Context-Aware Data Processing to Enhance Quality of Measurements in Wireless Health Systems: An Application to MET Calculation of Exergaming Actions

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(Invited Paper)

***Abstract*—Wireless health systems enable remote and continuous monitoring of individuals, with applications in elderly care support, chronic disease management, and preventive care. The underlying sensing platform provides constructs that consider the quality of information driven from the system and ensure the reliability/validity of the outcomes to support the decision-making processes. In this paper, we present an approach to integrate contextual information within the data processing flow in order to improve the quality of measurements. We focus on a pilot application that uses wearable motion sensors to calculate metabolic equivalent of task (MET) of exergaming movements. Exergames need to show energy expenditure values, often using accelerometer approximations applied to general activities. We focus on two contextual factors, namely "activity type" and "sensor location," and demonstrate how these factors can be used to enhance the measured values, since allocating larger weights to more informative sensors can improve the final measurements. Further, designing regression models for each activity provides better results than any generalized model. Indeed, the averaged R^2 value for the movements using simple sensor location improve from a general 0.71 to as high as 0.84 for an individual activity type. The different methods present a range of R^2 value averages across activity type from 0.64 for sensor location to 0.89 for multidimensional regression, with an average game play MET value of 7.93. Finally, in a leave-one-subject-out cross validation, a mean absolute error of 2.231 METs is found when predicting the activity levels using the best models.**

Manuscript received June 09, 2014; accepted October 09, 2014. Date of publication October 21, 2014; date of current version February 04, 2015. This work was supported in part by the National Science Foundation, under Grant CNS-1150079 and the TerraSwarm, one of six centers of STARnet, a Semiconductor Research Corporation program sponsored by MARCO and DARPA.

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Digital Object Identifier 10.1109/JIOT.2014.2364407

***Index Terms*—Accelerometer, context-aware, distributed wearable sensors, metabolic equivalent of task (MET), physical activity, quality metric, wireless health.**

I. Introduction

CHRONIC conditions affect nearly half of all individuals in the United States; 133 million Americans have at least one chronic illness [1], accounting for 70%–80% of health care costs [2]. Most patients with chronic conditions such as obesity, hypertension, diabetes, hyperlipidemia, heart failure, asthma, and depression are not treated adequately, and the burden of chronic illness is magnified by the fact that chronic conditions often occur as comorbidities. Obesity, e.g., is becoming a cost and health epidemic in the world [3]. The ever-increasing trend has the potential to affect over half of the population of the United States by 2030 [4], potentially resulting in exploding medical costs. Indeed, work in [4] 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. Further, this trend if curbed to 2010 levels of obesity, has the potential to save almost $550 billion in medical expenditures over the next two decades [4]. Engagement in physical activity has been shown to be effective in mitigating complications associated with many chronic diseases. Because of this, many approaches to measuring physical activity in adults and children have become popular. In particular, wireless health systems that use wearable motion sensors have been proposed to remotely and continuously measure physical activities [5], [6].

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 [7], [8]. Accelerometer systems generally output information that can calculate energy expenditure and the metabolic equivalent of tasks (METs) in order to indicate to users their activity levels. METs are an approximation to the level of energy expenditure the metabolism achieves, where a given number represents the overall level of work and effort the metabolism achieves (e.g., 4 miles/h, 7 METs for casual soccer). From this, an approximation to the energy expenditure of a given user can be achieved. Many approaches exist in determining this information, from calculating activity intensities [9]–[11] to use proprietary counts and formulas from product manufacturers [12]. Fundamentally, as described in [13], counts are specific to brands of accelerometers and, therefore, their methods cannot easily be adapted to one another. There are more recent methods, which take their regressions and formulas from general daily activities and treadmill activities that simulate running [14], [15].

