Toward Smartphone Assisted Personal Rehabilitation Training

When utilizing internal sensors, modern smartphones are inexpensive and powerful wearable devices for sensor data acquisition, processing, and feedback in personal daily health applications.

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For the first time in history, our generation and future generations will no longer be young. It is estimated that human life expectancy in the Stone Age was around 20-34 years. We can consider this as the natural life expectancy at birth for our species. However, nowadays, those born in Japan can expect to live 83 years. This implies there has been roughly a tripling of life expectancy for humans in the last few thousand years, which vhas dramatically altered the way societies and economies work.

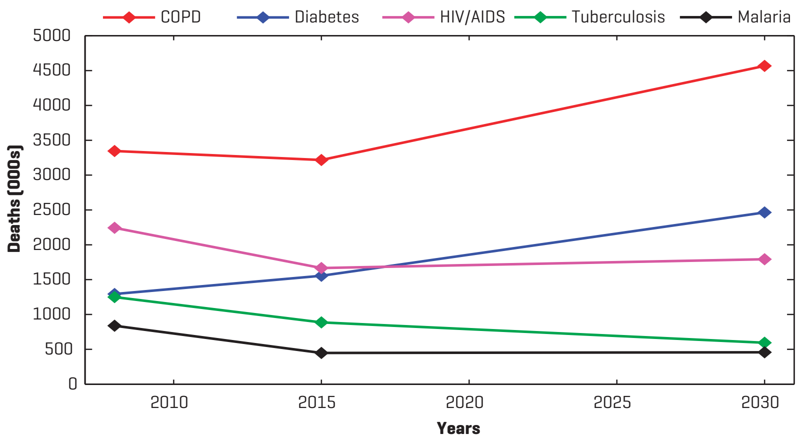
Aging can be viewed as a triumph of development rather than any evolutionary changes in human biology: People are living longer thanks to technological and medical advances, better healthcare, education, and economic well-being. With increasing healthcare costs and a shortage of medical professionals, we are seeing a paradigm shift from hosting chronic patients in hospitals toward managing patients in their own home environment.

While deaths due to major diseases (such as AIDS/HIV and heart failure) are on the decline, the worldwide prevalence and related deaths of chronic diseases—such as chronic obstructive pulmonary disease (COPD), diabetes, and cardiovascular diseases (CVD)—are continually increasing (see Figures 1 and 2). COPD is predicted to become the third leading cause of mortality by 2030 [1]. It is estimated that 210 million people have COPD worldwide and 10.4 percent of the population older than 40 years have moderate to severe COPD that results in airflow limitation and significant extra pulmonary effects (e.g. muscle weakness and osteoporosis) [2]. Patients suffering from COPD have difficulty breathing and develop "air hunger." Breathlessness is a common occurrence forcing patients to avoid physical activities and enter into a vicious cycle: By exercising less, their muscles become weaker and less efficient; patients become more breathless and then gradually avoid exercising altogether.

How can COPD patients break this cycle and increase life expectancy?

Exercise training is a well-recognized method to treat symptomatic patients with COPD; physical activity programs appear essential to safely improve health state, including exercise capacity, functional status, health-related quality of life, peripheral muscle force, and physical activity in daily life. For example, generally healthy people can regularly jog and run, and even over-train, without immediate health consequences. In COPD patients, both over-training and undertraining can lead to the quick and detrimental worsening of health conditions, resulting in exacerbations, hospitalization, or death. For this reason,

Figure 1. Estimated mortality rates due to different diseases (World Health Organization July 2013).

