Energy Expenditure Estimation in Boys with Duchene Muscular Dystrophy using Accelerometer and Heart Rate Sensors

Amit Pande, Gretchen Casazza, Alina Nicorici, Edmund Seto, Sheridan Miyamoto, Matthew Lange,
Ted Abresch, Prasant Mohapatra and Jay Han

Abstract— Accurate Energy Expenditure (EE) Estimation is very important to monitor physical activity of healthy and disabled population. In this work, we examine the limitations of applying existing calorimetry equations and machine learning models based on sensor data collected from healthy adults to estimate EE in disabled population, particularly children with Duchene muscular dystrophy (DMD). We propose a new machine learning-based approach which provides more accurate EE estimation for boys living with DMD. Existing calorimetry equations obtain a correlation of 40% (93% relative error in linear regression) with COSMED indirect calorimeter readings, while the non-linear model derived for normal healthy adults (developed using machine learning) gave 37% correlation. The proposed model for boys with DMD give a 91% correlation with COSMED values (only 38% relative absolute error) and uses ensemble meta-classifier with Reduced Error Pruning Decision Trees methodology.

I. INTRODUCTION

Duchenne muscular dystrophy (DMD) is a progressive, X-linked recessively inherited muscular disorder with an approximate prevalence of 1 per 3,500-5,000 males, making it the most common and severe form of childhood muscular dystrophy [1](Emery 2002, MMVR 2009). Boys with DMD are usually confined to a wheelchair by the age of ten years and have a median life expectancy of thirty years [2]. Functional impairments often result in gait abnormalities and decreased physical activity as their disease progresses.

An important aim in the clinical management of boys with DMD is to preserve functional abilities for as long as possible. There is limited evidence as to whether exercise training in DMD is helpful or harmful. The small number of training studies have focused on resistance training in ambulatory boys and concluded that submaximal resistance exercises had only small positive effects on muscle strength and timed functional tests but, did not cause any physical damage [3]. International guidelines recommend ambulatory boys to perform voluntary active exercises (such as swimming) and to avoid eccentric exercises. Due to the absence of the protein dystrophin, which supports muscle fiber strength and prevents muscle injury, muscle fibers in DMD patients are abnormally vulnerable to contraction-induced injury [4] and therefore, eccentric exercises should be avoided.

A Pande, G Casazza, A Nicorici, S Miyamoto, M Lange, T Abresch, P Mohapatra and J Han are affiliated with University of California Davis, USA ({amit@cs, prasant@cs, gretchen.casazza@ucdmc, alina.niorcini@ucdmc, jay.han@ ucdmc, sheridan.miyamoto@ucdmc, matthew.lange@ucdmc}.ucdavis.edu, tabresch@gmail.com)
E Seto is with School of Public Health, University of Washington, Seattle, USA (eseto@uw.edu)

However, these clinic or laboratory measures may not capture the true loss of independence, real life activities, social interactions and quality of life. The ability to accurately measure everyday physical activity and activity-related energy expenditure (EE) is crucial for the development of effective interventions to combat the detrimental effects of reduced physical activity associated with DMD. Mobile sensors enable point-of-care intervention to improve physical activity and its monitoring in healthy and patient population.

Different measuring techniques have been used in disabled populations including questionnaires, activity diaries, heart rate (HR) monitoring, motion sensors (pedometers, accelerometers), indirect calorimetry, and doubly labeled water. Activity questionnaires and diaries, while inexpensive, are time consuming, rely on accurate recall and reporting by the individual, and have been shown to be inaccurate, especially in children [5,6]. In normal populations, HR monitoring has been shown to be less accurate in estimating Energy Estimation (EE) for low intensity activities, which comprise the majority of the activity for disabled populations [5,6]. Accelerometers are more accurate for non-disabled populations because they measure activities across several planes allowing measurements of the duration, frequency and intensity of physical activity. Disadvantages include the inability to measure activities where the patient is not moving the part of the body being monitored by the accelerometer (cycling, sitting, standing) [7].

Indirect calorimeters such as the COSMED k4b2 have been validated and used as reference standard for measuring EE [8]. However, the bulky size of COSMED limits its use in point-of-care technologies, and prevents its use in the monitoring of daily activities.

