Dealing with Childhood Obesity: Passive versus Active Activity Monitoring Approaches for Engaging Individuals in Exercise

Giancarlo Valentín and Ayanna M. Howard, *Senior Member, IEEE*
Human-Automation Systems (HumAnS) Lab
Georgia Institute of Technology, Atlanta, GA (USA)

***Abstract*— Childhood obesity is a growing health problem. Indicators show that the rate of obesity for children age 12-19 years old has risen from 5% percent to 18% over the last ten years. Strategies to solve this childhood obesity epidemic range from educating children about nutrition to enabling possibilities for physical exercise. These general approaches, although useful, are ineffective when not adapted into the day-to-day activities of children's lives. However, given the growing popularity of mobile devices, an opportunity exists to use these technologies to design health-based applications that empower this target demographic. In the following paper, we compare two methods for engaging individuals in exercise based on passive versus active-encouragement. The passive method utilizes a wearable device that records exercise activities throughout the day whereas the active-encouragement approach utilizes a smartphone device to send encouraging reminders to the user during the day. The preliminary results, obtained with adolescents and young adults, show that for average users, active-encouragement using a smartphone can produce higher activity levels than the passive alternative. This provides the precursory evidence necessary for justifying further evaluations with younger children.**

Keywords: *Wireless Health, Exercise Apps, Health Coaching, Childhood Obesity*

I. Introduction

A. Motivation

According to the Center for Disease Control (CDC), the percentage of children aged 6-11 years in the United States who were obese increased from 7% in 1980 to nearly 20% in 2008 [1]. Similarly, the percentage of adolescents aged 12-19 years who were obese increased from 5% to 18% over the same period. In 2008, more than one third of children and adolescents were overweight or obese. These trends have led the US to have the highest prevalence of overweight individuals amongst countries in the Anglo-sphere [2]. For overweight and obese youth, the odds of developing a health-related complication, such as high blood pressure and/or diabetes, is significantly higher compared to normal weight youth [3]. Overweight children are more likely to become overweight adults and therefore at risk for even further health complications [4]. Thus, there is a growing need to incorporate long-term exercise strategies into youth's everyday activities in a way that encourages compliance.

B. Prevention Approach

To reverse this growing obesity trend, it has been recognized that prevention efforts must start with a focus on children [5]. In addition to a proper diet, physical activity is the most effective method for preventing obesity. To deal with the obesity epidemic, a number of technology interventions, including the use of mobile apps and wearable computing [6,7] have arisen to motivate youth to start and continue improving their health and become physically active. Recent developments in these technologies have brought focus to devices capable of monitoring daily physical activity while providing valuable feedback to the user. The idea behind these approaches is to maximize activity throughout the day even if no single period is exclusively designated for exercise. Through this approach, the user is encouraged either directly (through activity indicators) or indirectly (through animations or games) to make more active choices throughout the day.

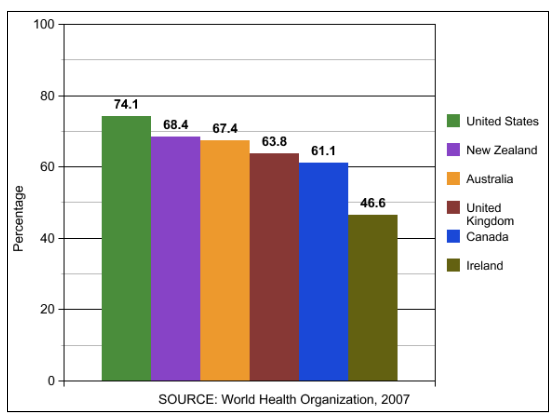

Figure 1. Percentage of overweight individuals in Anglo sphere as of 2007.

C. Existing Devices

Accelerometers can provide an objective measure of activity and differs from pedometers in that they can measure the intensity of physical activity as well as frequency [8]. In a number of studies, "accelerometer counts" have been calibrated against energy expenditure [9], and researchers have published thresholds of activity counts equating to different intensities of physical activity for children [10, 11]. Although most mobile devices (smartphones) have accelerometers, using them in a continuous mode of operation has a huge effect on battery life. Therefore, a number of initiatives have focused on the use of external sensors to monitor for exercise activity.

