Michael Dow and Samuel Zelman

Date Submitted: May 1, 2016

Accelerometer-Based Automatic Counting of Arbitrary Repetitive Motions

Abstract:

Already there is a large consumer market on devices that track steps and other standard measures. However, there are many more movements that can be quantified by wearable devices. This can be particularly useful to motivate a physical therapy patient's compliance. This system was designed to be flexible enough to handle multiple movements of exercise. Wearable devices with accelerometers were attached to a participant's body to track repetitions during exercise. 18 participants completed a series of 10 exercises (arm circles, bicep curls, bridges, sit-ups, elbow extensions, leg lifts, lunges, push-ups, squats, and upper trunk rotations), twice each, for 30 seconds. Three analysis techniques were used to count the repetitions: threshold crossing, threshold crossing with a low-pass filter, and a Fourier transform with a low-pass filter. Results indicate that some exercises like arm circles and push-ups are tracked well by most analysis methods, while less periodic, irregular motions like upper trunk rotations are more difficult to track. The methods that used low-pass filtering performed reasonably well, with an 80.75% accuracy. This indicates that our system is capable of tracking a large number of activities, even ones for which it was not originally designed.

Focusing Question:

How accurately can an accelerometer count exercise repetitions without knowledge of the specific activity?

Introduction:

The demand for physical therapy is currently, as well as predicted to be, beyond the available supply ("Supply and Demand," 2015). The American Physical Therapy Association predicts a deficit of 26,969 physical therapists by 2020 ("Supply and Demand," 2015). Clinical activity tracking devices could potentially be used to accurately track patient exercises, removing the necessity of frequent physical therapist visits. From 2010 to 2015, the average premium for health insurance increased by 27%, while an average worker's earnings only increased by 10% ("Employer Benefits," 2015). However, the activity tracking devices can benefit the customer by limiting the need to visit a therapist for simple tasks.

Clinical activity tracking devices use inertial sensors to track daily movements. Activity tracking devices are wearable devices that utilize an inertial sensor unit that contains some assortment of a gyroscope, a magnetometer, and a three-axis accelerometer. A major limitation of current clinical devices is the cost. The Modus Health Stepwatch is $500 (Heath, 2014). ActiGraph's wActiSleep-BT Monitor is $299 ("Actigraph Graph," 2013). Despite the cost, these products have the ability to significantly lessen the burden on physical therapists by allowing patients to track their exercises from home or in a hospital setting.

Additionally, various consumer oriented activity-tracking devices are already in use, but what they can infer is limited. Through the use of inertial sensors, products such as the FitBit Surge and the Nike FuelBand analyze exercises and count exercise repetitions [5] [6]. However, the inertial sensors on these products, generally accelerometers and altimeters, focus on daily activities (i.e walking, running, sleeping) rather than calisthenics.

Researchers have previously investigated the accuracy of accelerometers' analysis on counting the number of repetitions in an exercise. Researchers at Microsoft investigated tracking weight training and calisthenics (Morris, Saponas, Guillory, & Kelner, 2014). The objectives of the investigation were to segment the periods of exercise from periods of inactivity, recognize which exercise was being performed, and count the repetitions of those exercises.

German researchers from the Technical University of Darmstadt tracked a person's daily exercises for use in motivation and social media (Seeger, Buchmann, & Laerhoven, 2011). Accelerometers placed on several locations on the body calculated the movement mean and variance per second, with only autocorrelation being used to count the repetitions.

Our project provides information that physical therapists could use to provide more efficient training while their patients are at home or in a hospital. Patients could exercise towards a given goal without the constant overwatch of the therapists. In turn, this would save patient money and decrease the number of patients a physical therapist has to see at one time. We expect our project to provide meaningful for physical therapist practices.

Most new smartphones contain inertial sensors, such as 3-axis accelerometers and gyroscopes, which can be utilized through applications. Several of these, such as Moves, Strava, and RunKeeper, count the number of steps walked/ran, and the amount of distance biked. These consumer oriented applications are limited in their capabilities. Most are unable to count certain exercises, such as weight training or calisthenics.

Methods:

18 participants, ages 15 through 25, took part in this study. The subjects completed a series of 10 exercises, twice each, for 30 seconds. The smartphone was either held in the participant's hand, or strapped to their waist or chest (Table 1). A strap was used to hold the phone in place during the exercise. During the exercise, the smartphone recorded 3-axis accelerometer data. The number of repetitions was recorded by both the participant and the observer. In any case where the numbers were not equal, the exercise was repeated. Between each exercise, the participants were allowed an optional one minute break. The smartphone used for data collection was the LG Optimus S running Android.

