Design and Development of the MedFit App: A Mobile Application for Cardiovascular Disease Rehabilitation

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Abstract. Rehabilitation from cardiovascular disease (CVD) usually requires lifestyle changes, especially an increase in exercise and physical activity. However uptake and adherence to exercise is low for community based programmes. We propose a mobile application that allows users to choose the type of exercise and compete it at a convenient time in the comfort of their own home. Grounded in a behaviour change framework, the application provides feedback and encouragement to continue exercising and to improve on previous results. The application also utilizes wearable wireless technologies in order to provide highly personalized feedback. The application can accurately detect if a specific exercise is being done, and count the associated number of repetitions utilizing accelerometer or gyroscope signalsMachine learning models are employed to recognize individual local muscular endurance (LME) exercises, achieving overall accuracy of more than 98%. This technology allows providing a near real-time personalized feedback which mimics the feedback that the user might expect from an instructor. This is proved to motivate users to continue the recovery process.

Key words: Cardiovascular disease, Mobile Application, Support Vector Machine, Wearable Sensors, Repetition Counting

1 Introduction

Cardiovascular disease (CVD) is the leading cause of premature death and disability in Europe and worldwide [1]. While mortality and morbidity rates are improved with effective cardiac rehabilitation (CR) [2], uptake and adherence of community-based CR are very low [3]. Key reasons for this include: lack of disease-specific programmes, travel time to such programmes, scheduling issues, and low self-efficacy associated with a perception of poor 'body image' or poor exercise technique [4]. Ideally, a personal instructor could visit the patient's home, provide a tailored programme and monitor the exercise quality and give personalized feedback. Unfortunately, this is not feasible in practice for a variety of reasons, including financial.

The mobile application described in this paper provides a solution to the problem: it allows tailored exercise classes to be completed at any time in a patient's home by offering personalized video exercise classes and feedback during exercise based on the data from wearable sensors (i.e. whether the exercise was completed and, if so, the number of repetitions). It also provides summary feedback and statistics on the completion and overall performance for specified periods of time (day, week, month, etc.). Finally, while the main focus of cardiac rehabilitation is exercise, it is also important to provide the patient with expert information in order to change their behaviour towards a more healthy lifestyle relating to the targeted areas of: smoking cessation, stress management, alcohol use, diet and medication adherence. The overall system is designed to be patient-centric with all technology and functionality choices informed by behaviour theory. The behavioral change techniques and social cognitive theory have been used in conjunction with the focus group feedback to develop and design the content of the application. The mHealth development and evaluation framework have been used to provide a best practice framework for the MedFit app development [5]. The selected behaviour change strategies are being delivered within the intervention through the various app components such as push notifications, testing, feedback, and videos.

The application has three main functionalities provided to the user: 1) A list of personalized exercise classes that guide users through different exercises using video and audio modalities; 2) Feedback provision to the user on the different aspects of activity measurements; 3) Capability to supervise a patient if wearable sensors are worn whilst exercising. The contributions of the work can be divided into two groups: design choices for the application, including wearable sensors that are utilized, and the feedback provisions to the user. Three feedback techniques were selected based on the health behaviour change models and implemented in the application. The experiment results are reported on separate integral parts of the application, while the clinical trial with the medical patients using the complete application is scheduled in the near future.

2 Mobile application design

An android application is developed as a prototype of the front-end of the proposed system. The application is aimed at the patients who suffered a cardiac event and are in Phase III of the recovery process[1]. The design of the graphical interface is carefully considered to make sure that patients can easily use the application. The mobile application development framework [5] used follows an iterative process for developing technology-based interventions, by facilitating and encouraging end-user engagement.Focus groups with cardiac rehabilitation participants (n=26; 65% male; mean age 64±18.2 years) were undertaken to

[1] http://www.uofmhealth.org/health-library/ty6411abc

get feedback on the first prototype of the application. This feedback was then translated into feasible technical improvements.

