GymBuddy: Mobile Personal Fitness Trainer for Weight Training

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***Abstract*—Awareness in health and fitness have been trending among the younger population, due to their desire in staying healthy and achieving an appealing body shape. Many concerned individuals would attempt to achieve these goals by exercising in the gym or in-home, but beginners are often unfamiliar with the correct exercising techniques and their muscle endurance which could lead to ineffective exercising or even sports injury. This lack of knowledge is often compensated by hiring personal trainers, but many consumers find personal trainers unaffordable or cause inflexibility in scheduling sessions with them. This project aims to improve the exercise effectiveness by developing a mobile healthcare system, GymBuddy, that designs a personalised training programme for users. GymBuddy uses a Myo armband to measure electromyography (EMG), arm position and acceleration and a mobile application to provide real-time advice, exercise suggestions and the users' past exercise data.**

I. Introduction

A growing desire to live a healthier lifestyle and to stay fit is seen in recent years, and therefore more individuals have been participating in fitness activities. This trend has led to a high uptake of gym membership as well as fitness mobile apps or devices, where the number of fitness app users have been growing 87% quicker than the industry average [1].

In order to achieve a certain fitness goal, it is important to do the right amount of exercise as well as avoiding sports injury. Beginners without extensive fitness experience would often struggle to perform optimal training, due to the lack of knowledge about various exercising techniques, the use of muscle groups, and the importance of rest [2]. Traditionally, novice users would employ personal trainers to design a personalised training programme to ensure the effectiveness and monitor the correctness of their exercise. However, not all novice gym members are able to afford hiring a personal trainer, and also more and more individuals prefer in-home fitness activities nowadays due to convenience. Therefore, beginners are likely to over-exercise that caused sports injury, or under-exercise that leads to ineffectiveness of working out.

Weight training is one of the most popular gym and in-home fitness activities due to its effectiveness in developing the strength and size of muscles. However, it is involves lifting weights where users could easily injury themselves if the incorrect load or intensity of exercise is chosen. Therefore, this project aims to address these issues by developing a smart and on-the-go personal trainer, GymBuddy, by using a Myo armband together with an iOS application. GymBuddy will design a personalised training programme, which suggests a fitness activity with an appropriate weight and intensity, through monitoring the users' posture when exercising and the level of muscle fatigue in real time in order to achieve the users' fitness goal. GymBuddy will also provide insight and analytics into the users' previous exercise activities to remind and motivate users. This project will be mainly geared towards the upper-body exercises (listed in Appendix) as Myo armband is designed to track hand and arm movements through capturing electromyography (EMG) and tracking arm positions. The proposed system will be affordable, flexible, and personalised in order to achieve maximum fitness results with a high degree of flexibility.

II. Hypothesis

The aim of this project is to investigate the effect of having an auto-generated training programme through muscle fatigue detection and arm position tracking on the effectiveness of fitness activities. The following hypotheses are proposed according the the project aim:

1) Novice subjects using the GymBuddy wearable system will develop larger muscular gains in size than those not using the system.
2) Novice subjects using the GymBuddy wearable system will be more satisfied with their workout than those not using the system.

III. Related Work

The personal wellness coach [3] is a wearable device which can collect and analyse health data, and provide real-time feedback. It helps users to achieve customised training goals and monitor their heart rate to prevent harm. This virtual coach is able to differentiate between struggling and non-struggling states, and count the repetitions in order to provide real-time encouragement to the user. However, this system requires a computer for data processing, thus the mobility of this system is rather limited. Additionally, the sensors used are bulky and obtrusive, limiting the users' uptake during the usability study.

Buttussi and Chittaro in [4] developed MOPET, which is a wearable system for fitness training. MOPET is implemented using a PocketPC, together with the heart rate monitor and a 3D accelerometer. This context-aware and user-adaptive system provides the user with GPS navigation for jogging routes, visualises information about their speed and heart rate, provides motivational and safety advice, and suggests appropriate exercises, based on the user model. The user model consists of personal information, physiological information and the users' experience with a given exercise. Curiously, MOPET's user interface features a 3D embodied agent that speaks and provides real-time suggestions. This wearable system is mainly geared towards outdoor exercises, such as jogging, however the context and user awareness techniques used in this paper will come useful in our project.