The ability to attach low-cost sensors to the body to track movements has given rise to the field of exergaming [10]. The usage of exergames, or active video games for health, to promote physical activity where there was once sedentary behavior [16]–[19] has presented results in light-to-moderate physical activity [20]. These games can affect the body composition of overweight children [21], though how exergame systems output the actual health information can vary. As exergaming through the use of accelerometers has increased in prevalence in response to the worldwide health epidemic, so has the need to approximate energy expenditure from such systems. The calculation of energy expenditure for exergaming movements using wearable accelerometer sensors, however, has not been addressed in literature previously. Precise measurements for caloric expenditure in exergaming has been calculated in a number of studies [17] that use invasive measurements of oxygen consumption (VO_2) to get precise measurements of energy expenditure [16], [17], [20], [22] or heart rate [18]. Thus, the focus of this paper is to propose an approach for measuring energy expenditure of exergame movements from wearable accelerometers.

This paper will propose a framework for context-aware MET calculation. This paper takes the approach in [7], [8], [13], [23], and [24] as a basis to create an acceleration approximation to the METs [25] achieved during exergame activities in an active sports video game such as in [10]. The proposed approach, however, can be applied to any MET calculation method in order to improve its accuracy and reliability. That is, this proposed framework aims to build upon quality metrics that are important in developing wireless health platforms. In Section II, this work briefly discusses these quality metrics and describes how our MET calculation framework improves these metrics. The general theme of our quality enhancement method is context-awareness. This paper particularly focuses on two contextual factors, "activity type" and "sensor location," and attempt to incorporate such information through the data processing flow. It will present representations for each movement and sensor node 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. This work will present MET values for the actions and overall game play for a soccer exergame, by measuring oxygen consumption during the repetition of those activities. The soccer exergame is considered due to soccer's popularity as a worldwide sport, and soccer video games are also immensely popular. For example, electronic arts's (EA) FIFA 12, a soccer video game, was the fastest selling sports video game of its time [26], whereas EA's FIFA 14 had over 5 million users for its demonstration version before the full commercial product had even been released [27].

II. Preliminaries and Related Work

Wireless health systems perform best by providing quantitative data for the desired goals of producing efficient and effective qualitative data. Desired systems must accurately measure desired features of a given system and provide metrics that can be used for various factors from quality of data processing to approximations based on applications such as caloric expenditure of a given wearable sensor system. Thus, the design of such a system must take several preliminary factors into consideration and then delve into the application specific roadblocks for each desired outcome.

A. Quality Metrics

A wireless health system is typically composed of a front-end sensing platform and back-end data analytics. It is then essential that the front-end sensing platform provides constructs that consider the quality of information driven from the system and ensure the reliability/validity of the outcomes to support the decision-making processes make it through the back-end framework. In general, a comprehensive quality framework must incorporate the following metrics: 1) quality of data; 2) quality of information; and 3) quality of user, as explained later in this section. Our focus in this paper, however, is not on dealing with challenges arising from user-induced errors. In other word, dealing with quality of user is out of the scope of this paper. For the two other types of quality metrics, however, we build our MET calculation framework such that contextual information about sensors and activities are used to enhance quality of information. We also use a preprocessing algorithm to deal with noise in the sensing data.

Quality of data: Sensors are not perfect. They may be miscalibrated or malfunctioning, and often encounter environmental interference that can result in noisy, imprecise data. The frequency of sampling and the latency associated with delivery of a sensor reading can also impact the utility of the reading. In addition, there is a spectrum of the quality of reading that is obtainable from sensors of the same type. These concerns are related to the quality of data; metrics for describing the quality of sensor data include accuracy, timeliness, confidence, throughput, and cost. Sensors must be calibrated and validated for functionality everyday using intelligent algorithms that do not require user intervention. Such data quality metrics can be directly incorporated into our proposed framework. In this paper, we are only concerned about the effect of noise on MET measurements. Thus, as will be discussed in Section III-C, we combine the three accelerometer readings over a sliding window in order to compensate for noise.

Quality of information: Typically, raw data from simple sensors are interpreted and fused into higher level information that can be used by a user, health-science researchers or health-care providers to make decisions. This includes translation of raw sensor readings into movements along with their timing characteristics. The degree of utility of the derived high-level information for a particular purpose is captured by quality of information metrics. Quality of information metrics for physical activity monitoring will need to be determined and logged and validated in conjunction with gold standards. We take an approach that uses contextual data about the system to enhance quality of information and, therefore, final MET measurements. In particular, sensor locations (and their associated contributions to MET calculation and movement detection) and activity type are used to 1) develop a sensor weighing approach for MET calculation and 2) develop activity-specific MET calculation approaches.

