only. Lou (Lou et al. 2007) gives a brief overview of how DM an ML could be used for knowledge discovery for rehabilitation of cardiac diseases.

Summarized, there is a lack of understanding of how one can optimize training schedules in a (semi-) automatic manner. Also there is a missing link between the information within a schedule and monitored vital signs.

4 FitPit – The Fitness Cockpit

The FitPit infrastructure is based on a highly distributed, modularized and flexible architecture concept. Every module represents a set of well-defined capabilities, like shown in Figure 1.

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**Figure 1.** Architectural overview of FitPit – The Fitness-Cockpit.
According to the well-known client-server pattern, the modules can be divided into a client and a server part like described below:

- **Endpoints:** The FitPit Endpoints are the functional backend for administration, visualisation and message interaction. All FitPit endpoint modules have access to a common database. The whole information and message exchange between components in the infrastructure is realized over a Java Message Service (JMS) based communication layer.

- **Sensor data:** Incoming sensor data is received by the Health Device Connector (HDC) first. The HDC is able to receive messages in terms of vital signs over standardized and proprietary protocols and embeds the required information into a uniform message format. These messages will be sent to the Health Device Gateway (HDG). The HDG converts the incoming messages to JMS messages and propagates the messages to the FitPit infrastructure. A HDC can be implemented as software on a hardware box in a gym or as a mobile application on a smartphone. The HDC can easily be extended by a flexible plugin concept based on the OSGi Framework.

- **Cockpit:** The FitPit Cockpit, also shown in Figure 2 is the user interface for trainers in a gym. The trainer can maintain training schedules, monitor vital parameters of clients, or can view additional information and events generated by other modules of FitPit.

- **Kiosk:** The FitPit Kiosk is the visual interface for clients in a gym. The Kiosk is used to associate Medical Health Device with the client account and to record spot check measurements like weight or blood pressure values.

![Figure 2. Screenshots showing patients(left) and real-time monitoring of vital signs (right).](image)

Beside the previously described base infrastructure components FitPit contains data processing modules. The central data processing node in the architecture is TiEE (see also 4.1). Incoming sensor data streams from the HDG are processed and analyzed by TiEE in real-time. Recognized trends trigger event information to the Cockpit. This information helps the trainers to monitor the client exercises and to recognize deviations from ideal ranges of vital parameters during the exercises. The PerfectPlan (see also 4.2) module analyzes the success of proceeded training schedule concepts based on the context and the reached goals. The results are stored in a knowledge base. This knowledge base will be used to support a trainer during the creation of a training schedule for a specific client or generates recommendations for changes in current training schedules. This information will be shown to the trainer in the Cockpit as well.

### 4.1 TiEE – Trend detection in streams of vital signs

TiEE – The Telemedical ILOG Event Engine was developed by Fraunhofer ISST to monitor patients in the sense of telemedicine (Meister n.d.). Telemedicine bridges the distance between patients and physicians using information and communication technologies (ICT), e.g. a patient measures vital signs at home. We expanded engines to facilitates methods to monitor a patient during sports activities and send notifications to, e.g. a trainer or other responsible persons.

The conceptualisation is based upon two basic ideas (Meister 2011):
Event processing: An event is anything that happens or is contemplating to happen (Luckham 2002). Also the measurement of a vital sign could be interpreted as an event. Event processing enables one to process incoming events in real-time using filtering, aggregation and pattern detection mechanisms. Complex event processing (CEP) is an extension to derive more complex events based upon light weighted ones. To expression interrelations between events CEP allows for the usage of temporal relations.

Information logistics: Information should be transported at the right time to the right place to prevent persons from information overload. In the first step a set of single data items like vital sign measurements should be aggregated to relevant information or higher order decisions. Relevant means, to meet the information demand and/or information need of a person.

Below we’ll give a broad overview about the architectural insights of TiEE, especially the concepts of telemedical events, telemedical ILOG listeners (TIL) and TIL-profiles.