IV. System Design

Fig 1 illustrates the top-level architecture of the proposed system. The system consists of a Myo armband which acts as the central sensing unit, together with an iOS app to act as an interface for the user.

Myo is an armband that allows its users to wirelessly control technology with motion and gestures. While its current applications majorly serve an entertainment purpose such as controlling audio and video systems using gestures, much progress has been made to allow integration in educational and research projects. For example a team at the University of Lisbon has used the Myo armband along with an Arduino board and robotic glove to build a low-cost hand rehabilitation system [5].

The Myo armband is an amazing hardware device that contains "medical grade stainless steel EMG sensors and a highly sensitive nine-axis IMU containing three-axis gyroscope, three-axis accelerometer, and three-axis magnetometer" [6]. The presence of these sensors within the armband allows the extraction of EMG, spatial data and gestural data from the user while they exercise.

The second integral hardware device used in the system is iPhone. The main reason for this choice is the ease and flexibility that is provided by Swift along with the availability of external libraries that aid in specialised tasks such as Torch for machine learning. Furthermore, the iPhone provides us with enough computation power to process the data extracted from Myo band and represent it for the user in the form of visualisations.

So far we have described the high-level infrastructure of our project, describing how the two integral hardware components connect to aid the user. In this section, we delve deeper to discuss the three broad modules that form the basis of our app. These modules are: Fatigue Measurement, Real-time Sensing and Training Program Recommendations. Each of these modules are discussed further is the sections below.

A. Exercise Tracking

In order to ensure the effectiveness of working out, it is important to exercise with the correct position and intensity. At the moment, a few electronic systems were designed to track exercise posture correctness by using camera-based tracking technology, but none of the existing systems track the exercise intensity as well. It is important to monitor the muscle condition of a person who is working out to ensure he is not over-training to hurt his muscles or under-training to lower the exercise effectiveness.

The Myo armband from the Thalmic Labs is a recent wearable technology developed to track muscle activities and hand gestures wirelessly by analysing electromyographic (EMG) signals. It consists of 8 electrodes to capture EMG signals, a 3D gyroscope and a 3D accelerometer, and communicates wirelessly with mobile devices using Bluetooth. This device provides an opportunity to track exercise activities that involves arm movements, and the muscle condition of the user by analysing EMG signals.

1) Muscle Fatigue Measurement: Muscle fibre will contract when it receives an electrical stimulation, which is known as action potential. When muscles fibre fatigues, the propagation of action potentials along muscles, or namely Muscle Fibre Conduction Velocity (MFCV), will slow down since lactic acid will be built up around muscle fibres which hinders the propagation of action potentials. MFCV could be calculated by dividing the distance between electrodes by the delay of EMG signals between the electrodes [7]. Also, spectrum of the EMG signal will be compressed as the MFCV decreases [8].

When Lee and Chee were conducting muscle fatigue analysis, they have used the mean frequency (MNF) and root mean square (RMS) of EMG to evaluate the level of muscle fatigue [9]. They have suggested that MNF decreases with fatigue level while RMS increases with fatigue level.

It is possible to extract raw EMG sensor data from each of the 8 EMG electrodes on the Myo armband by using the SDK released by Thalmic Labs [10]. When comparing MFCV to MNF, MNF recovers more quickly than MFCV [11] and have a less linear decrease than MFCV. This suggests that MFCV would give a more detailed view on muscle fatigue and recovery [12]. However, it will be relatively more challenging to determine the MFCV as it would require the exact distance between two electrodes as well as the delay of EMG signal, because there would be many pairing combinations among the 8 electrodes. Although MFCV would provide better insights in muscle condition, MNF and RMS of the extracted EMG signals from all electrodes should be sufficient to deduce the muscle fatigue at a high level view, and would also suit the Myo armband more. The rate of decrease of MNF could act as an index to represent the level of fatigue. The equations for MNF and RMS calculation are stated as below:

$$RMS = \sqrt{\frac{\sum_n {A_n}^2}{N}} \qquad MNF = \frac{\int_0^\pi \omega S_x(e^{j\omega}) d\omega}{\int_0^\pi S_x(e^{j\omega}) d\omega}$$

where A_n is the n^{th} EMG amplitude measurement of N observations, ω is frequency $(rads^{-1})$ and S_x is the power spectral density of the EMG signal.