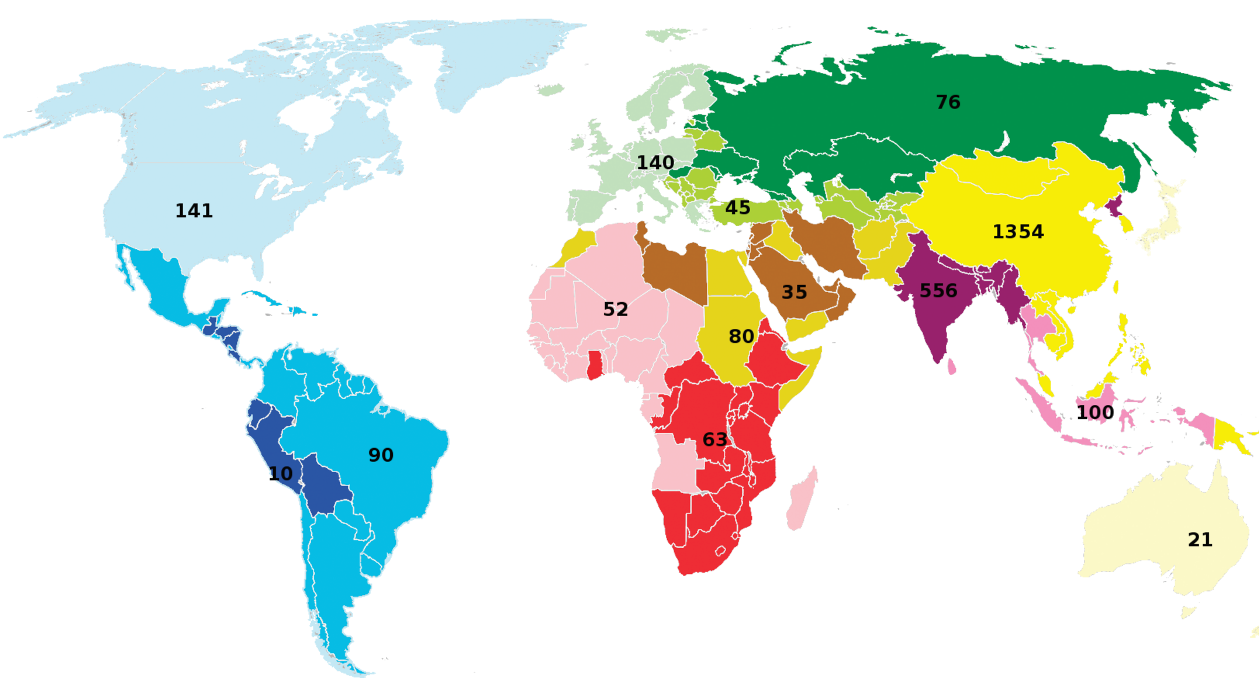


chronic patients often fear exercise if not under therapist supervision given the potential consequences of incorrect exercise techniques. However distance and cost often inhibit patients from attending a rehabilitation center regularly, especially in developing countries where COPD prevalence is higher.

While therapists can recommend daily exercises as "homework," both therapists and patients have currently no means to assess exercise performance during independent training. It is therefore essential to develop new systems and service concepts that permit chronic disease management at home. The use of smartphones, ubiquitous sensors, and network technology in healthcare systems could enable patients to perform additional physical training on their own, in addition to supervised training with a therapist.

During rehabilitation exercise, different errors can occur at the same time and should be identified accordingly. It is also essential to provide an error estimation algorithm that can handle different exercises with minimal adjustments to support training variety. Analyzing exercise performance is usually done by means of cameras—depth cameras and optical motion capture systems in combination with passive markers. In general, vision-based systems allow users to extract a human skeleton automatically, but require constrained environments to install and calibrate cameras. Due to these limitations, error-monitoring approaches started focusing on individual exercises or specific wearable training devices that helped to stratify error conditions. Various ambient and on-body device developments identified opportunities for continuous training and coaching in fitness and sports outside the lab setting. Often these approaches relied on multi-sensor information and pattern recognition methods, requiring individual learning of motion-pattern models. Although wearing multiple on-body sensors could provide high feedback accuracies, their cost and handling is challenging for patients. Smartphones, on the contrary, provide several integrated sensors to analyze data in real time and provide train-

Figure 2. Mortality rates due to COPD in different parts of the world, numbers in '000 (data from Lopez, A.et.al. 2006).



ing performance feedback. To minimize costs and other entry hurdles to personal rehabilitation training, smartphones may be the answer.

SMARTPHONE-BASED TRAINING APPROACH

COPDTrainer is a new smartphone-supported training application that considers the aspects mentioned previously and integrates into the usual clinical rehabilitation routine [3]. For COPDTrainer, a smartphone serves as a single measurement, estimation, and feedback device for assessing patient exercise performances. Recognition performance was evaluated for classifying execution errors, which is necessary to deploy the system in practice and especially in a clinical application. In this setting, the ability to perform particular motion exercises differs between trainees, due to individual motion constraints. Chronic patients, who often suffer from pathologies and muscle weakness, may not be able to perform exercises at the same speed or range of motion as another trainee. To overcome this problem the training approach adopted by COPDTrainer includes Teach and Train-modes as illustrated in Figure 3.