Quality of the user: Human error may result in improper placement of sensors required for a specific application. The quality framework must identify potential error caused by users and provide alerts for their correction. This information needs to be further logged to assist clinicians and researchers to identify user's noncompliance. Additionally, as age-associated differences in conscientiousness exist [28] participants needs to be assessed using the conscientiousness component of the Revised NEO Personality Inventory [29] and this measure will be used to account for potential age-related discrepancies in the quality of data between younger versus older cohorts.

B. Research on Exergaming

Work in [10] presented an active exergaming application as a potential solution for childhood obesity. Mortazavi *et al.* present a soccer exergame that argues intensity values from velocity calculations guarantees a certain level of physical activity. Further, Bouten *et al.* cite [9] 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 [18], [19], and [30], the results presented do not focus on the exercise levels achieved by each activity and, instead, focus on primary goals such as cheating prevention [10], range of motion [19], or effectiveness of exergames for long-term studies [16], [18], [30].

Only a few papers, such as [31] compare the energy expenditure of particular forms of exergames. The method in [10], which is based on the well-cited IMA value calculated in [9] to show the need for movement specific regressions is based upon general daily activity movements. Kozey *et al.* [13] show 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. Mortazavi *et al.* [10] use 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 [31], but with an appropriate accelerometer approximation. Further, this work will consider accelerometer placement in the location presented in [10] for classification purposes as well as the hip and ankle, two common locations for activity monitoring [32].

C. MET Calculation for Exergaming

Work in [25] 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. Ridley *et al.* [33] have 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.

D. Regression Models for MET Approximation

Many devices [34] have been used and tested in several studies to predict the MET physiological variable using values from uni- and triaxial accelerometers. Kozey *et al.* [13] 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 the results showing approximations from the METs in [25] 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 [13] resulted in authors from [25] 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 [35] discussed how there are more than 30 regression techniques that produce very different results. Hendelman *et al.* [36] discussed 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 nonuniversal 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 MET equations for soccer exergaming activities.

Albinali *et al.* [37] began identifying improvements by using activity-specific models for regression. By capturing a variety of activities on 24 subjects, from gym activities to daily living, they see an improvement of 15% in their estimates. They show that having multiple sensors on the body to accurately capture the data improves models, but having multiple regression models and using not only actively captured data but "simulated days" helps improve results. This work will take this approach by using multiple sensors on the body, create activity-specific regressions, and will not only capture data on each individual movement type but also a "simulated game play" session at the end of each collection trial.

Alshurafa *et al.* [38] and Crouter *et al.* [39] showed that more advanced regression models can provide even more accurate results of MET calculations. In particular, Crouter *et al.* [40] showed that using separate regressions for different classes of motions provided for more accurate results and lower mean errors. This work will adapt such methods for soccer-exergaming by developing regression models for each activity identified, showing that having MET calculation equations for each activity will result in more closely related regression models than a general regression. While different types of divisions can be examined, this was chosen as it is closely related to the classification results already required in playing any such exergame.

Kozey *et al.* [13] and Lyden *et al.* [14] review evaluations of different accelerometers with counts derived from movement specific regressions. While counts will not be used, the movements specific regressions method will be applied to this work, with raw gravity values of accelerations instead of proprietary count values. In this work, the different groupings are set forth by the different movements recognized by any given system. This method, however, can be applied to any setting with any contextual information on the difference between classes (or clusters of classes) that are being considered. 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.

E. Extensions

The methods presented in Section III are intended to demonstrate the use of contextual information, knowledge about the given movements, in order to present a stronger model for predicting energy expenditure. Readers should consider the quality metrics presented earlier along with contextual information provided from knowledge and potentially other sensors in order to improve the development of models and regressions to other applications as necessary.

III. Methods

The trial run in this work, as with many initial wireless health applications, consisted of two separate phases. The first such phase is a data processing phase in which a collection protocol is set up to determine the feasibility of a given application and generate models for large-scale usage. The second phase is the processing techniques used on that data to generate those models.