2) Posture Correctness Tracking: Throughout the exercise, GymBuddy will be monitoring the correctness of a given exercise, and providing feedback to the user when necessary. The correctness will be judged on a number of factors: speed of repetitions (frequency of a movement pattern), orientation, and position of arms.

The speed of repetitions will be evaluated by continuously recording the absolute value of acceleration, given by the Myo integration module [13]. This value will be smoothed, using a 5-second moving average filter, and compared with the desired value of acceleration specific to the exercise. Deviation from the desired value will be displayed to the user. Deviation can be positive or negative, thus indicating whether the user should speed up, or slow down.

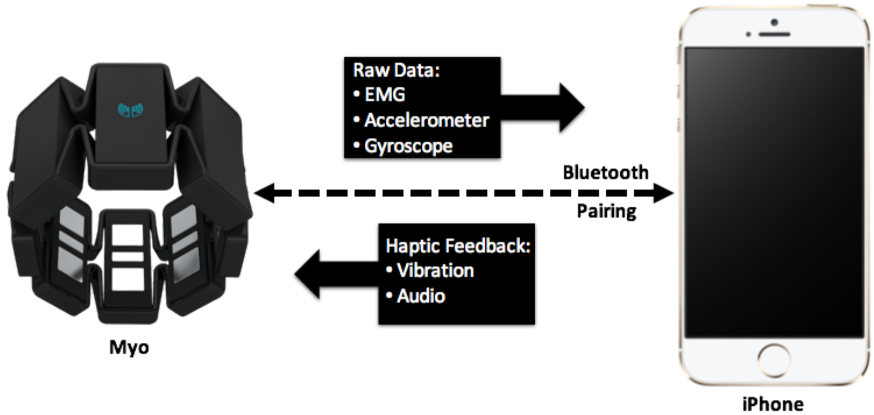

Fig. 1: High Level System Overview

Orientation will be evaluated continuously against models specified for the given exercise. These models be represented by 2-Dimensional arrays, containing orientation values [13] corresponding to one exercise cycle. A 5-second moving window will be used to record orientation, which would then be compared to the corresponding pre-set model. Deviations from the expected models will be used to calculate the orientation correctness scores on a scale from 0 to 100.

The orientation correctness score will be continuously displayed on the GymBuddy application, accompanied by a variable-colour background. The background colour will be green when the score is above 74, yellow when the score is between 25 and 75, and red when the score is below 25.

If the orientation score drops below 75, a short haptic feedback will be provided by the Myo band. If the score drops below 25, a longer 1-second haptic feedback will be provided by the Myo band, in order to alert the user of the incorrect exercise technique.

During the resting time, GymBuddy will continuously monitor the level of muscle fatigue by a normalised index, while applying a 3-second moving average smoothing filter. Once the resultant value dips below a pre-determined threshold, the subject would be deemed as having had enough rest to continue the exercise, and informed via a notification.

B. Real Time Feedback

The GymBuddy iOS application will have an ability to provide real-time updates during the exercise.

For example, when the user's level of fatigue is rising, GymBuddy will display a notification to the user with an encouragement, such as: "Don't give up, you can do it!". This can be achieved by implementing a Swift protocol [14] in order to receive fatigue index [15] from the Myo integration module in real time, and applying a 3-second simple moving average smoothing filter. Once the filtered fatigue index reaches a pre-determined threshold, the notification will be triggered once per exercise set.

Similarly, when the user's muscles are fatigued, GymBuddy will send a notification to remind users to take a break, such as: "Stop! You've had enough for now." This will also be achieved by applying a 3-second moving average filter, and triggering the notification once the filtered fatigue index reaches a certain threshold. Additionally, a 2-second haptic feedback (vibration) will be activated on the Myo band in order to alert the user.

