MET Calculations from On-Body Accelerometers for Exergaming Movements

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***Abstract*—The use of accelerometers to approximate energy expenditure and serve as inputs for exergaming, have both increased in prevalence in response to the worldwide obesity epidemic. Exergames have a need to show energy expenditure values to validate their results, often using accelerometer approximations applied to general daily-living activities. This work presents a method for estimating the metabolic equivalent of task (MET) values achieved when users perform exergaming-specific movements. This shows the caloric expenditure achieved by active video games, based upon raw gravity values of accelerations. Results show that, while a fusion of sensors monitoring the entire body achieves the best results, sensors placed closest to the primary location of movement achieve the most accurate approximations to the METs achieved per activity as well as the overall MET achieved for the soccer exergame under consideration. The METs achieved approach 7, the value considered to be actual casual soccer game play.**

I. Introduction

Obesity is becoming a cost and health epidemic in the world [1]. The ever-increasing trend has the potential to affect over half of the population of the United States by 2030 [2], potentially resulting in exploding medical costs. Indeed, work in [2] estimates that, over the next two decades, there will be a 33% increase in obesity and 130% increase in severe obesity in the United States, and that if the trend is curbed to 2010 levels of obesity, the nation has the potential to save almost $550 billion in medical expenditures over the next two decades. Because of this, many approaches to measuring the physical activity in adults and children have become popular. The growth of body-wearable accelerometers has given rise to a number of techniques to monitor one's energy expenditure when performing general daily activity [3] [4] [5]. This has given rise to one area of recent growth. The usage of exergames, or active video games for health, to promote physical activity where there was once sedentary behavior [6] [7] [8] [9] has presented results in light-to-moderate physical activity [10]. These games can affect the body composition of overweight children [11], though how exergame systems output the actual health information can vary [12].

Accelerometer systems generally output information that can calculate energy expenditure and the Metabolic Equivalent of Tasks (hereafter METs) in order to indicate to users their activity levels. Many approaches exist in determining this information, from calculating activity intensities [4] [12] [13] to using proprietary counts and formulas from product manufacturers [14]. Fundamentally, as described in [15], counts are specific to brands of accelerometers and, therefore, their methods cannot easily be adapted to one another. Generally, exergaming papers use approximations from accelerometers to known METs, such as in [12] to state the possibility of monitoring activity levels. However, even more advanced methods take their regressions and formulas from general daily activities and treadmill activities that simulate running [16] [17]. Online methods adapted to exergaming, such as [12] used regressions based upon values found for those running and treadmill activities. Precise measurements for caloric expenditure in exergaming has been calculated in a number of studies [7]; however, these studies use invasive measurements of oxygen consumption (VO_2) to get precise measurements in comparison to the energy expenditure [7] [6] [10] [18] or heart rate [8]. This paper will attempt to take the approach presented in [19] [3] [15] [5] [20] to create an acceleration approximation to the METs [21] achieved during exergame activities in an active sports video game such as in [12]. In particular, this work will present representations for each movement to give more detailed future possibilities instead of finding only a general value for the overall usage so that future systems will not require invasive techniques to gather accurate results.

[15] [16] review evaluations of different accelerometers with counts derived from movement specific regressions. While counts will not be used, the movement specific regressions method will be applied to this work, with raw gravity values of accelerations instead of proprietary count values. Taken into consideration will be the placement of the sensors, the number of sensors, and the activity intensities in order to generate more accurate expenditure values for individual movements as well as establish an MET value for exergames. This work will present MET values for the actions and overall game play for a soccer exergame. Using oxygen consumption values of users within a trial, a base formula approach is created for exergame systems so that future studies can be conducted from this approximation. Finally, this work will compare these results to those found via table look up to

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indicate the necessity analyzing specific data for each activity for future approximation systems, rather than apply other regressions and tabulated information on generalized activities. Further, authors will make the oxygen consumption data and accelerometer data available for future research to develop further techniques without needing to involve invasive oxygen consumption measurement devices.

