Support Vector Regression to Estimate the Metabolic Equivalent of Task of Exergaming Actions

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***Abstract*— Sedentary behavior is a root cause of several chronic conditions affecting health of adults and children in the United States and worldwide. The chronic conditions that result from this cause not only health concerns for these individuals but significant economic burden. Exergaming, or the merger of exercise and health information with video games, presents a solution that attempts to address the sedentary behavior of adults and children by making physically interactive video games that increase energy expenditure. Such games, particularly those that use the body as the controlling device for the game through the use of accelerometers, have elicit moderate levels of physical activity when measuring the metabolic equivalent of task (MET) of the associated activities. This work presents the support vector regression scheme in order to better correlate accelerometer measurements with MET values. Energy expenditure data collected on 14 individuals and their accelerometer data have regressions with the mean absolute difference (error) of the associated MET approximations is under 2 and as low as 0.58 for full gameplay, an improvement of well over 1 MET for all activities over related work.**

I. INTRODUCTION

Sedentary behavior is a root cause of several chronic conditions affecting health of adults and children in the United States and worldwide [1] [2]. Such physical inactivity often leads to overweight populations and obesity [3] that are associated with chronic conditions such as cardiovascular disease or diabetes. Cardiovascular disease and diabetes both present a significant economic burden in the United States as well as health, with cardiovascular disease accounting for an estimated $670 billion in health care costs in 2010 [4] and estimates suggesting diabetes may approach $900 billion in health care costs by 2015 [5].

As a result, many solutions using wireless wearable sensors have been presented to monitor activity [6] [7]. One such solution is the use of these body-worn sensors, such as accelerometers, to enable the actions of an individual to control a video game [8]. Exergaming, or the mix of physical activity to control an electronic game, has been shown to increase physical activity [9] as well as other directed goals, such as stroke rehabilitation [10]. Such exergames, such as the ones presented in [11] [12] [13] [14], show frameworks for potentially active video game play, but the energy expenditure of such systems needs to be further verified, whether by activity type [12] [13] or by intensity levels [11] [13]. Some work has been done to determine the energy expenditure and metabolic equivalent of task (MET) [15] of exergames to show that they can increase energy expenditure and be a useful intervention over time [16] [17] [18]. These systems do promote activity and thus, accelerometer approximations to this energy expenditure provide useful information about real exercise [19] [20] [21].

In order to provide useful information while exergaming, accelerometer approximations to the energy expenditure need to be created. Since it is difficult to measure the oxygen consumption while playing, such as in [22], approximations need to be developed that correlate closely to the caloric expenditure values. Work such as [23] [24] [25] developed advanced models of mapping accelerometer values to energy expenditure. However, each uses a unique regression off the data collected from the sensors, some of which were in proprietary accelerometer counts. Further, they document the need for individual accelerometer approximations for each unique activity being modeled.

The current work introduces an advanced energy expenditure estimation model for a soccer exergame, which often involves unique movements derived from reality but adapted for gameplay. It will measure the appropriate output in terms of METs, which can then be translated to caloric expenditure directly based on each user. By using advanced, non-linear models of regression, namely a support vector regression, it will provide stronger mappings between exergaming movements, the accelerometer readings for those inputs, and the METs generated. It will be shown, through a leave-one-subject-out cross-validation, that the robustness of such a model for exergaming movements by measuring the mean absolute error (by calculating the mean absolute difference) in each approximation is greatly improved over standard linear regression techniques.

II. RELATED WORKS

A. Common Regressions

Work in [26] showed an advanced, non-linear regression method for walking energy expenditure approximation. By using a support vector regression, instead of a standard linear regression, [26] shows reduced mean square errors for walking energy expenditure estimations. The results support that using advanced regression techniques can provide stronger results. This work will adapt such a methodology to the data collected and set of movements to a soccer exergame, to

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expand upon results beyond walking to many types of leg movements. Similarly, work in [27] uses an artificial neural network, which also models a non-linear regression method, to estimate METs of activities with low root-mean-squared error by combining it with the activity detection. This work will use the advancement of using the individual identified activity in order to develop movement-specific models that approximate the energy expenditure.

B. METs for Exergames

Work in [22] was one of the preliminary investigations into the MET values associated with exergaming movements. A trial conducted on six people showed that specific regressions are needed for each type of activity, because the regular table look up of energy expenditure does not allow for a vast amount of variability. Work in [22] developed MET values for a soccer exergame, using a simple linear regression, showing simulated gameplay manufactured an average of 7 METs. This work extends [22], namely, more advanced regression techniques are designed here to allow for robustness across subjects. Work in [22] is a simple regression and not data in cross-validation in order to measure error across subjects. This work will continue the work of developing accelerometer approximations for specific activities, in this case soccer exergame movements, but develops a more robust model to allow variability across subjects. First, this work will adapt the method shown in [22] to work on individual activities, and then will further apply a support vector regression in order to produce strong results in cross-validation.