Haptic feedback will be triggered by calling an appropriate method within the Myo integration module's protocol, which will in turn activate the haptic feedback. Notifications will be triggered using the UILocalNotification() class. Such modularity is desired in order to keep the application maintainable, and provide separation of concerns.

C. Training Programme Recommendation

In this module, workout routines are generated based on the user's inputs, muscle fatigue level, and historical data. This system is aimed at preventing potential muscle harm and motivating users to achieve fitness objectives. Machine learning techniques will be applied to personalise the exercise suggestions. In order to produce a dedicated plan, users need to give some information about their age, gender, weight, height, preferred muscle groups, one of the three workout modes (1. fat burning, 2. cardio training, 3. high intensity) and desired exercise duration.

Cardio-intensity level is an important factor to indicate a person's physical condition. It can be evaluated by Karvonen Formula (Table I) which estimates the maximum heart rates for different age groups and genders [3]. The maximum acceptable heart rate for different workout modes are shown in II.

The camera of iPhone will be used to collect the heart rate as this cannot be measured with Myo. A smartphone's camera can detect PhotoPlethysmoGram (PPG) signal and the pulse rate (PR) is evaluated by adaptive and statistical analysis [16]. Users should press the "measure heart rate" button and then put one finger on the camera to record their heart rate after each exercise if they are concerned about this factor and training goals.

The module will suggest the optimal exercises, weight of dumbbells and number of repetitions according to user's current condition and historical data. A typical workout routine is to do each exercise 3×8 repetitions which means users take a short break after finishing 8 repetitions, do 24 repetitions in total.

Moreover, sensors in Myo can detect the position of arms. This could be used to monitor the user's actions, and give

Gender \ Fitness Level	Male	Female
Non-Athletic Max Heart Rate	$220 - age$	$226 - age$
Fit Max Heart Rate	$205 - \frac{age}{2}$	$211 - \frac{age}{2}$

TABLE I: Karvonen Formula

Training Goal	**% of Max Heart Rate**
Fat Burning	60 to 70%
Cardio Training	80 to 90%
High Intensity	90 to 100%

TABLE II: Acceptable Heart Rate for Various Training Goals

feedback on whether the action is correct or not. GymBuddy is designed to support 6 upper-body parts, they are 1) chest, 2) biceps, 3) triceps, 4) shoulders, 5) back, 6) forearms. There are two or three activities for each body part. When a workout routine is determined, GymBuddy will show the correct actions. If users do not work out correctly, a warning message will be displayed. The accuracy of detection will be increased if the database stores the features of some common training mistakes [17] [18].

V. Evaluation

In order to evaluate effectiveness of this system, a group of students who are inexperienced with fitness training will serve as the test subjects. Half of the group will be provided with the GymBuddy wearable system and asked to exercise in a gym, while following guidance from the application. The other half of the group will be asked to exercise in a gym without the GymBuddy system. Each test subject will be required to exercise once per day for two weeks, and rate their own feeling of exertion using the Borg Rating of Perceived Exertion (RPE) Scale as well as user satisfaction [19]. Both groups will also have their muscular features (such as size of biceps) recorded before and after the test trials. Comparison of the muscular gains will help validating the first hypothesis, while the user satisfaction questionnaire will allow us to evaluate the second hypothesis. Borg Scale would allow the team to evaluate whether the system is identifying the correct exercise intensity through muscle fatigue detection, which suggests whether the system is giving appropriate recommendations.

VI. Conclusion

In this design report, we highlighted our aim to aid young adults in their pursuit of a fit body by providing helpful, personalised suggestions while they conduct weight exercises in the gym. This will be a crucial step for beginners who, in their attempt to achieve the desired body, might make fundamental errors of judgements while choosing the exercises, weights and number of repetitions for a particular body part. We discussed our plans to use a Myo band, worn around the forearm of the user while exercising, to record and assess the health of muscles using electromyography (EMG), and extract accelerometer and gyroscope data. This data will be sent to the user's iPhone via Bluetooth, where it is processed, recorded and compared with past data to recommend suggestions to improve. Furthermore, we delved deeper into the initial design choices we have made in order to start working on the project along with the final evaluation techniques we plan to employ to test our solution.

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