II. Related Works

A. Exergame Results

Work in [12] presented an active exergaming application as a potential solution for childhood obesity. The authors present a soccer exergame that argues intensity values from velocity calculations guarantees a certain level of physical activity. Further, they cite [4] for the method of calculating METs online, after using a regression from running on treadmills with well known MET values to present their caloric expenditure results to users. However, like many exergaming papers, such as [9] [8] [22], the results presented do not focus on the exercise levels achieved by each activity and, instead, focus on primary goals such as cheating prevention [12], range of motion [9], or effectiveness of exergames for long-term studies [22] [8] [6]. It seems only a few papers, such as [23] compare the energy expenditure of particular forms of exergames. The method in [12], which is based on the well-cited IMA value calculated in [4] to show the need for movement specific regressions is based upon general daily activity movements. [15] shows that each set of movements and accelerometers has and needs their own regression formulas, in that the comparisons are unique due to accelerometer types, outputs, and movements calculated. [12] uses general daily activity movements for regression, this paper will run regressions on the specific soccer movements with ground truth MET values, more accurate than regression on other movements based upon assumed MET values, similar to the MET calculations in [23], but with an appropriate accelerometer approximation. Further, this work will consider accelerometer placement in the location presented in [12] for classification purposes as well as the hip and ankle, two common locations for activity monitoring [24].

B. METs for sports exergaming

Work in [21] compiled a compendium on physical activity, which is used to compare against several activities of physical exercise, daily living, and sports. Indeed, this compendium is the source of many approximations to physical activity in monitoring papers. [25] has put together a compendium of energy expenditure on youth, in particular. However, neither has analyzed detailed motions and METs for those necessary in exergaming systems. In covering a wide range of general daily activities, many approximations can be used, but, in order to have a more accurate representation of exergaming, this work will collect exergaming specific movements in order to supplement such materials for future work. In particular, a comparison will be drawn between the actions of the exergaming environment and those of the actual sport it is comparing against, in this case being soccer.

C. Regressions for MET Approximations

Many devices [26] have been used and tested in several studies to predict the MET physiological variable using values from uni- and triaxial accelerometers. [15] discusses the use of multiple regression techniques to calculate MET values of common physical activities from accelerometer output. This work shows the necessity of calculating specific regressions for specific devices and activities. In fact, the work presents results showing approximations from the METs in [21] were, indeed, inaccurate for over 80% of the activities measured. Further, the accelerometer counts ranged from 11 to 7490, a wildly large range. The R^2 value from the regression techniques developed reaches 0.65 in the best settings. As a result, work in this paper will not use accelerometer counts, but instead, raw acceleration values so that comparisons will be easier to draw for future works. Further, the regression techniques should result in comparable results if the work is considered to be accurate. Finally, work in [15] resulted in authors from [21] to update previous work with corrected formulas. This work will also show that such corrected formulas, while appropriate for general populations and activities, do not allow for great variability across users that are possible due to a number of physiological considerations.

Work in [27] discusses how there are more than 30 techniques that produce very different results. Hendlemen et. al. [28] discusses the differences in energy expenditure from accelerometer data resulting from inconsistencies in the calibration process, making comparing results among studies difficult. Many systems compare results from devices based on non-universal metrics, such as counts, which are specific to one accelerometer. This work maps specific soccer motions using regression techniques that differ according to activity, using typical accelerometer outputs in units of gravity (based on acceleration as $\frac{m}{s^2}$) to establish metabolic equivalent (MET) equations for sports exergaming activities.

III. Method

A. Clinical Setup

Work in this paper presents a method to approximate metabolic equivalents (METs) of various exergaming activities. A more precise formulaic representation is needed in order to assist in a future study regarding caloric expenditure calculations for different forms of exergames, an IRB approved study (UCLA IRB #12-000730). The purpose was to develop a preliminary approximation for the METs produced when using exergame movements, in order to set up future studies analyzing the body composition changes. Participants were given three accelerometers to wear, including two GCDC +/- 2g accelerometers worn on the hip and ankle [29], and a +/- 5g Memsense IMU [30] worn on top of the foot to help simulate motion at contact with a soccer ball (and to correlate with work in [12]). Users were then attached to a metabolic cart that examines the volume of oxygen taken into

Fig. 1. User running trial with metabolic cart and accelerometers attached

the lungs during activity, a key measurement in determining actual MET values. In fact, the oxygen uptake, presented as $VO_2(\frac{ml}{min})$ can result in METs from the following formula:

$$MET = \frac{VO_2}{3.5 * m} \tag{1}$$

where m is the mass of the user in kilograms. Six male subjects between the ages of 22 and 31 were selected and ran the following protocol:

- Sit for 3 minutes to achieve normal breathing with metabolic cart
- Stand for 3 minutes to establish baseline rest
- Run designated activity for 3 minutes to establish oxygen uptake for activity
- Rest (Stand) for 3 minutes to establish baseline rest before next activity
- Repeat.