A. Clinical Setup

Work in this paper presents a method to approximate METs of various exergaming activities, an IRB approved study (UCLA IRB #12-000730). The approach relies on leveraging contextual information about the sensing platform in order to improve MET calculations based on regression models. The purpose of the study was to develop an approximation for the METs produced when using exergame movements, in order to set up future studies analyzing body composition changes. Participants were given three accelerometers to wear, including two Gulf Coast Data Concepts (GCDC) $+/-2\text{g}$ accelerometers worn on the hip and ankle [41], and a $+/-5\text{g}$ Memsense IMU [42] worn on top of the foot to help simulate motion at contact with a soccer ball (and to correlate with work in [10]). Users were then attached to a metabolic cart that examines the volume of oxygen taken into the lungs during activity, a key measurement in determining actual MET values. In fact, the oxygen uptake, presented as $\mathrm{VO_2(ml/\min)}$ can result in METs given by

$$\mathrm{MET} = \frac{\mathrm{VO_2}}{f \times m} \tag{1}$$

where m denotes the mass of the user in kilograms, and f represents a factor that changes based upon the general fitness of the group analyzed, 3.5 here in the case of healthy, active adults. Six healthy male subjects between the ages of 22 and 31 were selected and ran the protocol shown in Table I.

TABLE I
Data Collection Protocol

No.	Description
1	Sit for 3 min to achieve normal breathing with metabolic cart
2	Stand for 3 min to establish baseline rest
3	Run designated activity for 3 min to establish oxygen uptake for activity
4	Rest (Stand) for 3 min to establish baseline rest before next activity
5	Repeat

This allowed for testing of each activity, to be described in Section III-B, 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 3 min of exercise and to only use data after this point in analysis [43]. Fig. 1 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, we notice that in some cases the intensities are similar, such as in Fig. 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 [10], six soccer movements were selected for data collection. Those movements and their descriptions are shown in Table II. Each movement was repeated for the full 3 min. Users would perform 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 and repeat the action, approximately 3 s 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

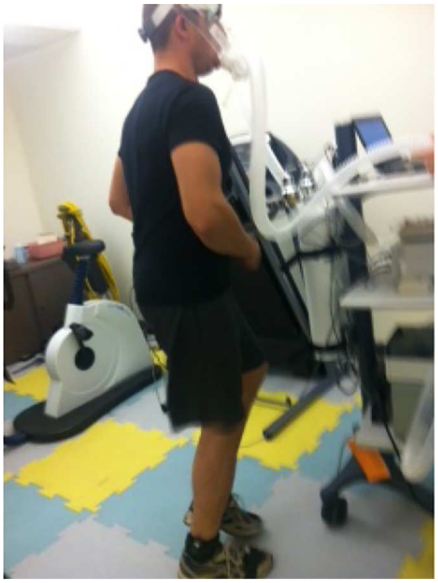

Fig. 1. Subject running trial with metabolic cart and accelerometers attached.

TABLE II
COLLECTED SOCCER MOVES

No.	Move	Description
1	Run	Running in place
2	Sprint	Sprinting in place
3	Pass	Passing ball directly left
4	Chip	Chipping a ball up and to left
5	Medium shot	Medium powered laces shot
6	Full powered shot	Full swinging shot
7	Simulated game	Simulated exergameplay

the 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 min 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 described in Table III, with 5-s movements and running in place for the duration of the 3-min trial, based off of an exergame like that of [10].

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. Context-Aware MET Approximation

Due to the variability in any individual's breathing pattern, the VO_2 data were calculated in 30-s averages. As a result, the accelerometer data needed to be synchronized in the same format. Further, systems, such as [9] and [44], 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-s windows, the magnitude of the acceleration vector is calculated by

TABLE III
SIMULATED GAME MOVEMENTS

No.	Description
1	Pass, pass, medium shot
2	Pass, pass, strong shot
3	Sprint for 5 s (defense)
4	Pass, chip, shoot
5	Running, fake shot, pass, strong shot
6	Sprint for 5 s (defense)
7	Sprint for 5 s

$$\|\boldsymbol{a}\| = \sqrt{{a_x}^2 + {a_y}^2 + {a_z}^2}. \tag{2}$$

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 the curve of best fit.