The data was manually trimmed based on visual analysis. Three methods of estimating activity counts were written in Python and several appropriate libraries including NumPy and SciPy. The analysis techniques are as follows:

- **Threshold crossing:** One of the data analysis techniques was threshold crossing, which calculated a threshold line positioned two-thirds of the range above the minimum. When the accelerometer crossed the line in one direction, it would add one repetition to the step counter. After each repetition count existed a refractory period of 0.1 seconds, in which a repetition was not counted.

- **Threshold crossing with a low pass filter:** This method analyzed the data with a low pass filter frequency cutoff of 0.01 multiplied by the time interval between data points. This filter minimizes high frequency noise, while still maintaining the general trend of the graph. After the filtering, the data was analyzed with the thershold-cross method.

- **Fourier transform with a low pass filter:** Standard fourier technique was used to plot the data on a frequency domain. Using the most prominent frequency, the number of repetitions were calculated based on the length of time of the data collection.

Results:

18 participants performed 10 exercises, twice each. The smartphone was placed on the body depending on the primary location of movement. The accelerometer recorded the exercise for 30 seconds. The number of repetitions of each exercise was counted. As seen Figure 1, the accelerometer data was transferred into magnitude of acceleration data. Then, the data was analyzed by three methods written in Python: Threshold crossing, Threshold crossing with a low pass filter, and Fourier transform with a low pass filter.

Exercises with more periodic and substantial ranges of motions were counted more accurately. Figure 2 shows the accelerometer and magnitude data for arm circles, push-ups, and upper trunk rotations. Arm circles performed well, with a small amount of excess noise in the magnitude graph. Upper trunk rotations was more difficult to count, having a large amount of noise in the graph.

Table 2 shows the accuracies of each method on each exercise. Threshold crossing proved to be the most accurate counting method, with an average root mean square error of 8.69 and a percent accuracy of 80.75%. Fourier transform also performed reasonably well with an average root mean square error of 9.00 and an overall accuracy of 78.43%. Threshold crossing without the filter did not perform well, and had a root mean square error of 13.38 and a percent accuracy of 49.14%. Squats were the easiest exercise to count, while upper trunk rotations were the worst.

Discussion:

The goal of this study was to determine the accuracy of a smartphone accelerometer when counting repetitions of a wide variety of exercises (Figure 2). The accelerometer data contained large variations due to the diverse movements of each participant. The project did not utilize automatic segmentation or recognition, which allowed us to place more focus on a robust system capable of counting a wide variety of exercises.. However, our data was trimmed based on visual analysis, which is prone to error. The Fourier transform may have outputted a skewed repetition count due to the impact of our data trimming

The location of the smartphone for each exercise was chosen based on where the majority of body movement was taking place. The orientation of the phone was not constant between each exercise. A random orientation of the phone allows for a more accurate representation of real-world situations.

A Microsoft study similar to ours, "Recofit," analyzed the repetition accuracy of weight training and calisthenics through an arm-worn accelerometer [Morris et al., 2014]. The use of segmentation and recognition allowed the researchers to improve repetition count accuracy. Data was analyzed with only the autocorrelation method, whereas we utilized three techniques. The researchers discovered that the use of individual learning models for repetition counting can improve accuracy.

Users of a consumer exercise tracking device will be motivated in their workouts. Patients, rather than having to go to a physical therapist to be motivated in their exercises, can instead be assigned a certain amount of exercises sets. Researchers at Stanford University, using 2767 participants with a mean age of 49, found that pedometer users had a 26.9% increase in physical activity over baseline [Bravanta, Smith-Spangler, & Sundaram, 2007]. An AJPM study found that granting Fitbits to 51 postmenopausal women led to increased physical activity over 16 weeks [Cadmus-Bertram, Marcus, Patterson, Parker, & Morey, 2015]. The long term effects of the trackers is yet to be determined, but the success of current step counters grants us a positive attitude towards exercise tracking devices.

Information gathered on the accuracy of our activity counting methods has the potential to reform the market for consumer activity trackers. Consumers would have the ability to use repetition trackers to count their calisthenic exercises. This would have an extended effect on clinical tracking devices that could be used in physical therapy practices. Patients could exercise in a home environment, rather than in a clinic. The data collected could also be used to determine the plausibility of accelerometer tracking applications.