This allowed for testing of each activity, to be described in the next section, and determine the oxygen uptake of each motion in order to obtain a ground truth MET value to obtain accurate caloric expenditure information for each exergaming activity. It is known that for constant load activities, a steady state is typically achieved by three minutes of exercise and to only use data after this point in analysis [31]. Figure III-A shows an image of a user running the designated protocol for data collection. It seems, as expected, the sensors closest to the greatest point of action might correlate most closely to the resultant METs. However, notice that in some cases the intensities are similar, such as in Figure 2(b) for the foot accelerometer, despite the METs being different. Thus a combination of results may produce the best value.

B. Exergaming Movements

From [12], six soccer movements were selected for data collection. Those movements and their descriptions are shown in Table I. Each move was repeated for the full 3 minutes. Users would enact the motions at their desired intensities (showing variability in the intensities recorded, as expected) and at roughly the same pace (enough time for users to settle

TABLE I
COLLECTED SOCCER MOVES

Move	Description
Run	Running in place
Sprint	Sprinting in place
Pass	Passing Ball Directly left
Chip	Chipping a ball up and to left
Medium Shot	Medium Powered Laces Shot
Full Powered Shot	Full Swinging Shot
Simulated Game	Simulated Exergame-play

and repeat the action, approximately 3 seconds between each action). This gives the activity intensities if one were to repeat each soccer action, which happens in many games. Repeated actions are more realistic in an exergame than a real soccer environment as most team play video games change the focus to the player with the ball every time the ball is passed between players on screen. However, as it is not entirely realistic to simply pass for 3 minutes straight a simulated game play mode was created for the testing environment (kept the same to generate uniform results). This simulated game play ran as follows (with 5 second gaps between movements and running in place for the duration of the 3 minute trial) based off of an exergame like that of [12]:

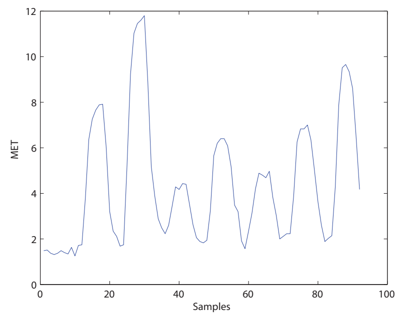
- pass, pass, medium shot
- pass, pass, strong shot
- sprint for 5 seconds (defense)
- pass, chip, shot
- running, fake shot, pass, strong shot
- sprint for 5 seconds (defense)
- pass, sprint, shoot
- sprint for 5 seconds

This set of actions simulates movement of the soccer ball in a soccer environment including a series of running actions and sprinting actions that happen throughout game play to give a more realistic overall game play MET value. It is intended to simulate a series of offensive moves and defensive running activities that occur throughout normal game play.

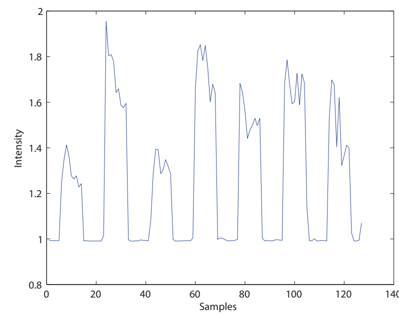
C. Regression Analysis

Due to the variability in any individual's breathing pattern, the VO_2 data was calculated in 30-second averages. As a result, the accelerometer data needed to be synchronized in the same format. Further, systems such as [32] and [4] use a variation of either the integrated absolute values or the magnitude of the accelerometer data. For this work, the magnitude of each accelerometer is considered in order to combine the x-axis, y-axis, and z-axis for an overall intensity calculation, as well as account for the effects of gravity by setting a new baseline value for inactivity. Thus, after each axis of the accelerometer is averaged over 30-second windows, the magnitude of the acceleration vector is calculated as follows:

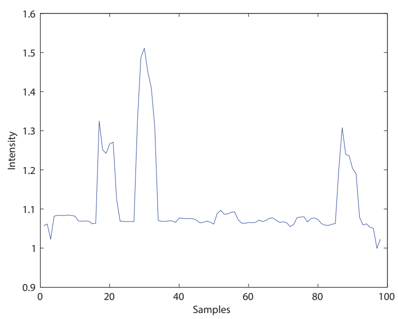
$$MAG_{accel} = \sqrt{x^2 + y^2 + z^2} \tag{2}$$