1) Binary Sensor Weighting Model: The idea behind this approach is that different sensors contribute to calculation of the MET values differently. Sensors that provide the most information regarding movements of interest can be used for MET calculation. Thus, a binary selection of the sensors will be applied to find the best subset of sensors for a particular physical movement monitoring application. Several approaches were taken in testing the best combination of sensors for the most appropriate and accurate regressions. The first is a simple selection of sensors, in which a two-dimensional (2-D) linear regression is run where

$$\mathrm{MET}_{\mathrm{reg}} = \alpha_0 + \alpha_1 \cdot s \tag{3}$$

where s is a potential combination of each sensor is given by

$$s = \sum_{i=1}^{n} c_i \cdot s_i \tag{4}$$

where i is the number of sensors available (e.g., 1 is hip, 2 is ankle, 3 is hip, etc.), and each c_i is 0 or 1 whether it is used or not. This method was first presented in [45]. Thus, the best regression may be selected from the most appropriate range of data. In particular, this method might be best used in relation with sensor selection techniques for other purposes, including classification [46] and power usage [47] by determining how many sensors should be necessary for any given application. In our experimental results, however, we perform an exhaustive analysis and find the MET values for all combinations of the sensors used for data collection in this study.

2) Sensor Weighting and Activity-Specific Model: If all the sensors will be used, then perhaps binary selection of each sensor would not produce the best results. A more complicated regression would allow for fractional constants. For this work, three nested for loops were written to range the constants c_i from 0 to 1 in this case in increments of 0.1. This included 0 and 1 so as to encompass the previous method's results as well, with all formulas saved, so that the best results could be selected

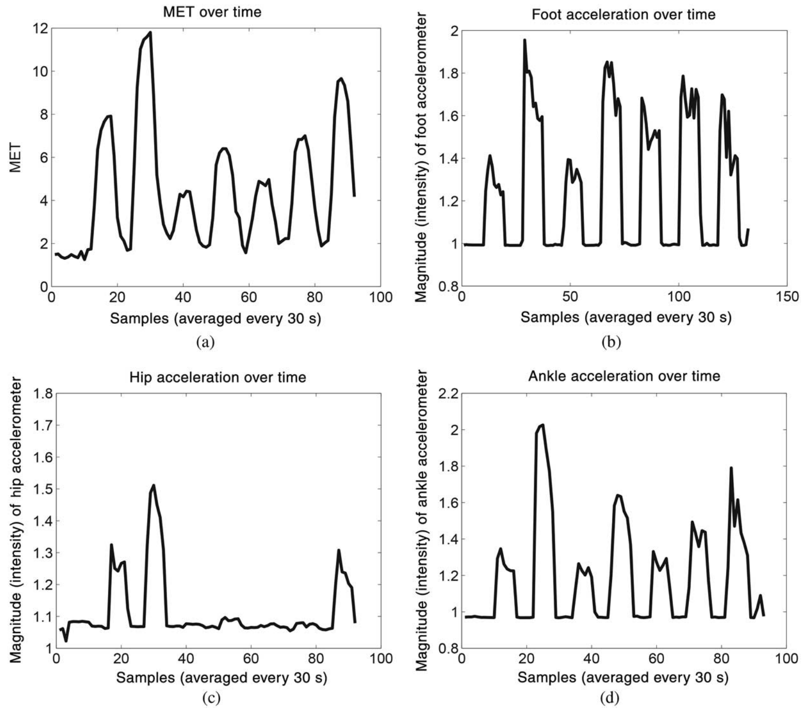

Fig. 2. User 1 values for (a) METs and magnitude of accelerations for (b) foot, (c) hip, and (d) ankle.

when the number of sensors are decided from any other application, or the best picked here. This sorting was based upon the R^2 value of the regression.

Once the appropriate weighting of each sensor was found, the comparison between MET and $\mathrm{MET}_{\mathrm{reg}}$ can be analyzed further. As indicated in Section II, analyzing each activity independently can provide stronger regression results, rather than developing a universal model for the all movements. An extra iteration of the method indicated here is run per activity, to develop individual regression models for each activity and the simulated game play independent of each other. Thus, any future exergaming system that has a classification system, will not only identify the movement performed, but the appropriate regression model necessary to calculate the most accurate approximation of caloric expenditure. As will be shown, this activity-specific regression technique provides a much stronger linear regression for each movement.