The Teach-mode allows therapists to personalize the system for a trainee under direct supervision. For example, during the regular physiotherapy practicing times any selectable exercise can be performed and the trainee learns from the therapist how to attach the phone and perform a particular exercise. Once an exercise is selected, illustrations are shown on the screen to remind the patient about the exercise execution. In Teach-mode, the therapist initially guides the patient during the first trials to perform the exercise accurately. Teach-mode recording begins once a large button on the phone's screen is pressed. A preset number of exercise repetitions (10 by default) will then be acquired from the phone's inertial sensors. From the recorded data, all necessary exercise model parameters, such as mean and variance of the duration and the range of motion of the limb during the 10 repetitions, are estimated and stored for further use during Train-mode. The derived

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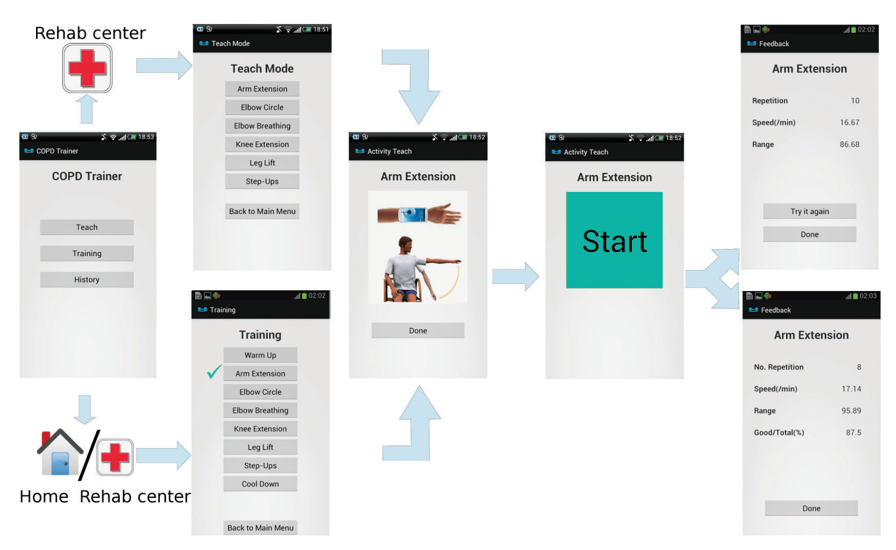
parameters are shown on the smartphone, so the therapist and trainee can review them. If the therapist concludes the trainee did not perform the exercise with sufficient quality, the session could be repeated. Moreover, the system checks consistency of the exercise repetitions and can reject a Teach-mode session that shows extensive execution variability. These choices consider the regular clinical routines, where therapists have only 30 to 45 minutes per patient for assessment, therapy, and exercise training. Thus, complex interactions with the device were avoided.

During Train-mode, the derived exercise models are arranged in a "to-do list" for the trainee to complete. This mode is intended for use by the trainee to exercise without therapist supervision, at the rehab center or at home. After selecting an exercise to be performed and starting the Train-mode, inertial motion data is recorded from the phone's sensors and processed in real time to count the exercise repetitions and detect errors. While training, COPDTrainer will provide acoustic feedback on the counted repetitions and notify when errors occur. For example, if the trainee practiced an exercise with the therapist before but starts to perform repetitions faster than during the Teach-mode, the system will provide the feedback "move slower." This feedback could prevent injuries from repetitive erroneous movements. Finally, after the configured number of repetitions is detected, the system will ask the trainee to stop and displays a summary of the execution performance.

Based on the observation that many fitness exercises have a repetitive structure, from training with free weights to cardio fitness motion, a sinusoidal motion model was considered. This method was chosen over others for two reasons: (1) Using machine-learning techniques requires a training set to obtain the classifier model. In particular, a sufficient number of exercise error instances would be required, but it is not feasible to let patients perform exercise errors due to the risk of injuries. (2) With machine-learning techniques, it is difficult to differentiate variations in performance of the same exercise from

Figure 3. COPDTrainer training approach.



execution errors. Hence, error classes were formalized by considering deviations from the correct execution using the sinusoidal model.