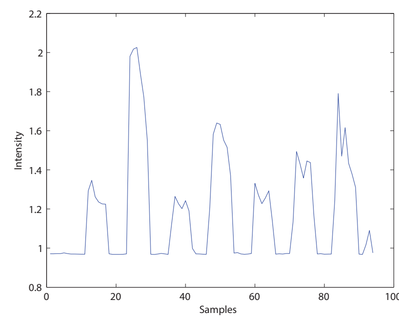
(a) METs



(b) Magnitude of Acceleration for Foot Sensor



(c) Magnitude of Acceleration for Hip Sensor



(d) Magnitude of Acceleration for Ankle Sensor

Fig. 2. User 1 values for (a)METs and accelerations for (b) foot, (c) hip, and (d) ankle

TABLE II
R^2 VALUES FROM REGRESSION ANALYSIS

Description	R^2
MET vs. Foot	0.2431
MET vs. Ankle	0.5662
MET vs. Hip	0.2342
MET vs. Foot + Ankle	0.4655
MET vs. Foot + Hip	0.3355
MET vs. Hip + Ankle	**0.7147**
MET vs. Foot + Hip + Ankle	0.5472

This value is collected for each accelerometer. Then the peaks of each intensity point and each MET point were correlated and a regression analysis was run to determine a line of best fit, using Matlab's polyfit functionality.

IV. RESULTS

A. Regression

Figure 2(a) shows the METs as calculated from VO_2 data and associated accelerometer magnitudes for one of the users of the trial are shown in Figures 2(b), 2(c), and 2(d) respectively. Table II shows the results of the regression run on the analysis. At each movement point the peaks were detected after the three minute mark and used for the polyfit regression run in Matlab. A combination of the hip accelerometer and ankle accelerometer seem to do better than using the foot, like is used in [12]. The combination of accelerometers resulted in adding the intensities at each point to derive a combined intensity value. It seems there is perhaps too much activity at

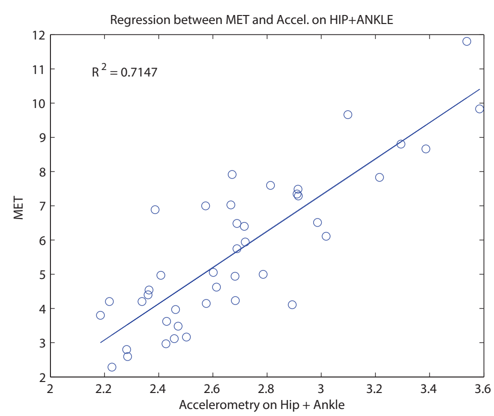


Fig. 3. Regression run on data from Hip accelerometer and Ankle accelerometer at peaks

the top of the foot, or rather, perhaps the peaks themselves should not be used. As can be seen in Figure 2(b), the average intensity value over a period seems to differ from the peaks, however, this analysis is left for future work, as it does not correlate in time with the oxygen consumption, and therefore requires further analysis. The best fit line produces the following equation:

$$MET = 5.289 * (MAG_{hip} + MAG_{ankle}) - 8.5548 \quad (3)$$

where in this case, the magnitude of each accelerometer is summed together. The sum, or an average, would result in the same regression. A sum is taken in order to calculate the intensity at a given point in time. This follows from the plot in Figure 3. As can be seen from the plot, there is significant variability from user to user, calculating based off of simple METs from a table such as done in [12] to derive MET formulas will not provide accurate representations unless those tabled values consider a wide enough population. Regression analysis must be run on a large number of subjects with varying levels of intensities and body composition in order to do better; however, finding the exergaming specific METs can improve approximations for those not wishing to run a clinical study. As such, a more detailed online calculation of caloric expenditures can be run when knowing the MET values for each activity as has become clear here.