3) Optimal Sensor Weighting: The sensor-weighting technique described in Section III-C.2 is a heuristic approach. Instead of weighting the regression as such, a multidimension regression can be run to select the weights in a completely variable format such that an objective function (e.g., regression error) is minimized. In this case, the MET estimations are given by

$$\mathrm{MET}_{\mathrm{reg}} = \alpha_0 + \sum_{i=1}^{n} \alpha_i \cdot s_i \tag{5}$$

where the s_i are just as in the previous section. In this case, instead of looping through the c_i and setting the weights directly, the algorithm will select the weights through a multidimensional linear regression. This approach finds the best fit by minimizing the amount of mean-square error. The method can be applied to both algorithms discussed previously. That is, the multidimensional regression can be used to optimally weight sensors either with or without integrating the "activity type." In our experimental results, we will demonstrate the accumulated improvements made by integrating the two contextual factors (e.g., sensor weighting and activity type) within the MET calculation model. A concern about such a system would be the accuracy of determining such an "activity type." If such a system is not accurate in determining the motion, then it is better to use a general approximation. The movements in this work are, however, accurately detected. The method described in [10] reaches 81% precision and 80% recall on the desired movements, while improvements on such an algorithm approach 90% [48]. Thus, it is safe to assume an "activity type" specific regression is a safe model to develop, as each movement will be identified with high accuracy.

D. Cross Validation

In order to verify the strength of such regression models, one must measure its ability to predict appropriately the MET values being outputted. As a result, a leave-one-subject-out cross validation is run to verify that the model presented on the given data set can predict the appropriate MET values. In particular, for each subject, the regression model is run on the subset of data training data. Then, the testing data from the left-out subject are run. The MET from the regression model is compared against the ground truth, and the results are averaged across all users for each movement as

$$\mathrm{MET}_{\mathrm{move}} = \frac{1}{n} \sum_{i=1}^{n} \left|\mathrm{MET}_i - \mathrm{MET}_{i_{\mathrm{reg}}}\right| \tag{6}$$

where n is the number of subjects in the data set.

TABLE IV
R^2 VALUES FROM SENSOR SELECTION REGRESSION ANALYSIS

No.	Description	R^2
1	MET versus foot	0.2431
2	MET versus ankle	0.5662
3	MET versus hip	0.2342
4	MET versus foot + ankle	0.4655
5	MET versus foot + hip	0.3355
6	**MET versus hip + angle**	**0.7147**
7	MET versus foot + hip + ankle	0.5472

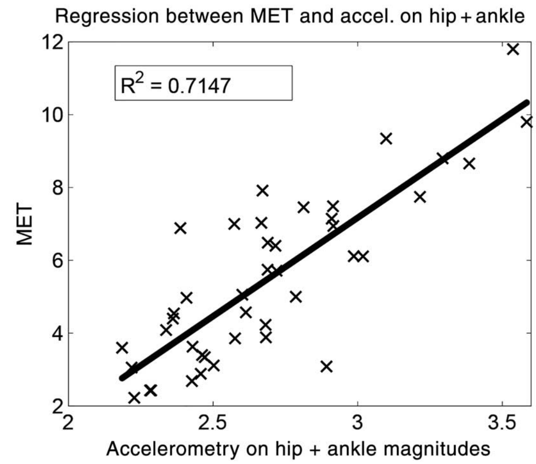

Fig. 3. Regression run on data from hip accelerometer and ankle accelerometer at peaks.

IV. EXPERIMENTAL RESULTS

This section covers the three processing techniques designed for this protocol. Beginning with the general sensor location problem, this section covers the progression to the generalized multidimensional technique for activity type regressions.