Our objective is to develop an algorithm to accurately estimate EE in boys with DMD from sensor data collected using small, pervasive wearable accelerometers and heart rate monitors, to be used in future point of care technologies for disabled populations. This can be used for monitoring population with DMD as well as serve as antecedent to future research in developing new EE models for disabled populations. We have developed a new non-linear regression (machine learning) based algorithm to estimate EE for children with DMD which gives 91% correlation and Root Mean Square Error of 0.0167.

To the best of our knowledge, this is also the first work that tests whether existing EE algorithms designed for normal adults is applicable and accurate for pediatric DMD patients. Previous studies [9,10] have focused on activity monitoring, not EE estimation.

2.1 Subjects

Seven subjects with DMD between the ages of 6-10 years were recruited from the regional neuromuscular clinic at the UC Davis Medical Center. Subjects completed an informed written consent approved by the Institutional Review Board of The University of California Davis.

2.2 Experimental Design

Subjects were asked to perform a series of activities in our exercise laboratory at UC Davis while simultaneously monitored by an accelerometer, a heart rate monitor, and the COSMED K4b2 (COSMED, Concord, CA) metabolic system. For accelerometer measurements, we used smartphone devices placed in a waist pack, and oriented in a standardized position. A chest strap was used for the heart rate monitor.

2.3 Exercise protocol

Before each test, the COSMED K4b2 components were calibrated according to the manufacturer's instructions. Subjects were then fitted with the pack containing the phone (accelerometer) and the COSMED K4b2 metabolic system. Subjects were asked to perform the following activities, one right after the other, in the ordered listed:

3 minutes of lying supine on an exam table, 3 minutes of sitting, 50-meter slow paced walk (lasting approximately 1-2 minutes for participants), 50-meter self-selected typical comfortable speed walk (45-60 sec), and 50-meter fast walk (20-60 sec) with approximately 1 minute rest between the walking protocol.

Speeds were chosen based on ratings from the OMNI scale with easy walking rated as 0-2 or "not tired at all", medium pace as 2-4 or "getting a little tired" and fast walking pace 4-6 or "getting more tired" (Robertson et al. 2000). The final activity was a 6-minute walking test (6MWT). Cones were set up at a 25 m distance in the hallway and the children walked as fast as possible back and forth between the cones for 6 minutes (McDonald et al 2010). Heart rate (Polar heart rate monitor, Woodbury, NY), oxygen consumption, carbon dioxide production, respiratory exchange ratio (RER) and ventilation rate were continuously monitored.

Data from the COSMED metabolic system was averaged over the 30-60 sec of each collection period. Energy expenditure was calculated using the following equation: COSMED K4b2 EE (kcal·min-1) = ((1.2285*RER)+3.821))* VO2 where VO2 is the oxygen consumption in L per minute, and RER is respiratory exchange ratio. All data was processed according to the following procedures:

1. The COSMED output was resampled to obtain per-second estimates of EE and Heart rate.
2. Smartphone sensors were oversampled at 4 Hz and then downsampled to obtain higher   frequency resolution (more accurate sensor readings).   Oversampling improves resolution and reduces noise in the readings.   Resampling was done to obtain per-second estimates of Accelerometer readings (Ax, Ay and Az relative to the x,y and z axis of the smartphone)
3. The accelerometer readings were synced with the COSMED readings using paper markers.
4. The local coordinates from the smartphone accelerometer readings were translated into global coordinates (two components – horizontal and vertical).
5. Additional information about subject measurements such as age, height and weight were used as attributes for training data mining algorithms and validating existing algorithms.

2.4 Machine Learning/ Statistical Analysis

We used bagging ensemble technique with reduced-error pruning decision tree as the underlying classifier to predict EE [11,12,15,16]. The bagging ensemble technique is presented here because it was superior to models generated using other techniques (eg, multilayer perceptron, support vector machines, linear regression, naïve Bayes, reduced-error-pruning decision trees and naïve Bayes). The bagging technique (or Bootstrap aggregation) is an ensemble meta-algorithm to improve the stability and accuracy in statistical regression obtained by decision tree. The decision tree was built using Information-theoretic criterion for selecting the nodes. Once the tree is built, reduced error pruning is used, where each node, beginning with the leaves, is replaced with its most popular class. We divided the data for the model into n = 10 folds, where, n-1 folds are for supervised learning and one fold is used to test the model for errors. The errors obtained in a fold is added to the weights of nodes of next fold in the training set. Ten-fold cross validation was used to evaluate the model in order to ensure that the model was tested on data that it had not seen while training, to minimize chance for over-fitting. Data processing was done in MATLAB Version: 8.1.0.604 (R2013a) while data mining (machine learning algorithms) was done using Weka software 3.6.10.