These existing external devices can be subdivided into three major categories. The first category encompasses multi-sensor systems to monitor a wide range of the user's physiological signals during the span of an exercise session [12]. Due to the large number of sensors used, systems of this type tend to be uncomfortable for the user. Additionally, the battery life of such systems is typically insufficient for a full days' use. The second category uses console-based video games to encourage users to become physically active. In fact, based on evidence that showed the video game, Dance Dance Revolution (D.D.R), was more effective than some school gym activities, the state of Virginia committed to installing Dance Dance Revolution into seven hundred and sixty-five schools [13]. Unfortunately, being widely adopted by gaming enthusiasts, these video games are limited to use within indoor environments and, as a result, cannot be used while the user is performing other physical activities outdoors. Devices in the third and final category involve mobile sensors and typically target the segment of the population that regularly engages in physical activity [14]. The Nike FuelBand (Figure 2a), the Fibit monitor (Figure 2b), and the Jawbone Up (Figure 2c) are representative devices in this category.

(a) *(b)*

(c)

Figure 2. a) The Nike FuelBand wristband. b) Fitbit activity monitor, c) Jawbone Up wristband.

Given the increase in mobile-applications (apps) that focus on fitness [8] and the popularity of mobile sensors, we selected representative technologies from the two domains to investigate the effect each method has on engaging individuals in exercise. We are most interested in understanding whether there is a significant difference in activity level based on passive approaches (i.e. self-monitoring of physical activity levels) versus active-encouragement (i.e. external-reminders about physical activity levels). We hypothesize that since active-encouragement personalizes the interaction, such methods can lead to an increase in physical activity levels when compared to passive methods.

II. Application

A. Active Encouragement Approach

For implementation of our active-encouragement approach, we utilize a smartphone with an internal tri-axial accelerometer that could be used for monitoring physical activity (Figure 3). For our application, we utilize the LG Optimus phone, which runs an Android-based OS. Data from the tri-axial accelerometer is recorded and used as input into a basic exercising mobile app called *Fit Up* (Figure 4). Regardless of the user's current activity, the app runs in the background indefinitely. For this experiment the slowest sampling rate *SENSOR_DELAY_UI* was selected for continuous monitoring of user activity. Although this rate varies depending on the specific hardware, it was recorded as 10-13 samples per second for our mobile application. To ensure accurate calibration of a user's activity level, we calculated a data threshold value that corresponded to 'idle' physical activity. To determine this threshold value, we calculated the values associated with static alignment along each x,y,z dimension of the accelerometer data, which occurs when a user is in an idle state such as sitting or sleeping. The corresponding threshold values were then used to filter out the accelerometer readings. If a reading along a dimension was less than its threshold value, it was not recorded (Equation 1). Otherwise the data was calibrated with respect to the threshold value and then recorded.

$$\begin{array}{l} \quad\quad If\left(reading_i > threshold_i\right) \\ Sum_i = Sum_i + \left(reading_i - threshold_i\right) \\ \quad\quad else \\ \quad\quad\quad reading\ not\ recorded \end{array} \tag{1}$$

where $reading_i$ represents the current reading along one of the dimensions (x,y,z) and Sum_i represents the sum of activity along that direction.

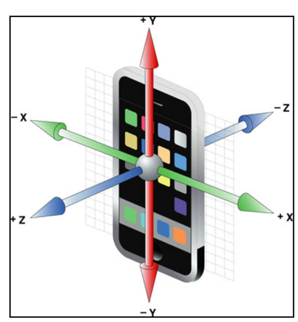

Figure 3. Typical mobile phone with dimensions recorded by tri-axial accelerometer.