A. Binary Sensor Weighting Results

Fig. 2(a) shows the METs as calculated from VO_2 data; associated accelerometer magnitudes for one of the users of the trial are shown in Fig. 2(b)–(d), respectively. Table IV shows the results of the regression run on the analysis. At each movement point, the peaks were detected after the 3-min mark and used for the polyfit regression run in MATLAB. A combination of the hip accelerometer and ankle accelerometer seems to do better than using the foot, like is used in [10]. It seems there is perhaps too much activity at the top of the foot, or rather, perhaps the peaks themselves should not be used. As can be seen in Fig. 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 model:

$$\mathrm{MET}_{\mathrm{reg}} = 5.3 \times (\|\mathrm{hip}\| + \|\mathrm{ankle}\|) - 8.6 \qquad (7)$$

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 Fig. 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 [10] 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. Activity-Specific Results

As suggested, regressions based on context information can provide stronger results. In this case, knowing the activity and running variable weighting on each of the activities results in significantly stronger results. In Table V, we show several key factors. The first is that, some of the individual regressions shows stronger results than found in Table IV. Second, notice the generalized sensor-selection method used in Section IV-A. While results seemed strong in the general case, notice how weak the results are, in particular for certain movements like the medium strength shot. This sensor location and selection method list the best possible combination in each movement type, as depicted in Table VII. The results are not simply the hip and ankle sensors as discussed in the generalized case, but different sensors for different movements. Thus, for exergaming movements similar to other works, activity specific regressions perform better generally than overall regressions, even with problem movements such as the medium shot. When empirically determining the weighting, all the results improve generally. When developing an exergame, one can choose to use an overall regression based upon the simulated game play only, or can create formulas that are chosen based upon any classification result given. For each movement, as expected, the multidimensional regression produces the best results. In the example presented in this work, the multidimensional regression has four parameters, one being the constant, the other three being scaling factors on each of the sensors. The best parameters for each movement are listed in Table VIII. Finally, the average R^2 value is calculated for each movement, including and removing the medium shot as it appears to be a problem movement. Such movements should be investigated further, needing more data for more valuable models.

C. Cross Validation Results

The results of the leave-one-subject-out cross validation are shown in Table VI. The mean absolute difference shown results in an error of about 2 METs, which would still put the general intensity levels in the correct ranges. This shows that the method and R^2 values show a model that can accurately predict the intensity of a new individual. The widest range of error comes in the effort put forth while running. This is likely due to the different physical conditions of the subjects, the speed with

TABLE V
R^2 VALUES OF BEST REGRESSION FOR EACH ACTIVITY

Movement	Run	Sprint	Pass	Chip	Med. shot	Full shot	Sim-game	Avg. w/out med. shot	Avg.
Sensor-selection	0.81	0.85	0.81	0.56	0.10	0.66	0.71	0.73	0.64
Variable-weighting	0.86	0.89	0.85	0.66	0.74	0.68	0.76	0.78	0.77
Multidimensional regression	0.98	0.95	0.99	0.75	0.90	0.94	0.78	0.90	0.89

TABLE VI
MEAN ABSOLUTE DIFFERENCE FOR EACH MOVEMENT USING ACTIVITY-SPECIFIC MODELS OF REGRESSION

Run	Sprint	Pass	Chip	Med. shot	Full shot	Sim. game	Avg.
2.336	2.550	2.021	2.061	2.107	2.085	2.460	2.231

TABLE VII
SENSOR LOCATION CHOICES FOR EACH ACTIVITY TYPE IN SENSOR SELECTION REGRESSION

No.	Movement	Locations
1	Run	Ankle
2	Sprint	Hip + angle + foot
3	Pass	Ankle + foot
4	Chip	Hip + ankle
5	Med. shot	Hip + ankle
6	Full shot	Foot
7	Sim. game	Hip + ankle

TABLE VIII
VALUES FOR EACH PARAMETER IN THE MULTIDIMENSIONAL REGRESSION

No.	Movement	α_0	α_{hip}	α_{ankle}	α_{foot}
1	Run	–35.5	52.6	10.5	–30.6
2	Sprint	2.83	18.5	–10.6	–9.37
3	Pass	105.6	99.0	–69.7	–139.5
4	Chip	14.5	15.7	–7.99	–21.0
5	Med. shot	–10.0	–10.7	7.38	17.4
6	Full shot	–7.23	–4.91	9.20	5.40
7	Sim. game	5.69	–3.17	7.83	–7.61

which they ran, and the strain this put on the body. While there is obvious room for improvement, as will be discussed further in Section V.