2.5 Existing Equations

We used generalized non-linear equations [17] originally developed based on the Tritrac-R3D accelerometer: where H and V are the horizontal and vertical accelerometer-based counts, respectively for the k-th minute, and a, b, p1, and p2 are the generalized parameters that are modeled based on the subject's mass in kg and their gender (p1=male, p2=female).

$$EEact(k) = aH(k)^{p1} + bV(k)^{p2}$$

$$a = \frac{\left[12.81 \times mass(kg) + 843.22\right]}{1000}$$

$$b = \frac{\left[38.90 \times mass(kg) - 682.44 \times gender + 692.50\right]}{1000}$$

$$p1 = \frac{\left[2.66 \times mass(kg) + 146.72\right]}{1000}$$

$$p2 = \frac{\left[-3.85 \times mass(kg) + 968.28\right]}{1000}$$

The resulting activity energy expenditure (EEact) is the amount of energy expended in KJ above resting energy

expenditure (NOR-CHEN). For comparison with normal adults, we used a model developed from experiments on 23 healthy people. The model to estimate EE in healthy adults combined accelerometer and heart rate measurements, A protocol similar to the one outlined in this paper was followed for normal adults: obtaining sensor values and COSMED readings. In that analysis, two models were developed – one using linear regression (NOR-LIN) and another using Ensemble Bagging Technique over normal adults' data (NOR-ENS). Further details of the healthy adult EE study are the subject of a different paper, currently under review.

III. RESULTS

3.1 Subject Characteristics

Physical characteristics of the subjects are shown in Table 1. All subjects completed the study protocol without any problems.

TABLE I.   CHARACTERISTICS OF SUBJECTS IN THE STUDY

Attributes	Range
Age, year	8.3±1.7
Height, cm	121.4±10.4
Weight, kg	28.7±5.8
BMI, kg/m2	19.3±2.1
Fitness: 1 min recovery HR, bpm	321.3±126.4
Fitness: 6 min walk test	120.7±16.3

3.2 Feature Selection

The goal of feature selection is to reduce the number of attributes used in the model and to understand the predictive power of the original set of attributes. Correlation Feature Selection (CFS) was used to identify a subset of attributes, for reduction of input attributes [13]. Age, Height, Weight, Horizontal, Vertical and Net Acceleration measurements, as well as Heart Rate measurements, were retained, while BMI, recovery HR and 6 minute walk test values were removed. The CFS technique was used with a greedy stepwise search to find the subset S with the best average merit, which is given by M_S

$$M_s = \frac{n\,\overline{r_{P_D}}}{\sqrt{n + n(n-1)\overline{r_{P_f}}}}$$

Where n is the number of features in S, $\overline{r_{P_D}}$ is the average value of feature-outcome correlations and $\overline{r_{P_f}}$ is the average value of all feature-feature correlations. We used the information-gain (IG) metric to measure the relative predictive power of each final attribute in our dataset, Training set 'T' [14]:

$$IG(T,\mathbb{A}) = H(T) - H(T|\mathbb{A})$$

H() represents the information entropy and is an attribute. Figure 1. shows the plot of IG for all the attributes. It demonstrates that for children with DMD, heart rate readings have the highest information gain contribution to EE
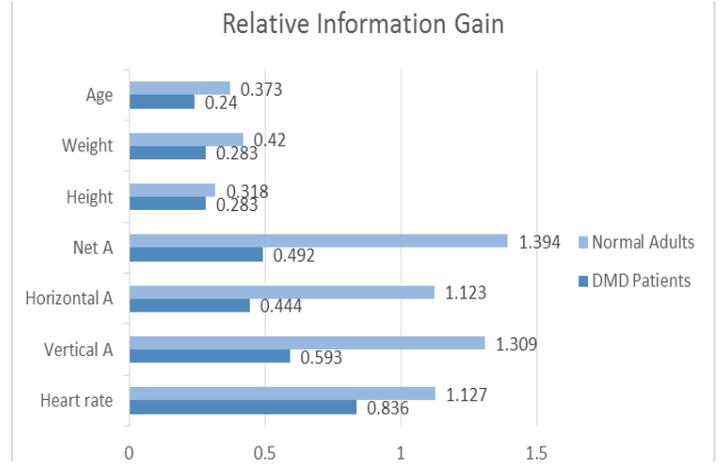