For each exercise, a therapist or expert could choose a representative motion feature that represents a sinusoidal pattern. The feature can be based on a single raw axis of acceleration, gyroscope, and magnetic field sensor, or fused from several sensors of the phone, such as orientation estimates. For example, in a lateral arm abduction exercise, where the phone is attached to the wrist, the anterior-posterior orientation angle could be used as motion feature. The smartphone position at the body and feature need to be selected only once per exercise type. Exercises could be shared between patients, therapists, and clinics subsequently. Since the Teach-mode is performed under therapist supervision, no real-time feedback will be provided. Once the trainee completes an exercise session with a preset number of repetitions, the application loads the stored data and extracts the exercise model parameters.

The selected motion feature was filtered using a moving average to remove tremor-induced noise and sensor noise. The window size was set proportional to the amount of data acquired. This approach provided consistent results across different exercises. Since the number of repetitions is preconfigured, it was assumed that the total data amount recorded is proportional to the movement speed during the exercise execution: When a trainee performs the exercise faster, muscular tremor is lower, and thus, data averaging is reduced. Bounds were applied to the averaging window size to prevent ineffective averaging for very fast and slow repetitions.

By estimating the position of positive and negative peaks in the filtered motion feature, exercise repetitions were counted. For the arm abduction exercise, the selected feature is maximal when the arm is raised to shoulder height. It reaches its minimum value when the arm returns to the neutral position (arm aligned to the trunk). An adaptive, hill-climbing algorithm was then used to detect positive and negative peaks, given a starting peak threshold. While there are many alternatives, such as simulated annealing or tabu search, hill-climbing can achieve sufficient or better results if runtime is constrained, such as in the real-time system targeted here.

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The detection of local maxima and minima remains susceptible to detecting additional peaks (insertion), e.g. during vibrations, or to missing peaks (deletion) if the signal amplitude decreases. In situations where there was one insertion or deletion error in sequence, the alternating order of positive and negative peaks was interrupted. If two consecutive positive or negative peaks were derived, a peak correction algorithm was applied. This peak correction works by first removing redundant peaks and then inserting missing peaks that were missed during the first iteration of the hill-climbing algorithm. Time intervals between two consecutive peaks were also used to determine if there could be peaks missing. After segmenting the signal in single repetitions the following five parameters were derived: number of repetitions, mean and standard deviation of repetition duration, and mean and standard deviation of the range of motion. The repetition duration was derived from the time interval between two adjacent minima. The range of motion was derived from the magnitude difference between adjacent negative and positive peaks. The number of repetitions could be obtained by counting the number of maxima.

In contrast to the Teach-mode, Train-Mode operation requires online period estimation and subsequent performance analysis. A sliding window was used to segment the incoming data stream. The sliding window size was set to cover two average repetitions based on the parameters estimated in the Teach-mode, with an overlap of 75 percent between consecutive windows. The overlap ensures timely feedback during a newly detected repetition. To provide timely feedback, i.e. before the trainee starts a subsequent repetition, the first half of a repetition was evaluated to estimate duration and range of motion estimates. In preliminary tests, we observed the error incurred by considering only half of a repetition was negligible. The derived duration and range of motion estimates were used to compare with the parameters estimated in the Teach-mode. For duration and range of motion, each repetition performance is estimated based on a Gaussian distribution. The performance of each exercise is classified into three class types: in-between, under, and above the ranges. In total, we considered nine different classes to which each performed exercise repetition could be associated. After the performance class corresponding to the ongoing repetition was evaluated, an audio feedback was provided to the trainee, who was notified if a repetition was erroneously performed.

COPDTRAINER EVALUATION

Advised by three therapists, and after consulting COPD guidelines, speed of motion (corresponding to the period frequency) and range of motion (corresponding to the feature amplitude) were derived from the sinusoidal pattern of each exercise repetition. In kinesiology speed and range of motion, together with their relative tolerances and the number of repetitions, are considered standard measures for exercise monitoring. Estimating movement speed during exercises is useful to educate patients in breathing techniques (i.e. by exercising the patient can learn how to breathe with correct timing). Based on these exer-

Figure 4. Performance classes, feedback, and condition used to identify exercise quality.