D. Caloric Expenditure

The purpose of such MET calculations is to ultimately calculate the energy expenditure through caloric expenditure. The MET is an approximation of the metabolic expenditure of the body. Further, using a method from [49], the caloric expenditure can be extracted from this information using the following equation:

$$\text{Calories} = \frac{k \times \text{MET} \times m}{200} \times t \tag{8}$$

where k is the same factor used in the MET predictions, m is the mass in kilograms, t is the time in minutes, and 200 is a scaling factor. Thus, to ultimately prove the validity of such a system, the caloric expenditure of the trial is shown in Table XI. This table shows the actual caloric expenditure achieved by the model for each given user over the course of the trial, summed over each activity (3 min per activity).

V. DISCUSSION AND FUTURE WORK

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 [25] 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 IX, the final two columns show what soccer (casual and intense) would be with the corrected models 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. Table X shows the average MET and standard deviations for all the movements and the simulated game. It seems the simulated game play energy expenditure 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 cutoff 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. Further, movement data are necessary to better validate models of specific movements, such as the medium powered shot discussed in the Section IV. This is shown with the mean absolute error of the model predicting the METs in cross validation. It is still a more accurate model but room is clearly left for improvement.

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, instead of signal processing simply on 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

TABLE IX
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)
170	76	28	7.91	11.80	4.40	6.40	4.97	7.0	9.66	7.57	10.80
187	82	29	4.20	7.34	2.29	6.49	2.97	5.0	7.29	7.47	10.68
174	68	29	4.20	8.66	5.06	4.94	4.11	7.83	9.82	7.16	10.23
183	79	26	3.80	7.03	2.60	3.97	3.11	6.11	7.49	7.38	10.54
174	70	31	4.54	6.51	3.49	4.63	3.17	4.23	5.74	7.36	10.44
175	66	22	6.89	8.80	2.80	3.63	4.14	5.94	7.60	6.83	9.75

TABLE X
AVERAGE METs FOR EACH ACTIVITY

No.	Activity	AVG $\pm$ STD
1	Run	5.26 ± 1.70
2	Sprint	8.36 ± 1.92
3	Pass	3.44 ± 1.09
4	Chip	5.01 ± 1.20
5	Med shot	3.75 ± 0.79
6	FP shot	6.02 ± 1.30
7	Sim-game	7.93 ± 1.55

TABLE XI
CALORIC EXPENDITURE ACHIEVED BY EACH USER DURING THE TRIAL

User	1	2	3	4	5	6
Calories	208	153	159	141	118	138

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. Variability must be better modeled into such systems. When conducted in a laboratory setting perhaps, the body strains more by wearing the oxygen equipment. Variability needs to account for more users, different factors on the actual MET value, and account for users becoming more efficient over time. Further, this variability can be compared over population ranges. The data in this study are taken from healthy young adult subjects. Separate models can be created for overweight/obese adults, and for healthy and overweight/obese children as well, in order to create an even more general framework for MET approximations across all population types. Finally, the sensor selection approach indicated here can be further analyzed, such as in [50], in order to reduce the computational complexity and power optimization. As was seen here, the power optimization can be improved by roughly one-third to two-thirds depending on the movements monitored and sensors desired.

The MET and caloric expenditure information presented in this work are applicable to exergaming and other physical activity monitoring tools with the use of accelerometers. This information should be provided to a user in order to better represent their physical activity information. Further, this data can be transmitted to any user's clinical professional. Doctors can use this information to assess the length of time playing video games, the activity levels achieved playing those games, and using this information to better assess the physical activity levels achieved with real data instead of simple questions asked in periodic checkups.

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. Further, by using context information, stronger correlations can be determined when the activity information is given. Each individual movement regression results in a stronger model for approximation than any of the generalized formulas. 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. Finally, this paper also concludes that soccer exergaming can reach an MET value of 7.93 even across variable subjects, which is roughly the same as the predicted value for actual light/casual intensity soccer.

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