III. METHOD

This section describes the data collection procedure and trial conducted for MET approximations. This study was a UCLA Institutional Review Board (IRB) approved study # 12-000730, where 14 healthy adults, from ages 18-35, were selected to run through the same protocol defined in [22]. This trial consists of six movements and a simulated gameplay phase to relate the data with actually playing a game and the mix of movements necessary. The movements are running in place, sprinting in place, passing a ball left, chipping a ball left, medium powered shot, and a strong powered shot. Each movement was repeated consistently for three minutes to measure the constant load of each movement, as necessary to determine the oxygen consumption levels of a user. Three minutes of rest between each set of moves allowed for the user to return to a state of rest. The simulated gameplay, in order to compare directly, was used from [22] where the movements are mixed along with running actions to mimic the game described in [11]. User's wore a mask connected to a metabolic cart in order to measure the volume of oxygen consumed during the movements. This data was averaged over 30 second windows. The motion data was captured by wearing accelerometers strapped to the body in three locations. The accelerometers were Shimmer3 [28] wireless IMUs with a +/- 6g accelerometer sampled at 50 Hz. Those locations are the hip, on the right side, the ankle, on the outside of right leg, and the foot, on top of the right foot, as shown in Fig. 1.

Fig. 1. User wearing sensors on the hip, ankle, and foot for collection trial

Activity	AVG $\pm$ STD
Run	6.08 ± 3.32
Sprint	9.27 ± 3.14
Pass	4.39 ± 2.18
Chip	5.77 ± 2.58
Med Shot	5.13 ± 3.34
FP Shot	6.76 ± 2.61
Sim-Game	8.24 ± 2.09

TABLE I

A HIGH STANDARD DEVIATION OF METS FOR EACH ACTIVITY

A. Data Processing

Data that was collected involved the volume of oxygen consumed during three minutes of constant load activity. From this information, listed as $VO_2(\frac{ml}{min})$, MET can be calculated as

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

where k is a factor that scales based upon the physical condition of the user (3.5 in the case of the trial in this work), and m is the mass in kilograms of the user. Since the data is collected from the IMUs at 50 Hz, the data needs to be averaged. Similarly to [22], the magnitude of acceleration is calculated, then averaged over 30 second windows. The peaks as well as flat rest data are selected and used for the regression.

B. Cross Validation

While the R^2 correlation coefficient of a regression reports the fit of the regression to the data, this does not necessarily account for variability across the users, even those shown in [22], greater variability is found over the 14 subjects collected here. A leave-one-subject-out cross-validation is run to test the generated models' variability across each test subject. Table 1 shows greater variability than reported in [22], where in [22] most standard deviations were reported to be under 2, even close to 1 in many cases, here they range between 2 to 3 $METs$ that, if reported incorrectly, is a wide range for physical activity (perhaps the difference between low and moderate physical activity). For each test subject, the training data is split between each activity. Each of these activities have their own model. The test data is then run on the model to see what determined predicted MET value is produced, labeled MET_{reg}. Then the mean absolute different (MAD) is calculated for each activity and reported to determine the best results. The MAD is calculated as

$$MAD = \frac{1}{n}\sum_{i=1}^{n} abs(MET - MET_{reg}) \tag{2}$$

where n is the number of subjects, MET the ground truth measured value and MET_{reg} the output of the regression model. A model's robustness will be determined by a low MAD (also reported as mean absolute error in some works).

1) Sensor Selection Method: The sensor selection method, first reported in [22], was implemented using the polyfit function in Matlab. For each activity, the seven different training configurations had each model created. The configurations were using only the hip, only the ankle, or only the foot sensor data, or the combination there of. Then the R^2 of each model is evaluated on the training data alone to pick the best reported model as they choose. This model is then used to calculated the absolute difference of predicted MET.

2) Support Vector Regression: Using LibSVM [29], a support vector regression is created, using an epsilon-svm and a radial basis function kernel. Similarly to the Sensor Selection method each activity model has its reported MET_{reg} value outputted and the absolute difference stored for the overall mean absolute difference.

IV. RESULTS

As seen in Table 2, the robustness of each method is shown. The mean absolute difference of each movement type is shown, validating the need for movement, specific models. Certain movements, including the simulated gameplay, have much better mean absolute difference values than other associated moves. Further, the movement models can be separated easily by using a classifier to find a move type first. The Support Vector Regression performs better in every movement, and is particularly strong for the simulated gameplay. This would lead one to believe a robust, advanced regression model, can produce highly accurate energy expenditure values for such an exergame.

V. FUTURE WORK

There is higher variability still presented by the increase in data. Thus, more data needs to be collected, and across different body types to account for various states of well-being from fully healthy and active to completely sedentary and obese. Further, models that allow for more variability across types should be compared. Finally, the variability between such exergaming movements and the energy expenditure values, should be compared over longer periods of actual gameplay.

VI. CONCLUSIONS

Exergaming has shown the need for advanced energy expenditure models for the specific type of motions necessary for such games. By calculating the energy expenditure through the usage of oxygen consumed by a user, this work developed a model and approximation method for estimating the metabolic equivalent of task (MET) of each activity in a soccer exergame through the usage of a support vector regression. This higher dimensional regression tool, in cross validation, had a mean absolute error (mean absolute difference) of less than 2 for every movement, and in some cases under 1. This low error is a full MET, in some cases 2 METs, better than similar linear regression techniques, providing a significantly more accurate accelerometer approximation to energy expenditure for exergaming movements.

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Activity	Run	Sprint	Pass	Chip	Med. Shot	Strong Shot	Simulated Gameplay
Sensor Selection	2.99	3.06	1.97	2.54	3.12	2.29	1.83
SVR	1.37	1.55	0.82	1.09	1.65	1.08	0.58

TABLE II

THE MEAN ABSOLUTE DIFFERENCE FOR EACH ACTIVITY IN CROSS-VALIDATION FOR THE SENSOR SELECTION METHOD AND THE SUPPORT VECTOR REGRESSION

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