Figure 1: Relative Information Gain (IG) of different attributes on the EE Estimation. We observed substantially reduced significance of accelerometer output in children with DMD compared to normal adults.
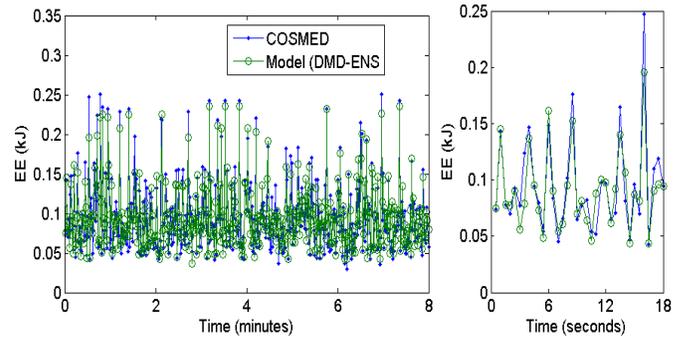

Figure 3: Plot showing EE values obtained by COSMED and those estimated by Ensemble Model for DMD patients (DMD-ENS).

estimation. In the DMD group, accelerometer values (Net A, Horizontal A and Vertical A) have lower relative information contributions for determination of overall EE, compared to normal adults where accelerometer readings have higher impact than heart rate. Other factors, such as age, weight and height have small IG for both populations. The reduced predictive power of smartphone accelerometer's readings can be attributed to the unique body movement of DMD patients which makes it impossible for one single accelerometer to capture their body motion effectively.

3.3 Ensemble Model

Using the data obtained from the DMD children, we identified a total of 12 attributes (11 features and 1 output attribute) and 7560 total instances, to develop a new model of EE. We used the Bagging ensemble technique with Reduced Error Pruning Regression Tree as the underlying regression model to predict the EE values. The regression model generated from this choice outperformed others in terms of output correlation (91.2%) and Mean Absolute Error (MAE, 0.012): neural networks, linear regression

(81.12%, 0.019), Decision Stump trees (58%, 0.025), Stacking (0.0289%, 0.03) and Additive Regression (78.73%, 0.2). This newly developed algorithm (DMD-ENS) builds a regression tree using information variance and prunes it using reduced-error pruning (with backfitting).

3.4 Comparison with existing algorithms

Results from the performance of the DMD-ENS model compared with the models built over normal adults are shown in Table 2. It can be seen that existing adult models give a very poor performance (only 40% correlation) and MAE of 0.02-0.04.

TABLE II.   PERFORMANCE COMPARISON OF DMD-ENS MODEL WITH MODELS FOR NORMAL ADULTS

Model	Correlation to EE	Mean Prediction Error
DMD-ENS	91.2%	0.012
NOR-CHEN	40.62%	0.0289
NOR-LIN	41.59%	0.030
NOR-ENS	37.91%	0.038

In our range of observations, the mean value of COSMED readings over the sample population (over one second epoch) was 0.09. Thus, an error of 0.04 is significant.

IV.   DISCUSSION

The purpose of this study was to test the use of accelerometer and heart rate sensors to estimate energy expenditure in boys with Duchene muscular dystrophy. Compared to the EE data obtained from the COSMED K4b2, EE estimation based on our proposed model (DMD-ENS) has superior accuracy and correlation for EE during resting and low-energy activities, as well as for higher energy, and moderate exercise activities. While this single model appears to work across a range of activities in a clinical setting, further investigation into the validity of this EE estimation model for daily activities outside the clinic is needed.

Further investigation into the bodily placement of multiple sensors will provide information into the relative information gained by sensors in specific bodily locations. It is conceivable that information from each of these sensors will independently effect accuracy of this EE model for disabled populations, depending on the particular conditions of the disability and impairment.

We found that most of the participants found the sensors easy to use, unobtrusive and would be willing to use it on a daily bases as a tool to monitor their physical activity and energy balance as part of their treatment program.

In this study, we used a smartphone accelerometer along with a heart rate monitor to account for both modalities in estimating EE. It may also be possible to mount an accelerometer with heart rate monitor, making the use of smartphone redundant.

There are some limitations of our study. First is the small sample size. We plan to continue collecting data from DMD patients to validate our results. The second limitation is that laboratory based measurements may not correlate to regular daily activity and should be further validated in home or community settings.

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