Figure 3. Architectural overview of the TiEE platform for real-time processing of vital signs.

TiEE is capable to process different kinds of vital signs like shown at the bottom of the architectural overview in Figure 3. Related to the motivating use case in chapter 2, this could be the measurement of weight, blood pressure or pulse and oxygen saturation. Due to the fact that most manufactures of vital sign sensors use different kinds of proprietary data formats, we conceptualized the concept of telemedical events. As we have defined in (Meister 2012) a telemedical event is a measurement of a telemedical value and an instance of a telemedical event type, formatted in the HL7 Telemedical Event Format. HL7 is a worldwide used standard to exchange medical data between information systems. So, using telemedical events and the HL7 Telemedical Event format we could process incoming measurements of vital signs from different sources.

The processing of incoming telemedical events is realized by two concepts: Telemedical ILOG Listener and TIL-profiles. A telemedical ILOG listener (TIL) is some kind of event processing agent (EPA) that “monitors an event execution to detect certain patterns of events” which is specialized for one type of telemedical event (Meister & Stahlmann 2012). An EPA is a very generic and modular way to encapsulate knowledge to process data. So, we need TILs to facilitate an optimized processing for every type of vital sign. A TIL is characterized by the following conceptual elements:

- **Input:** A TIL is highly specialized on the processing of one telemedical event type. Therefore the definition contains only one single input connector.
- **Logic:** Within the logic one has to formalize the rules to process the incoming telemedical events. According to Etzion, processing is a three step procedure [26]: First, one has to get rid of unimportant events by filtering them. Second, within the remaining events one can define rules and
pattern to detect interesting system state or situations. Third, some kind of result has to be derived as an output to the rest of the world.

- Output: The definition of TILs contains more than one output connector. Depending on the matching and derivation process there is more than one possible outcome.

The second concept next to a TIL is a TIL-profile. A TIL-profile is based upon the idea of event processing networks (EPN). An EPN is a concept to organize event processing agents (EPA) “into networks to communicate with one another” (Luckham 2002). Reflecting this definition a TIL-profile could be defined as a network of patient specific TILs to derive higher order decisions. A TIL-profile is characterized by the following conceptual elements:

- Input: A TIL-Profile realizes a patient-specific filtering of telemedical events thus it reduces the amount of data. Therefore the definition of such a profile contains only one single input connector.
- Logic: For every type of vital sign one has to register one TIL. In the following the output of the TIL’s is processed within the TIL-Profile by additional filtering, pattern detection and transformation into higher order decisions, like described above for TILs.
- Output: The definition of TIL-profiles contains more than one output connector. Depending on the matching and derivation process there is more than one possible outcome.

Now, putting the three concepts mentioned above together - how does TiEE advance the processing of vital signs?

A basic requirement of the processing process is to reduce the amount of data and derive relevant information or higher order decisions. Regarding to the event flow, first of all a telemedical event has to pass the filter rule of a TIL-profile. Only those events will be passed on that are instantiated for the specified patient. Depending on the medical situation a TIL-profile is configured with different types of TILs. Following the event flow the on passed telemedical events are now asking to pass into a TIL.

A TIL is trying to detected characteristic patterns within the stream of telemedical events, so called trend patterns. A trend pattern is an abstraction of a set of telemedical events and characterizes the progression of the measured values as described in Figure 4. Based upon the research of Charbon et al. (Charbonnier 2003; Haimowitz 1994) we distinguish five basic types of trend patterns. So, we derive an abstraction, the pattern, from a set of underlying measurements to reduce the amount of data and cope with the problem of information overload. The derived pattern is described using different types of parameters, e.g. the statistical spread or the amount of increase/decrease.