Figure 4. Experimental setup for the Active-Encouragement approach

Our basic exercising application, *Fit Up,* was developed to provide active encouragement during a user's daily living scenario. *Fit Up* consists of an avatar animation that evaluates the user's amount of activity ($currentPoints$) based on the accelerometer data and provides messages according to how far they have progressed towards their daily goal (Figure 5). If a substantial portion of the daily goal has not been achieved by the beginning of every hour, the application vibrates for a time in milliseconds corresponding to the amount of remaining points to the goal (Equation 2). The vibration is intended to remind the user of their current status. In order to guarantee the vibration, the mobile phone is never allowed to go into a state of full sleep.

$$\begin{array}{l} If\ currentPoints < \frac{1}{2}Goal \\ Vibrate(goal - currentpoints)ms \end{array} \tag{2}$$

where $CurrentPoints$ correspond to the amount of activity undertaken by the user at the current time of consideration and *Goal* corresponds to the activity goal for that given day.

If half of the goal has been accomplished the user is told (via the animation) to keep the current pace. When the goal has been reached, the user is congratulated. The user's the activity data used in this analysis is recorded in an external micro SD card for analysis. A user's daily goal is determined a priori for the purposes of the current experiment but in other scenarios can be modified to fit the user's needs.

Figure 5. The Paul avatar tells the user when more exercise is required to meet the daily goal.

B. *Passive Approach*

The Nike+ Fuelband is a wristband that tracks the user activity and syncs it with a mobile device or computer. It also allows the user to set a daily goal in terms of a quantity labeled as 'Nike Fuel' which is monitored daily [16]. The user's progress is represented by LED's lighting up from red to green throughout the day. Once the data is synced with the Nike software it is analyzed and the results are illustrated to the user via graphical methods pertaining to the amount of activity during a day, week or month (Figure 6).

For the Nike FuelBand, the pertinent activity data was obtained from activity reports provided at the end of a day of activities such as the one shown in Figure 6. Additionally, Nike provides a software API that enables access to different features, such as obtaining raw data for a particular user. For example, the maximum resolution of one reading per minute could be used to measure activity for every hour in the day.

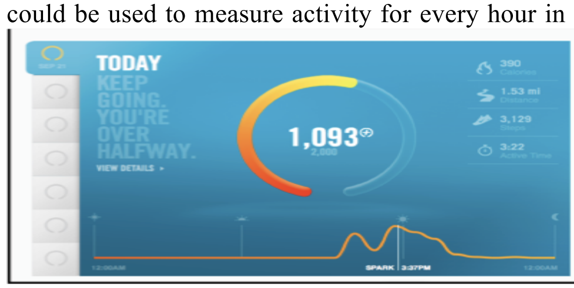

Figure 6. Daily Activity report provided by the Nike website [16].

C. *Calibration*

In order to properly convert the readings for each device (i.e. accelerometer on mobile phone and Nike FuelBand), a calibration routine was instituted to convert readings into a common unit. In this research, we selected to utilize the common unit provided by the Nike FueldBand called Nike Fuel [17]. Nike "Fuel" is an activity indicator that roughly corresponds to calories. Nevertheless, it is intended to be a more homogeneous metric across users, regardless of height, weight and wrist placement.

To obtain a suitable conversion, a calibration process was carried out with a user wearing both the FuelBand and the *Fit Up* application running on the mobile phone. The data corresponding to the Fuelband was stored in a 60x24 Matrix corresponding to the readings for each second of each hour.

Since the *Fit Up* application records more accelerometer data than the equivalent readings with the FuelBand, the *Fit Up* readings were averaged over samples and seconds until they were collapsed into an array comparable to the one resulting from the FuelBand. The three dimensional readings corresponding to this array were projected onto the positive number line using the L2 (Euclidean norm) as shown in Equation 3:

$$L_2 = \sqrt{x_{reading}^2 + y_{reading}^2 + z_{reading}^2} \tag{3}$$

where $X_{reading}, Y_{reading}, Z_{reading}$ are the accelerometer readings from the mobile device corresponding to each dimension.

For calibration, the user wore the two devices at the most commonly placed locations – the phone in their pocket and the FuelBand on the left wrist. The calibration process was conducted over the span of an hour and the results of a 10 minutes period can be observed in Figure 7.

