RECOLIFT: AN ANDROID WEAR FITNESS TRACKER FOR STRENGTH TRAINING

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BY

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THESIS

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ABSTRACT

Despite the plethora of fitness trackers on the market, few monitor signals other than number of steps and heart rate. With the increasing mainstream acceptance of general-purpose smartwatches however, we have the capability to track more complex activities. We propose RecoLift, an Android-based system to track exercises and repetitions in weight training and bodyweight training activities based on the work of Morris et al. Our goal is to provide a system which provides feedback to the user in an autonomous, online fashion, harnessing both smartwatch and smartphone sensors. This system is separated into three key phases: *segmentation*, during which we use the periodicity of the signals to determine if an exercise is being performed, *recognition*, which calculates signal features to determine which exercise is being performed, and *counting*, which uses periodicity to calculate the number of repetitions in a set. Early classification results show 94% accuracy for our segmentation phase and 99% accuracy for our recognition phase, with counting phase results within two repetitions of the true count on average.

To my mother, for her love and support.

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I would also like to thank Morris et al. for their outstanding paper (REFERENCE) which my thesis is based on. Their work enabled me to showcase the skills I have acquired over the duration of my undergraduate studies.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

If we were to peruse the headlines on a technology news website such as *The Verge* or *ArsTechnica*, a vast majority of the posted articles would revolve around the new Apple Watch. Google has been pushing their new Android Wear platform for over a year now, and Pebble has been working for even longer, with their original Kickstarter launching on April 11, 2012 (REFERENCE). At least in the eyes of these device manufacturers, smartwatches comprise the next wave in mobile computing.

Occurring concurrently is the recent public interest in personal analytics. Fitbit and Jawbone have become the two frontrunners in this space. Their product lines of fitness trackers primarily record data related to general purpose fitness, such as resting heart rate, number of steps taken per day, and calories burned. Both Google and Apple have also taken to this space, incorporating fitness tracking in their own wearable devices by including an optical heartrate on the undersides of their watches and various MEMS sensors onboard the watches themselves. They have also opened up new APIs to allow developers free access to their personal data stream (REFERENCE), enabling such applications as runner route tracking and sleep tracking (REFERENCE). One space has remained relatively empty of fitness tracking applications however, and that is strength training.

Strength training comprises of three distinct disciplines: weightlifting, powerlifting, and bodybuilding. Weightlifting involves two lifts only, the clean and jerk and the snatch. These two lifts are the only lifts among strength training exercises that are tested at the Olympics (REFERENCE). Both of these lifts are highly technical and not often performed by beginners, with the exception of CrossFit, a new lifting paradigm which starts beginners on high-repetition Olympic lifts. Powerlifting focuses on three lifts only, bench press, squat, and deadlift. Like weightlifting, the primary goal of powerlifting is to maximize the weight lifting among the three lifts. The main distinction, aside from the difference in lifts, is powerlifters tend to focus on raw strength, whereas weightlifters focus on speed. Finally, bodybuilding is significantly different than both weightlifting and powerlifting. Strength does not matter in bodybuilding, and as such, bodybuilders focus on a plethora of smaller, isolated lifts to improve their physique. It is not uncommon for a bodybuilder to spend two hours in the gym performing 30 or 40 sets at eight repetitions per set (REFERENCE). This can be problematic, as gym goers often neglect to record their lifts, leading to confusion during the next session in the gym.

To this end, we have created an application based on the work of Morris et al. in *RecoFit* (REFERENCE) which tracks exercises without user intervention using the commonly available Android Wear platform.

As mentioned, this work is based on *RecoFit* by Morris et al. (REFERENCE), which uses the intuition that exercise is distinctly periodic and can be well-discerned from non-exercise. They achieve 86% segmentation accuracy and 98% recognition accuracy using a custom-built arm-worn device which samples at 50Hz. Additionally, their computation is done on local desktop machine, eliminating the need for energy optimizations beyond the sampling rate of the IMU. Our solution uses readily-available hardware which has been gaining traction in the consumer space (REFERENCE) to expand the possible userbase. We also consider battery life optimizations on the Android devices while still maintaining comparable levels of accuracy, allowing a user to spend an hour at the gym and continue their day without smartwatch or smartphone recharging. Finally, because we utilize the Android smartwatch, we can make stronger assumptions about placement of the smartwatch. This enables us to perform classification on a higher-dimensional dataset.

Pernek et al. propose an algorithm to count the number of repetitions of an exercise using dynamic time warping (DTW), a dynamic programming technique which allows for comparison between two non-temporally aligned signals by calculating a mapping which minimally warps and shifts one signal onto another. To differentiate between exercise and non-exercise, Pernek et al. utilize a thresholding algorithm which triggers when the device's accelerometer signal peaks approach the magnitude of the peaks in their prerecorded dataset. Their method performs very well with regard to repetition count, although their solution is not entirely autonomous during operation, requiring input from the user at the beginning of each exercise.

Seeger et al. describe a system which utilizes a network of embedded wearable sensors across the body to compute high-dimensional features for exercise classification. Equipping a user with an accelerometer above the right knee, a heart rate sensor, an accelerometer attached to a weight lifting glove, and a chest strap, this system is able to highly accurately detect and count exercise. However, this system is suboptimal due to the infrastructure required. A user attending an incredibly upscale gym may have access to these sensors, but the average user would not. Wearing so many sensors would also obstruct the user during lifting, which could cause both damage to the sensors and discomfort to the user.

Muehlbauer et al. follows a similar pattern to Morris et al. and our own solution by dividing the task into three phases, segmentation, recognition, and counting. Autocorrelation analysis is used during segmentation to determine of a user is performing an exercise. After determining that an exercise is being performed, a number of features are calculated such as mean and standard deviation. These are passed into a k-Nearest Neighbors classifier which comprises the recognition phase. Lastly, counting is perfored using simple peak counting. Muehlbauer et al. performs well, with 85% segmentation accuracy and 94% recognition accuracy, although their segmentation thresholds are based off heuristics, and they do not address online performance.

REFERENCES