B. METs

While the regression can indicate a more accurate way of calculating METs in an online fashion while participating in exergaming activity, it may also be interesting to see a general MET value for each activity, including a comparison to what [21] uses as the corrected formulas for METs per person. Since there is great variability among individuals from height and weight to age, the corrected formula is supposed to indicate the appropriate MET for that individual. As can be seen in Table III, the final two columns show what soccer (casual and intense) would be with the corrected formulas for each of the individuals involved in the study. As can be seen, there is still little variability. However, looking at the MET value of each individual for each of the actions shows great variability across the user base, a reason for needing large populations for future regressions, but also for the regressions themselves, as the basic table approximation can vary for specific actions like these of soccer exergaming, showing need for specific values for exergaming. Exergaming systems should take the approach of [12] to ensure only those reaching a certain level are accepted as appropriate activities, though even then, variability will exist due to intensity desired as well as physical fitness of user. Table IV shows the average MET and standard deviations for all the movements and the simulated game. It seems the simulated game play can reach that of soccer, a promising result for exergaming research. Further, having an MET for each movement can allow for better realism, using such an MET calculation as a cheating prevention cut-off instead along with other techniques to ensure realism and activity. Finally, it is obvious that a general level of activity can be guaranteed but that specific caloric expenditure approximations may need more user information than simply accelerometer intensities.

TABLE IV
AVERAGE METS FOR EACH ACTIVITY

Activity	AVG $\pm$ STD
Run	5.26 ± 1.70
Sprint	8.36 ± 1.92
Pass	3.44 ± 1.09
Chip	5.01 ± 1.20
Med Shot	3.75 ± 0.79
FP Shot	6.02 ± 1.30
Sim-Game	7.93 ± 1.55

V. FUTURE WORK

This work presents a baseline approach to calculating the METs of a soccer exergame ranging from its movements to a simulated game play calculation. These values and the regression formula will be used as a baseline for an extended study on the overall values reached actually playing particular exergaming systems. Further, varying signal processing techniques can be used to better enhance regression techniques, such as multiple levels of regression as shown in [27]. For example, the ankle sensor seems to match that of the METs visually in most cases, however the regression techniques were not promising due to great variability in a few areas that skew the results, including lining up intensities to the actual oxygen consumption, which tends to lag in real time. Future work should consider not only the alignment techniques but the method of combination across multiple sensors. Further, instead of the peaks, perhaps an average across the climb, peak and descent of each activity can be taken. Finally, when a more accurate determination of METs achieved during exergaming is concluded upon, such a system must be re-incorporated into an exergaming system to give accurate long-term caloric expenditure calculations for users of these exergaming systems, in particular due to the heavy importance placed on sensor location for classification techniques as the primary requirement for many of such systems. Further, accelerometer data and oxygen consumption for the activities will be made available for future expenditure research.

VI. CONCLUSION

This work developed a procedure and a regression technique to determine the METs achieved when participating in soccer exergaming. Several sensor locations were tested, as well as results compared with the individual locations and the fusion of multiple locations. As exergaming research expands to target the growing childhood obesity epidemic, caloric expenditure results must be verified to ensure an appropriate intervention is possible and measurable to a certain degree of accuracy. This work produces an oxygen consumption data set for exergaming activities and produces METs of each particular action, instead of general use values. Instead of using table values to approximate METs and create a regression from this, this work used actual volume of oxygen uptake to determine an accurate representation of the METs found when participating in many movements in an exergaming specific fashion instead of those from general daily activities. Finally, this paper also concludes that soccer exergaming can reach an MET value of 7 even across variable subjects, which is roughly the same as the predicted value for actual light/casual intensity soccer.

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TABLE III
COMPARING TRUE EXERGAMING MET VALUES WITH AINSWORTH

	Ht (cm)	Wt (kg)	Age (yrs)	Run	Sprint	Pass	Chip	Med Shot	FP Shot	Sim-Game	Ains (Light)	Ains (Intense)
1	170.18	76.20	28	7.91	11.80	4.40	6.40	4.97	7.0	9.66	7.57	10.80
2	186.69	81.65	29	4.20	7.34	2.29	6.49	2.97	5.0	7.29	7.47	10.68
3	173.99	68.04	29	4.20	8.66	5.06	4.94	4.11	7.83	9.82	7.16	10.23
4	182.88	79.38	26	3.80	7.03	2.60	3.97	3.11	6.11	7.49	7.38	10.54
5	173.99	70	31	4.54	6.51	3.49	4.63	3.17	4.23	5.74	7.36	10.44
6	175.26	65.77	22	6.89	8.80	2.80	3.63	4.14	5.94	7.60	6.83	9.75

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