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Decrease of measured vital signs over time</td>
<td>Statistical</td>
<td>Description of the statistical characteristics of the progression like the mean.</td>
</tr>
<tr>
<td></td>
<td>Increase of measured vital signs over time</td>
<td>Relational</td>
<td>Description of the relation between the processed events like causality or temporality.</td>
</tr>
<tr>
<td>Saltus Up</td>
<td>Sudden slope up within the progression of vital signs</td>
<td>Characteristic</td>
<td>Nominal description of the characteristics of the value like high or low.</td>
</tr>
<tr>
<td>Saltus Down</td>
<td>Sudden slope down within the progression of vital signs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steady</td>
<td>No changes within the progression of vital signs</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 4. Characteristics of trend patterns derived by TiEE.

In summary, every TIL derives trend patterns for a specific telemedical event, i.e. a type of vital, and forwards them up to the referring TIL-profile. Now, this TIL-profile has to detect higher order patterns within the set of forwarded trends. This means to correlate trends as follows:

- Trends of same underlying types of vital signs: The repeated increase, decrease etc. of a set of vital signs could be abstracted to a single trend pattern.
• Trends of different underlying types of vital signs: It is obvious that there is a relation between weight and blood pressure in cases of cardiac decompensation. A TIL-profile has to detect the increase of both during a given time window and derive a new abstraction, emitting a new trend pattern.

Upon rules registered in the TIL-profile, information logistics decisions are made to generate and send relevant information to a person.

4.2 PerfectPlan – Intelligent training schedule optimization

PerfectPlan is a system conceptualized by Fraunhofer ISST for optimizing training schedules. The system is based on Data Mining and Machine Learning methods. DM refers to methods that analyze the dataset in order to identify patterns. DM allows the consequences to be drawn from the data to represent typical sequences (Runkler 2010). ML deals with the algorithms that identify complex relationships to be features of the underlying mechanism that generates the data (Alpaydin & Linke 2008). These features are used to make predictions based on the new data.

Methods of machine learning and DM techniques are used to generate an optimal and personal training schedule for the speedy recovery of a patient. A training schedule identifies the work that needs to be done to achieve a goal. A training schedule consists of training days on which a series of exercises are to be done. PerfectPlan sets a goal to adapt each exercise targets and consequently the whole training plan to the patient, to offer an optimal variant for the quick and successful recovery without further complications.

There are some parameters to be considered for the building of a training schedule. The most important are shown in the table below to form a patient profile. Intensity, duration, repetition and frequency of exercise will be adjusted within these parameters for the training schedule of a person.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnosis</td>
<td>The diagnosis reveals the problems for a patient and gives to a therapist a basis for a development of a training schedule.</td>
</tr>
<tr>
<td>Age</td>
<td>Age influences the intensity and duration of an exercise or a daily workout. Young people can train longer and more intense unlike the older people.</td>
</tr>
<tr>
<td>Weight</td>
<td>The weight plays an important role for the training, because the exercises would be more exhaustive for patients with overweight.</td>
</tr>
<tr>
<td>Sports activities in daily living</td>
<td>Frequent training will influence the physical constitution of a patient. Those ones will be better prepared for doing exhaustive and insensitive training. Therefore training goals for athletic patients are set slightly higher.</td>
</tr>
<tr>
<td>Frequency of training</td>
<td>Frequency is defined as the number of training days per week. Since the muscles need a certain recovery time, the training program has to be adjusted so the patient is physically able to do the exercise. Thus, the permutations of the types of training days (only cardio or strength training only) come in consideration.</td>
</tr>
<tr>
<td>Other or accompanying diseases</td>
<td>One also has to pay attention to other diseases and problems of the patient. As an example, a patient may have problems with the knee. Thus, the knee may not be burdened too much, because the patient may not be able to do the other exercises.</td>
</tr>
</tbody>
</table>

The entire optimization cycle can be represented as a Deming cycle (Plan-Do-Check-Adjust), like shown in Figure 5:

• Plan: In the first phase a training schedule will be created by a trainer or proposed to the patient by the system. Internally a schedule is represented as a Hidden Markov Modell (HMM). Exercises are shown as nodes which are connected through edges provided with probabilities.
• Do: The execution of the training schedule starts with an initial test as a documentation of patients' performance level. During the execution of the schedule training parameters will be documented, e.g., the duration, the used weight, etc. The patient is also monitored by different vital sign sensors, e.g., pulse or oxygen saturation. Afterwards the patient as well as the trainer will rate the training schedule, e.g., the subjective well-being.