Inquiry Process:

With this study, Michael and Sam gained valuable experience in the professional field of research. They accomplished their goal of finding the accuracy of various methods to count the repetitions of certain repetitive exercises. Michael and Sam's topic of inquiry was computer science. They learned the programming language, Python, and gained experience in libraries such as Matplotlib and SciPy.

References:

Morris, D., Saponas, S. T., Guillory, A., & Kelner, I. (2014). RecoFit: Using a Wearable Sensor to Find, Recognize, and Count Repetitive Exercises. *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems - CHI '14*. doi:10.1145/2556288.2557116

Seeger, C., Buchmann, A., & Laerhoven, K. V. (2011). MyHealthAssistant: A Phone-based Body Sensor Network that Captures the Wearer's Exercises throughout the Day. *Proceedings of the 6th International ICST Conference on Body Area Networks*. doi:10.4108/icst.bodynets.2011.247015

Bravanta, D. M., Smith-Spangler, C., & Sundaram, V. (2007). Using pedometers to increase physical activity and improve health: A systematic review. *The Journal of the American Medical Association,* 2296-2304. doi:10.1001/jama.298.19.2296

Cadmus-Bertram, L. A., Marcus, B. H., Patterson, R. E., Parker, B. A., & Morey, B. L. (2015). Randomized Trial of a Fitbit-Based Physical Activity Intervention for Women. *American Journal of Preventive Medicine, 49*(3), 414-418. doi:10.1016/j.amepre.2015.01.020

Actigraphy Devices Side-by-Side Comparison Guide (December 2013) - Sleep Review. (2014, January 22). Retrieved October 16, 2015, from http://www.sleepreviewmag.com/2014/01/actigraphy-devices-side-by-side-comparison-guide-december-2013/

Heath, T. (2014, July 27). Capital Buzz: Georgetown's Modus Health steps out on its own. Retrieved from https://www.washingtonpost.com/business/capitalbusiness/capital-buzz-georgetowns-modus-health-steps-out-on-its-own/2014/07/25/1a961496-11c6-11e4-98ee-daea85133bc9_print.html

2015 Employer Health Benefits Survey. (2015, September 22). Retrieved from http://kff.org/report-section/ehbs-2015-summary-of-findings/

(2015, November 13). A Model to Project the Supply and Demand of Physical Therapists. *American Physical Therapy Association*. Retrieved from http://www.apta.org/WorkforceData/

Acknowledgements:

- Dr. Mark Albert
- Loyola University Chicago
- IMSA SIR Department
- Rakesh Das and João Mendes
- Hanna Benelhachemi, Chaya Chaichitatorn, Sam Dawes, Sumra Iqbal, Andrea Natera, Arica Tamir, and Chandra Sekharan

Tables and Figures:

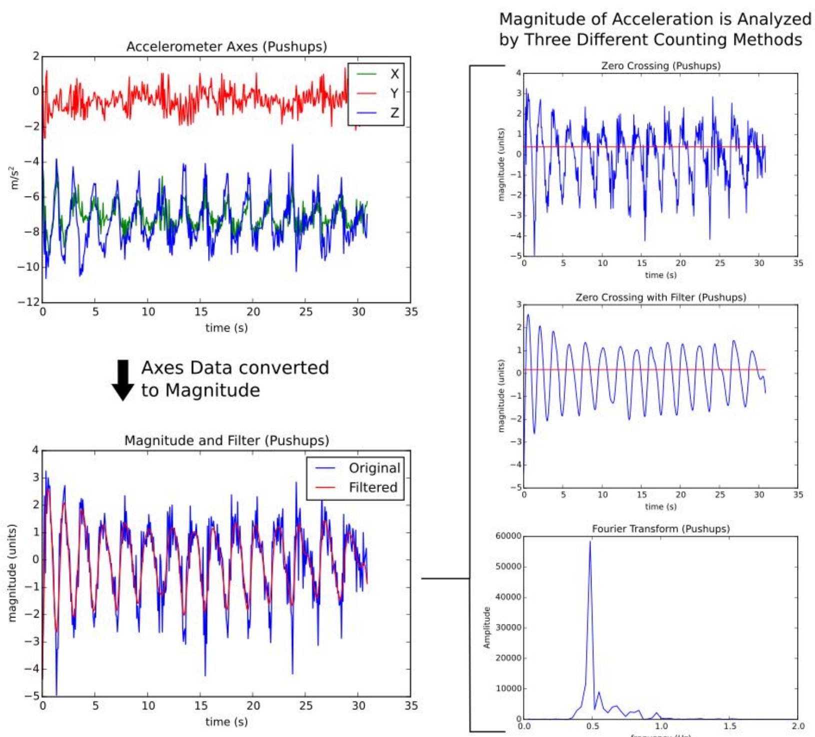

Figure 1. The data collected from the smartphone is analyzed by three different counting methods to find the most accurate. Push-up data was chosen due to its obvious repetitive motion.