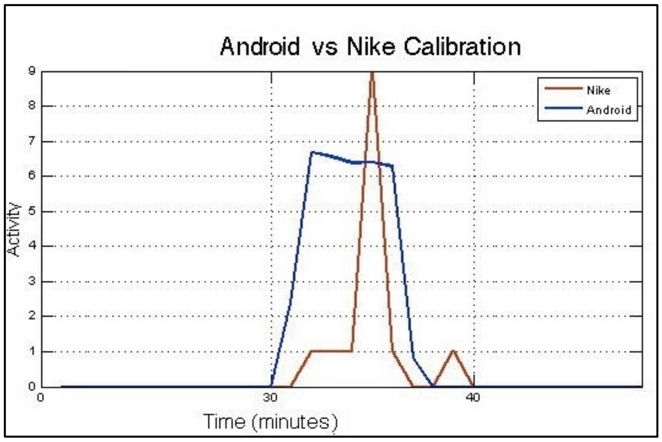

Figure 7. Ten-minute section of calibration activity

With the data processed for comparison, a polynomial fitting function was used to correlate accelerometer readings to Fuel points. The resulting third-order polynomial is shown below in Table 1 and the Fuel calculations in Equation 4.

TABLE 1. POLYNOMIAL COEFFICIENTS FOR FUEL CONVERSION

Coefficients	Values
a	-0.133467677
b	1.228513768
c	-1.966647972
d	0.026834394

$$Fuel(X = android_{pt}) = aX^3 + bX^2 + cX + d \qquad (4)$$

where $android_{pt}$ represents the readings of the mobile phone accelerometer being input into the equivalence function.

III. ANALYSIS AND PRELIMINARY RESULTS

A. Subject Pool

To compare physical activity outcomes derived from the passive versus active-encouragement approaches, six human subjects were provided with both the Nike FuelBand and the Fit Up application running on an *LG Optimus* Android phone. The subjects ranged in age from 17-34, 4 were male and 2 were female.

TABLE 2. BIOMETRIC DATA FOR ALL SUBJECTS

Subject	Sex	Age	Height (ft.)	Weight (lbs.)	BMI
1	M	25	5’7	175	27.4
2	M	35	5’9	190	28.1
3	F	24	5’2	155	28.3
4	M	24	6’0	161	21.8
5	M	17	5’8	157	23.9
6	F	n/a	n/a	n/a	n/a

B. Time Span

The use of both devices was compared for the span of six hours. This six-hour period started as soon as the subject felt ready to launch the application. Typically this occurred during the early hours of the day.

For the case of the mobile phone, subjects were asked to use the phone as their primary mobile device and carry it in the same way. The activities performed by the users included walking on level ground, walking up and down stairs, running, sitting.

B. Preliminary Results

Our preliminary results show that out of six users, five were more active with the Active encouragement application than with the Nike FuelBand (Table 3).

TABLE 3. COMPARISON OF USER ACTIVITY WITH EACH DEVICE

User	Nike FuelBand Points	Fuel Equivalent Android Points
1	181	302
2	501	534
3	453	512
4	667	404
5	196	278
6	412	550

Although the average user was more likely to have the Nike FuelBand during periods of strenuous physical activity than a mobile phone, during everyday activities, the user had the phone more often than any other device. Similarly, engagement in lower body activity with static arm positions resulted in the FuelBand being unable to detect any significant activity. With the mobile phone, the position on the user’s pocket resulted in more accurate detection of lower body activity. On the other hand, when the phone was placed on a back pocket or firmly attached to the waist, its accelerometer recorded very little activity due to the low amount of movement (Figure 8). As a result, data from the users attaching the mobile device to the waist clip were excluded from the analysis.

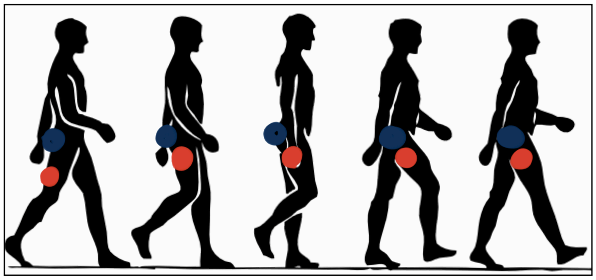

Figure 8. The blue marker represents the phone at the waist while red represents the phone in the pocket.