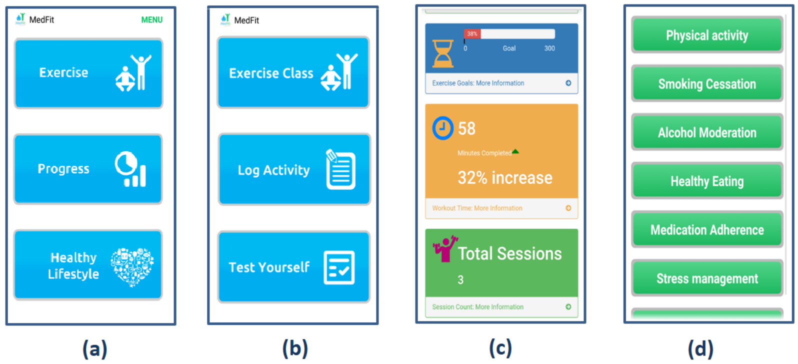

Fig. 1. Graphical user interface (GUI) of the application

As can be seen in Fig. 1(a), the main menu has three options: *Exercise*, *Progress*, and *Healthy Lifestyle*. There are three options related to the *Exercise*, as can be seen in Fig. 1(b). *Exercise Class* brings the user to the list of guided exercise classes that are personalized based on the evaluation of the classes performed earlier. The *Log Activity* section allows the user to manually log any exercise or physical activity that has been done outside of the application (e.g. swimming). The *Test Yourself* option allows the user to evaluate their progress using internationally accepted standard physical activity health tests [6]. The *Progress* option provides the users with the statistical representation of the activities performed so far (see Fig. 1(c)). The *Healthy Lifestyle* option brings the user to the key rehabilitation lifestyle topics picked by experts, as shown in Fig. 1(d).Apart from the design of the application, a lot of considerations went into the selection of wearable sensors that would allow the users to get the best possible feedback about their performance.

2.1 Multi-sensor connectivity

Wearable sensors became ubiquitous and are now available off-the-shelf to use with an impressive list of sensing modalities made available. After an in-depth analysis of the suitability of the available sensors, an off-the-shelf wearable fitness tracker was utilized to retrieved step count and heart rate measure (Fitbit Charge2[2]). These two measures, in combination with the statistical information related to the exercise provided by the application, are sufficient to provide in-depth and meaningful information to the user about their progress.

Additional, more in-depth analysis of the actual performed exercises is made available to the user using the Shimmer3 inertial sensor[3]. The Shimmer is a small

[2] https://www.fitbit.com/ie/charge2
[3] https://www.shimmersensing.com

wireless sensor platform with integrated accelerometer and gyroscope sensors, large storage and low-power standards-based communication capabilities. The Shimmer sensor data is used to detect whether a particular LME exercise is being completed (activity recognition) and count the associated number of repetitions. It enables the near real-time feedback to the user during the performance of the exercises. Fitbit measurements are used to give an insight on the heart-rate and step counts to the user. The performance measures are carried out with shimmer sensor data.

3 Motivational feedback

It is well accepted that motivation to continue and progress on any activity, including rehabilitation program, is closely related to the performance feedback available [7]. In this work, three main feedback delivery methods are employed, namely self monitoring, message notifications and near-real-time feedback.

3.1 Self monitoring

In a review of applications to promote physical activity among adults, providing feedback and self-monitoring were the most frequently used techniques [7]. The application provides a feedback on four main statistical measures of user performance. The number of exercise minutes completed, the number of exercises classes completed, the daily step count and the average heart-rate captured during exercises.

Fig. 2. Patient performance compared to other group members

In addition to personal statistics, the user can also compare his/her performance with that of other group members (Figure 2). In this Figure, the user status is highlighted in red on the Gaussian curve. The left and right graphs represent the number of classes (sessions) completed and the number of minutes spent exercising, respectively. The progress of the other users is marked, but anonymised, using yellow dots. This graphical visualization is created in order to notify the user that there are other people who are carrying out the same exercises. It allows the user to feel more part of a community of rehabilitators and increase the chance of adhering to the rehabilitation program. Furthermore, it allows the user to determine where he/she is standing in comparison to other group members (in an anonymized manner) and as a result become more motivated and engaged with the entire program to enhance his/her performance level. Users have the option of creating and opting in/out of these groups.

3.2 Message notifications

Previous research, has shown that most interventions provided personally tailored SMS messages [8]. This application provides a tailored feedback to be delivered to end users based on health behaviour change theory, as well as a delivery schedule based on the 'six A'programme of changing behaviour [9]. Messaging is provided to remind users to exercise, to give encouragement or just to give feedback on their progress. Text messages are sent three times a week in the morning and at the end of the week; the user receives a summary of their performance for the entire week. An example of a personalized message sent on Sunday to a user called Mike, who has completed more than half of his target goal by the end of the week, would look like this:

> "*Hi Mike, your physical activity goal for this week was at least 150 minutes. You fell short of your goal by 75 minutes this week. Think positively next week and keep your mind set on reaching your goal. You can do it!*".

3.3 Near real-time feedback

At the end of each exercise, the repetition count report acts as an important feedback mechanism for the patient. The 3D accelerometer and 3D gyroscope, from the Shimmer sensor unit, can provide accurate translational and rotational data [10]. Fourteen LME exercises associated with cardiac rehabilitation are used for evaluating activity detection and repetition counting (Table 1) [11].