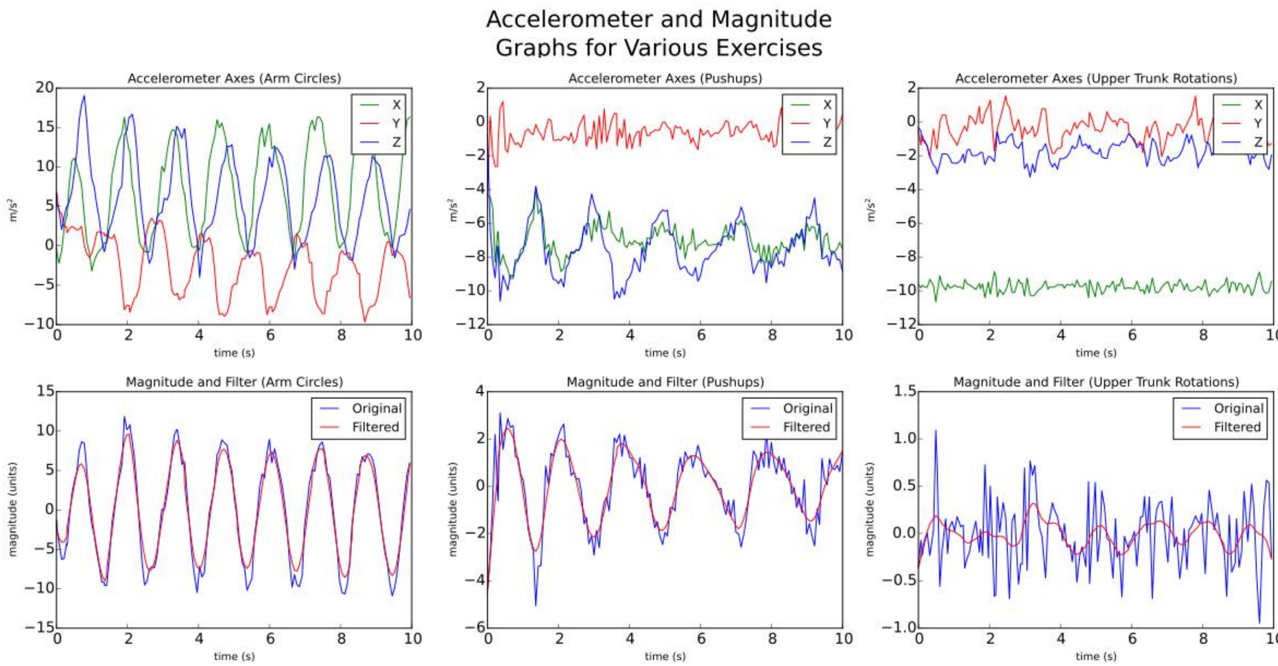

Figure 2. Different accuracies of the repetition counts are found depending on the type of exercise. These three motions were chosen as the most varied in repetitive motion.

Exercise	Smartphone Location
Arm Circle	Hand
Bicep Curl	Hand
Bridge	Waist
Crunch	Chest
Elbow Extension	Hand
Lower Trunk Rotation	Waist
Lunge	Waist
Push Ups	Waist
Squats	Waist
Upper Trunk Rotation	Waist

Table 1: Smartphone location for each exercise. The location was chosen based on where most of the movement took place on the body.

Exercise	Threshold Crossing	Threshold with Low Pass	Fourier	Root Mean Square Error
Arm Circles	1.99	9.65	8.08	7.36
Bicep Curls	16.70	7.36	12.29	12.71
Bridges	13.94	14.39	7.07	12.27
Crunches	7.32	8.56	12.18	9.58
Elbow Extensions	13.70	10.20	10.57	11.59
Leg Lifts	13.47	9.97	7.45	10.59
Lunges	16.95	1.83	0.76	9.85
Pushups	10.53	1.39	3.70	6.49
Squats	10.71	1.50	0.93	6.27
Upper Trunk Rotations	19.06	9.77	14.11	14.81
Root Mean Square Error	13.38	8.69	9.00	

Table 2. Each method provided differing levels of precision; the more precise exercises tended to be more periodic, regular motions. Mean squared error shows how accurate each exercise was counted. Standard deviation shows the dispersion of values for that particular set of exercises.