• Check: In the following step within the cycle PerfectPlan has to process the documented data, according to the training schedule. Therefore the system will classify the datasets according to the diagnosis and afterwards will detect similarities and dissimilarities based upon demographic parameters like weight or age using methods of DM. To enable PerfectPlan to propose an optimal training schedule it has to calculate an optimal permutation of exercises related to a given diagnosis. Thus, we have to evaluate the success of a given training schedule.

• Adjust: Based upon the results obtained from the check-phase PerfectPlan will adjust the underlying HMM for the given diagnosis.

As was mentioned above the training schedules are assessed by the therapist and the patient after completing the training. Initially we have chosen the following parameters for the assessment:

- Review of each individual exercise: Each exercise can be evaluated by the trainer and by the patient. Based on this evaluation, the exercises are prioritized globally. Thus, the rating makes a contribution on each exercise and the future selection of exercises for the training schedule.

- Review of the entire training schedule: Through the evaluation of the entire training schedule, the system can adjust the plan in comparison to other plans. By comparison, an optimal plan and optimal sequence of exercises can be selected.

- Permutations: Permutations can be viewed at two levels. The first level represents the permutation of the types of exercise. Thus, an optimal combination is selected for each patient. The order of the types of exercises can be adapted for different patient profiles. The relationships between individual exercises are considered at the second level. One can identify functional dependencies between exercises that permit or prohibit some kind of combinations.

According to the goal of optimizing a training schedule a basic question is: How to ensure the success of the training schedule generation? FitPit acts in two parallel ways: system-based and trainer-based. The system-based approach rates the success according to the goals defined within the planning phase...
of the PDCA. Those goals are represented as numeric values, thus they are processable and comparable by algorithms.

The trainer-based success evaluation is a human-based method to rate the overall success according to the following parameters:

- **Time efficiency**: Rate the time needed to reach the goals.
- **Therapeutically effect**: Rate the progression of the therapy, bearing the needed time in mind.
- **Problems**: Rate the amount of problems occurred during the execution of the training schedule.

Within a range from one to ten the trainer has to determine values for the parameters mentioned above. The rating will be reflected on the underlying HMM to modify the state transitions between as well as the overall therapeutic effect of the given training schedule.

In summary, PerfectPlan tries to calculate an optimal permutation of exercises based upon different kind of parameters as well as the health status, represented by vital signs.

## 5 Conclusion and Outlook

The on-going demographic change is constantly increasing the demand for preventative and rehabilitative measures to inhibit wide spread diseases, like heart attacks or diabetes. To maintain high quality treatment and cope with the problem of missing knowledge of unskilled staff we developed FitPit – The Fitness Cockpit. By combining continuous monitoring of vital signs with the execution of a training schedule we are now able to generate optimal training schedules based upon a diagnosis and patient demographic data. The solution therefore uses CEP, ML and DM to process all the collected data in an intelligent manner. Like for any other information system a basic problem is the collection of data. Within rehabilitation and prevention the usage of ICT is uncommon and very specific. So, usability and simplicity plays an important role for FitPit. It has to fit seamlessly with existing processes. Also, one should bear in mind the quality of decision support by generating optimal training schedules which depends heavily on the amount of training. To optimize the underlying Markov Model and transition functions we’ll foster the usage together with application partners. Future work will focus on the optimization of the probability distribution for generating an optimal training schedule.

## 6 References