Table 1. Local muscular endurance (LME) exercises for cardiac rehabilitation

Exercise	Type of LME	Exercise	Type of LME
Upper Body LME Exercises			
Ex 1	Bicep Curls	Ex 6	Pec Dec
Ex 2	Triceps extension (right)	Ex 7	Trunk twist
Ex 3	Upright row	Ex 8	Side Bends - alternating sides
Ex 4	Lateral raise (arms up)	Ex 9	Bent Over Row (right arm)
Ex 5	Frontal raise (arms up)	Ex 10	Press up against wall
Lower Body LME Exercises			
Ex 11	Squats	Ex 13	Standing bicycle
Ex 12	Lunges-alternating sides	Ex 14	Leg lateral raise (right)

Data Capture and Pre-processing: Shimmer3 unit is calibrated in order to obtain accurate and consistent data and is configured with a sampling rate of 512Hz for data capturing. The calibrated sensor unit is worn on the right wrist by each participant. For each LME exercise listed in Table 1 data is captured and a 30 second data segment is used, which corresponds to the length of the exercise. To introduce variability to the data, each exercise is performed by six participants (Age group between 20 - 40, 2 males and 4 females). A 30 second segment of the accelerometer sensor data in the 3D space for Bicep Curl is shown in Figure 3. The classification model is trained to identify whether the person is performing an exercise, therefore, random movements are also captured and added to the dataset. Random movements are 'standing relatively still' or 'shuffling around' to represent non-performing of an exercise. The data segments are grouped into two balanced classes: Class 1 for exercise data and Class 0 for random movements data. 80% of the data collected was used to train and validate the generated models utilizing 10-fold cross validation technique. The remaining 20% of the data was used for testing.

A total of 24 time and frequency statistical measurements from all 3 axes of the accelerometer data is used as a feature vector. The features include the mean, standard deviation, correlation coefficients, FFT coefficients, minimum and maximum values, RMS values, and entropy. The features are computed from the concatenated segmented data using a sliding window of 4 seconds. A window length of 4 seconds with 2 seconds of overlap is chosen as it is sufficient time for each repetition of the selected LME exercises to be completed.

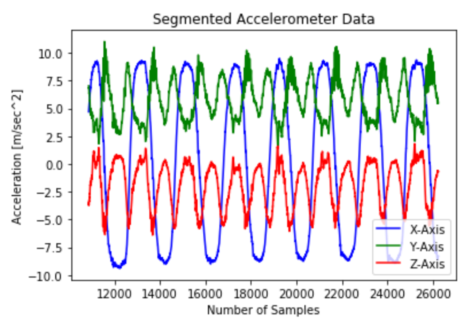

Fig. 3. Segmented Bicep Curls data for 30 seconds

Classification: There are a number of machine learning algorithms that could be used for classification. Since the dataset consists of two classes, an optimized support vector machine (SVM) classifier is chosen for this binary classification task [14]. One SVM model is created for each exercise with optimum hyper parameters. The models are used for recognition of each LME exercise from the random movement [12]. Ten-fold cross-validation as well as a regularization technique is used to avoid overfitting. A grid search for SVM hyper parameter optimization technique is implemented to improve the performance of the designed models by finding the optimal combination of hyper parameter values, including the regularization parameters and kernel options [13].

Classification results are measure using f-score, precision, and recall for each LME exercise recognition and are listed in Table 2. Individual accuracies of no lower that ≥96% are found using a single wrist-worn 3D wearable sensor, with an overall accuracy of ≥98%. The accuracy of the lower body exercises does not suffer form the sensor placement on the right wrist due to wrist movements that are also associated with these exercises.

Repetition Counting: Data from the best suitable axis, either from the accelerometer or from the gyroscope sensor is used to count the repetitions. The best axis data from the sensor is filtered using a Savitzky-Golay filter [15] of order 4 and a repetition counting algorithm (peak-to-peak detection (PP) or threshold crossing(ThC)) is used to count the repetition.

Repetition counting results for each exercise are accurate to 100% with repetition rate of a repetition per one, two and four seconds.

Table 2. Performance measures associated with each LME exercise

Exercise	Precision	Recall	F1-score	Exercise	Precision	Recall	F1-score
Upper Body LME Exercises							
Ex 1	1.000	1.000	1.000	Ex 6	1.000	1.000	1.000
Ex 2	1.000	1.000	1.000	Ex 7	1.000	1.000	1.000
Ex 3	1.000	1.000	1.000	Ex 8	1.000	0.963	0.981
Ex 4	1.000	1.000	1.000	Ex 9	1.000	1.000	1.000
Ex 5	1.000	1.000	1.000	Ex 10	1.000	1.000	1.000
Lower Body LME Exercises							
Ex 11	1.000	1.000	1.000	Ex 13	1.000	1.000	1.000
Ex 12	0.963	0.963	0.963	Ex 14	1.000	0.963	0.963

4 Conclusion

Physical activity, as part of cardiac rehabilitation, is crucial to reducing the likelihood of premature death and increasing the quality of life following CVD. While patients are encouraged to join community-based programmes, uptake and adherence are very low. Our mobile application is created to be a personal trainer/rehabilitator to the patient and to provide live and summary feedback in order to increase the motivation to continue exercising. The proposed system, whose design was driven by behavioural change theory in combination with patient feedback, is a starting point of the independent recovery plan for the patient and aims to motivate the user to uptake and adhere long term to a personalized programme. The application is currently undergoing extensive user/patient testing as part of a clinical trial with results to be reported in the future.

5 Acknowledgements

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