IV. CONCLUSIONS

In this paper, we compare two methods for engaging individuals in exercise based on passive versus active-encouragement. Preliminary results show that for most users the passive method produces lower levels of activity than the active-encouragement approach. Despite the advantages of each approach (Table 3), we believe that with the decrease in size and energy consumption in mobile phones, it will be possible for more active encouragement applications to be implemented directly on mobile phones. Additionally, we believe that active encouragement approaches are more likely to result in greater physical activity and should be considered in the development of future applications.

TABLE 3. BENEFITS OF EACH APPROACH

Mobile Application	Stand-alone Device
Mobile Application	Stand-alone Device
Active Encouragement	Longer Battery Life
Detects Lower Body Action	Can be worn all the time
No Syncing Required	
In-expensive	

V. REFERENCES

1. CDC. (2012, September.) Childhood Obesity Facts. [Online]. Available: http://www.cdc.gov/healthyyouth/obesity/facts.htm
2. Streib Lauren. (2012, September.) World's Fattest Countries. [Online]. Lauren Strein Available: http://www.cdc.gov/healthyyouth/obesity/facts.htm
3. D.S. Freedman, et. al., "The relation of overweight to cardiovascular risk factors among children and adolescents: the Bogalusa Heart Study," *Pediatrics*, 103:1175–1182, 1999.
4. M.K. Serdula, et. al., "Do obese children become obese adults? A review of the literature," *Preventive Medicine*, 22:167-77, 1993.
5. Lets Move. Learn the Facts. Online: http://www.letsmove.gov/learn-facts/epidemic-childhood-obesity [Sept. 2, 2012].
6. S.M. Arteaga, M. Kudeki, A. Woodworth, "Combating obesity trends in teenagers through persuasive mobile technology," *ACM SIGACCESS Accessibility and Computing*, *2009.*
7. A.K. Datta, A. Sumargo, V. Jackson, P. Pradip, "Dey, mCHOIS: An Application of Mobile Technology for Childhood Obesity Surveillance," *Procedia Computer Science*, vol. 5:653 - 660, 2011.
8. M. J. Mathie, A. C. F. Coster, N. H. Lovell, and B. G. Celler, "Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement," *Physiological Measurement*, vol. 25, no. 2, pp. R1–R20, 2004.
9. P. Freedson, D. Pober, and K. F. Janz, "Calibration of accelerometer output for children," *Medicine and Science in Sports and Exercise*, vol. 37, supplement 11, pp. S523–S530, 2005.
10. M. R. Puyau, A. L. Adolph, F. A. Vohra, and N. F. Butte, "Validation and calibration of physical activity monitors in children," *Obesity Research*, vol. 10, no. 3, pp. 150–157, 2002.
11. C. Mattocks, S. Leary, A. Ness et al., "Calibration of an accelerometer during free-living activities in children," *International Journal of Pediatric Obesity*, vol. 2, no. 4, pp. 218–226, 2007.
12. Y. Krupka. "Exercise Monitoring System." U.S. Patent 6132337, Oct 17, 200.
13. B. Schiesel, "P.E. Classes Turn to Video Game That Works Legs," New York Times 30 April 2007, on-line: http://www.nytimes.com/2007/04/30/health/30exer.html.
14. D. Etherington. "Startups Jumpstarting Fitness Motivation with Technology" Online: http://betakit.com/2012/02/24/startups-using-technology-for-fitness-motivation, [Oct. 1, 2012].
15. A. Gutman. "mHealth and the underserved, market gap perspective," Online: http://applicationsforgood.org/blog/mhealth-and-the-underserved-market-gap-perspective/, [Sept. 1, 2012].
16. Nike,Inc. Nike Fuelband Facts. Online: http://nikeplus.nike.com/plus/products/fuelband [Sept. 1, 2012].
17. Nike, Inc. Nike Fuelband User's Manual. Online: http://support-en-us.nikeplus.com/ci/fattach/get/221724/0/filename/FuelBand_Manual_Online_ENGv3.pdf , [Sept. 2, 2012].