Striving for Perfection: Measurement of Incremental Fitness Improvement

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ABSTRACT
TBA

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Kinect; Metabolic Conditioning;

INTRODUCTION

Motivation
Intensive workout programs such as P90x, Insanity, and Rushfit promise users to transform their bodies into the best shape of their life by following a 60 to 90 days workout regimen. These types of routines feature methodologies such as Muscle Confusion, Max Interval Training, or High Intensity Interval Training, which all fall into the Metabolic Conditioning exercise category—exercises that increase the storage and delivery of energy for any activity through the improvement of strength and endurance. While a multitude of users report great results, many do not endure long enough to reap the fitness benefits of these programs. Prior research (see related work section) has shown that motivation improves exercise adherence. Accordingly, it is our belief that one of the main reasons people fail to persevere these exercise regimen is the lack of observable progress from one workout to the next, a crucial motivating factor. Unlike strength training exercises–such as bench press or deadlift–the incremental improvements of Metabolic Conditioning workouts are often not apparent until weeks into the program, causing many users to lose motivation and quit the program early in the 60-90 days regimen. The goal of our study is to leverage motion tracking devices such as the Microsoft Kinect to create a software tool for calculating incremental progress for Metabolic Conditioning exercises and ultimately motivate users to adhere to their Metabolic Conditioning routine of choice.

Approach
The intensity of a MC type exercise movement can be measured by the amount of resistance (either body resistance or use of external weights), the volume of repetitions performed and the power or rate at which work is performed. It is our goal to use relatively inexpensive technology, such as the Microsoft Kinect, to measure exercisers progress with a reasonable accuracy. We aim to meet with our fitness experts to create a workout in the style of P90x and Insanity that features exercises that fit the following criteria:

- Requires little to no prior skill or training
- Requires strength to accurately achieve the best stance for that particular move
- Requires stamina to complete the exercise move at a fast rate.

We will use the performance of our experts with the generated MC workout routine and use these accumulation of these and a first set of participants' performance to establish the expert fitness benchmark. We then plan to both record the footage of each participant completing the routine and use the depth sensor to measure factors such as rate of exercise move, body form (predominantly angles between limbs), speed, height (where applicable), the duration and frequency of resting time, and the volume of repetitions performed. We will then calculate a score or percentage of the expert benchmark using the collected data as well as generating more granular data specific to each workout move completed. After the participant has finished the workout, we will show them the two different reports 1.) The expert percentage score and 2.) The granular exercise move specific report and ask them to determine which report would be most helpful for them in terms of tracking their performance from workout to workout.

Contribution
If successful, our work will show that currently hard to benchmark exercises can be evaluated in terms of performance with relatively inexpensive hardware. We predict that our measurement tool could be meaningful to potential users to track minute performance improvements and, ultimately, inspire them to continue working towards their fitness goals. Much research has already been done regarding measuring exercise performance using technology that has inspired and motivated this research project. We believe our work addresses a hole in this field that has not been explored that we believe will spark future work in the field of exercise motivation and progress analysis through the use of inexpensive technology.

RELATED WORK

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The notion of tracking one's progress and quantifying improvement is an old one. As early as the 18th century, Benjamin Franklin kept a daily journal to monitor his performance in thirteen personal virtues. Modern research provides formal basis for what Benjamin Franklin seemed to know intuitively: the idea that measurement improves adherence and ultimately promotes long-term behavioral change. For example, Dr. Melody Noland measured the effects of self-monitoring and reinforcement on adherence to unsupervised exercise [3]. Splitting the study subjects into three groups (self-monitoring, reinforcement supplied by another person, and control), she found that the self-monitoring and reinforcement groups reported a significantly higher frequency of exercise and better results than the control group [3]. Despite the encouraging results, Dr. Noland's methodology may today seem outdated: the self-monitoring subjects were required to keep a written log of their exercise [3], leaving much to be desired in terms of usability and automation of what may otherwise be a very tedious process. Indeed, the decade following the 1989 publication of Dr. Nolans research witnessed the onset of persuasive technologies, which likewise leveraged progress tracking as a means of sustaining desired behavior. One of the pioneers of the field, Dr. Sunny Consolvo and her co-authors explored the ways in which technology could be used to encourage behavioral change [2, 1]. In "Theory-Driven Design Strategies for Technologies that Support Behavior Change in Everyday Life", Consolvo et. al. did an excellent job drawing on prior research in behavioral psychology and situating their work in the context of relevant psychology theories. For instance, the Goal-Setting Theory stresses the importance of an ongoing feedback as progress is made as opposed to merely providing a reward when a goal is achieved [2]. Choosing data abstraction as one of the main design tenets of UbiFit, the software they created for the purposes of their study, Consolvo et. al. implemented an animated garden that tracks and encourages progress toward the desired goal [2, 1]. Our research takes a different approach by instead enabling the measurement of granular, incremental changes that the UbiFit garden interface does not capture. As such, our research enters a contented field of performance measurement tracking devices. Indeed, those interested in physical activity tracking devices have a myriad of options, such as Jawbone Up, Fitbit, or the Nike Fuel Band, all of which offer different ways of performance tracking. Relying predominantly on accelerometers, theses devices fail to account for improvements in form and are prone to count mindless handshaking toward the user's exercise score with much opportunity for the user to game the system. Unlike these commercial devices, our goal is to use Microsoft Kinect to develop exercise-tracking software that could accurately measure the incremental qualitative improvements in a person's form and overall execution of an exercise routine, rather than a raw quantity of physical activity in insolation.

METHODOLOGY

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Micosoft Kinect Data Collection

The Microsoft Kinect utilizes an infrared emitter and a IR monochrome CMOS (complimentary metal-oxide semiconductor) sensor to measure and sense depth. [Link to microsoft webpage] The emitter emits the infrared light beams and the CMOS sensor reads these IR beams that are reflected back to the sensor. These beams are then converted into depth information measuring the distance between an object and the sensor. Due to this functionality, we were able to measure and track depth and obtain an x, y, and z point for each of the data points. The Kinect SDK features built in functionality that provides a deep understanding of human characteristics. The SDK features skeletal tracking, facial tracking, and gesture recognition. The Kinect Fusion algorithm makes it relatively computationally inexpensive to continuously scan the scene by recovering the camera position from the previously scanned point. We took advantage of both the skeletal tracking functionality and the Kinect Fusion algorithm to store the x, y, and z points of the left ankle, right ankle, left elbow, right elbow, left foot, right foot, head, left wrist, right wrist, and spine. From this we were able to use our post processing script to determine the number of exercises moves done within the time period and, for a sample of the exercise moves (High marches, squat jumps, and jumping jacks), the participants' from while completing that move.

Post Processing

TBA

Participants

TBA

Limitations

TBA

RESULTS

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DISCUSSION

TBA

CONCLUSION

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REFERENCES FORMAT

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