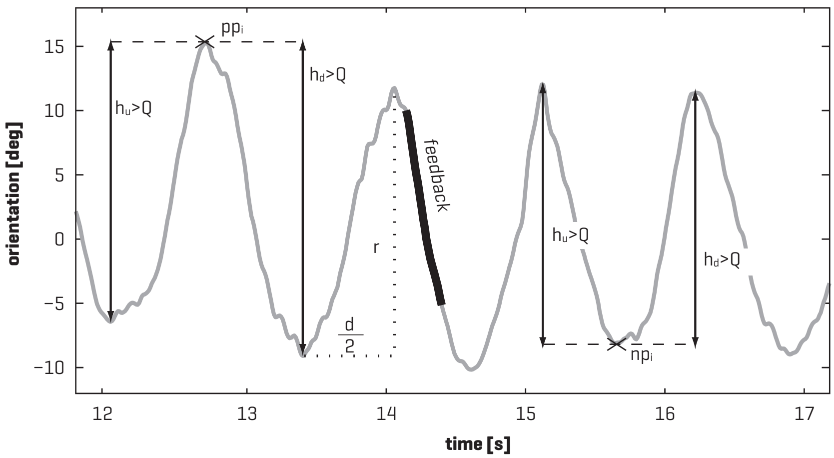
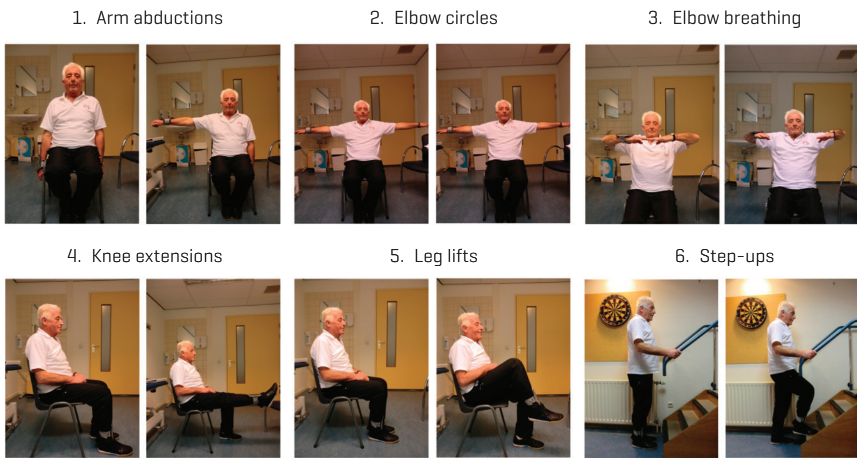


Figure 5. Illustration of the exercises selected for the training system evaluation. The patient is wearing the smartphone (red circle) on limbs that are involved in the different exercises.



cise quality parameters, it is possible to derive performance classes, such that the classes are applicable to various exercises performed by repetitive movements. During the Teach-mode, exercise repetitions are used to represent repetition range and duration parameters using two normal distributions. In the Train-mode, these model parameters are used to identify nine performance classes and can be seen in Figure 4. Six exercises, shown in Figure 5, were chosen for daily training at home according to the COPD guidelines and in consultation with therapists. The exercise set consisted of three upper limb muscle exercises: arm abductions (AA), elbow circles (EC), and elbow breathing (EB); and three lower body muscle exercises: knee extensions (KE), leg lifts (LL), and step-ups (SU).

To test and evaluate the training system, two sets of experiments were conducted. Initially, the system was validated with healthy participants using a scripted protocol, where all performance classes have been equally represented. Subsequently, the training system was evaluated in an intervention study with COPD patients performing normal therapy training sessions. The validation with healthy participants showed an overall accuracy of 96.2 percent. The intervention study with seven COPD patients showed a trainee performance classification rate of 87.5 percent, while repetitions were counted at 96.7 percent accuracy.

Based on those results, we concluded a smartphone-based training system can be used to assess the performance and execution quality of a rehabilitation exercises in COPD patients. Based on the system performance and feedback efficacy, we believe our approach and developed methods will be a vital basis for future investigations on training systems for different patient groups. Additional steps are needed to confirm the clinical relevance and integration into clinical practice. In this regard, we consider this work as a pilot study, providing the basis for validating COPDTrainer in a clinically supervised intervention at the patient's home. We hope the COPDTrainer application will become an everyday tool for patients to improve and maintain their health state.

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Biographies

Gabriele Spina received B.S and M.S. degrees in biomedical engineering from Università Campus Bio-Medico in Rome. Currently he is a Ph.D. candidate in the ACTLab research group at TU Eindhoven. His main research focuses in the use of emerging technologies (mobile, ubiquitous sensor and network technology) in healthcare systems to monitor patient's status and provide insight into daily life activities.

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