Estimating Oxygen Uptake during Non-Steady-State Activities and Transitions Using Wearable Sensors

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Abstract—**In this paper, we present a method to estimate oxygen uptake (VO_2) during daily life activities and transitions between them. First, we automatically locate transitions between activities and periods of non-steady-state VO_2. Subsequently, we propose and compare activity-specific linear functions to model steady-state activities and transition-specific non-linear functions to model non-steady-state activities and transitions. We evaluate our approach in study data from 22 participants that wore a combined accelerometer and heart rate (HR) sensor while performing a wide range of activities (clustered into *lying, sedentary, dynamic/household, walking, biking* and *running*), including many transitions between intensities, thus resulting in non-steady-state VO_2. Indirect calorimetry was used in parallel to obtain VO_2 reference. VO_2 estimation error during transitions between *sedentary*, *household* and *walking* activities could be reduced by 16% on average using the proposed approach, compared to state of the art methods.**

Index Terms—**Accelerometers, Energy Expenditure, Heart Rate, Non-Steady-State, VO_2**

I. Introduction

Ubiquitous sensing technologies that objectively and non-invasively monitor human behavior, started to provide insights into the relation between physical activity (PA) and health. Among the parameters used to objectively quantify PA, energy expenditure (EE) is the most commonly used single metric [1], [2], [3]. The measurement of steady-state oxygen uptake (VO_2) is considered to be the gold standard for estimating EE during light to moderate steady-state exercise [4], [5], where aerobic pathways are predominant. In this context, VO_2 measurements are proportional to metabolic heat production [4]. Due to the practical limitations of measuring VO_2 in free living, different methods to estimate VO_2 using miniaturized wearable sensors have been developed in the past.

VO_2 estimation methods are typically based on activity-specific linear regressions developed using steady-state data and therefore can describe the variations within each modeled activity during steady-state. However, transitions to activities with other VO_2 levels cannot be accurately estimated, since VO_2 dynamics differ during steady-state and non-steady-state periods. Proper modeling of non-steady-state transitions including transitions of activity types (e.g. sitting to walking) and activity intensities (e.g. walking at different speed) are necessary in order to provide accurate VO_2 estimation in free living conditions. Accurate identification of non-steady-state periods as well as quantifications of VO_2 during transitions could improve EE estimation because during non-steady-state periods total EE is composed of aerobic and anaerobic components. [4]. Earlier work on VO_2 transitions analysis focused mainly on Post-Exercise Oxygen Consumption (EPOC) [6], or VO_2 estimation for single activities [7], [8]. However non-steady-state VO_2 is very frequent during varying low intensities activities of daily living (ADLs). Studies showed that most activities performed in free living last shorter than the time needed to reach steady state. For example, 60% of all walking bouts last shorter than 30 seconds [9]. Identifying non-steady-state VO_2 can provide more insights on the aerobic and anaerobic dynamics during the onset of exercise as well as during ADLs characterized by short duration. While solutions have been proposed to model non-steady-state VO_2 for specific activities [7], [8] or transitions [6], a unified approach able to continuously estimate VO_2 is missing. Thus, we propose a novel VO_2 estimation method, which combines activity-specific VO_2 estimation using linear regression, with non-steady-state detection and transition-specific VO_2 estimation using non-linear equations.

This paper provides the following contributions:

1) We introduce a method to automatically locate periods of non-steady-state VO_2 by analyzing the coefficient of variation (CV) of the predicted VO_2. Using the CV allows for detection of transition both between and within activities. Then, we compare linear, exponential and logistic transfer functions to model non-steady-state VO_2 during individual transition types.
2) We evaluate the proposed approach on a dataset acquired from 22 participants performing a wide set of physical activities, including many transitions between activities and changes of intensity within activities. We show that the transition-specific modeling could reduce VO_2 estimation error by 16% during activity transitions, compared to state of the art methods.

II. Related Work

Accelerometer and HR monitors are the most commonly used single sensor devices in epidemiological studies. Accelerometers use features representative of whole body motion, as independent variables in the linear regression model developed to predict EE. However there are limitations due to the inability of a single linear model to fit all activities, since the slope and intercept of the regression model change based on the activity performed while data is collected [3]. On the other

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hand, the high correlation between HR and EE within one individual changes substantially between individuals [1]. The latest EE estimation algorithms extended approaches based on simple linear regression models performing activity recognition over a predefined set of activities, and then applying different methods - typically regression models - to predict EE, based on the activity [2], [3]. The regression models use accelerometer features and anthropometric characteristics as independent variables. Some authors included HR features as well in the activity-specific linear models, showing consistent improvements in EE estimation accuracy compared to algorithms using accelerometer only features [1]. However, none of these models explicitly models non-steady-state VO_2.

A. Non-Steady-State VO_2 Estimation

Non-steady-state EE is often defined as periods of time where VO_2 and carbon dioxide production vary by more than 5-10% [10]. Previous research on non-steady-state VO_2 focused mainly on metabolic responses to exercise (EPOC, [6]). However, VO_2 estimation is intrinsically a temporal problem and non-steady-state VO_2 is very common during low intensity ADLs as well. While VO_2 increases rapidly, normally reaching steady-state within 1-4 minutes, most activities performed in free living last less than the time required to reach steady state [9]. Most EE models are developed deriving EE from VO_2, and discarding the first 1 or 2 minutes of data [1], [3], to isolate steady-state. Thus, the predictions of these models will be negatively affected by the real life nature of ADL activities. Other models incorporate non-steady-state VO_2 but without providing details on the models accuracy during transitions [11], thus limiting our understanding of the models performance in non-steady-state conditions. Using physiological data to predict VO_2 involves slower dynamics present in both physiological changes (e.g. HR slowing increasing) and aerobic pathways (VO_2 reaching steady-state). However, these dynamics are different, typically with HR being much slower than VO_2 [12], [13].

Few attempts to model non-steady-state VO_2 are found in literature [14], [15], [16], [7], [8]. In [14], [15], the proposed system relies on HR data only, suffering from all limitations of non-activity-specific models, while [7], [8] analyzed walking data only. In [16], the authors used mono-exponential functions to better capture the relation between movement and EE during transitions between activities. However, the EE prediction ignores the fact that during non-steady-state EE cannot be derived from VO_2 alone, since total EE is composed of both aerobic (estimated via VO_2) and anaerobic components. Finally, one single mono-exponential equation might not be sufficient to model energy deficit and energy debt situations between different activities [5]. While solutions have been proposed to model non-steady-state VO_2 for specific activities [7], [8] or transitions [6], a unified approach able to continuously estimate VO_2 is missing.

III. Analysis and Estimation Approach

This section describes the problem of non-steady-state VO_2 estimation and our approach to such problem.

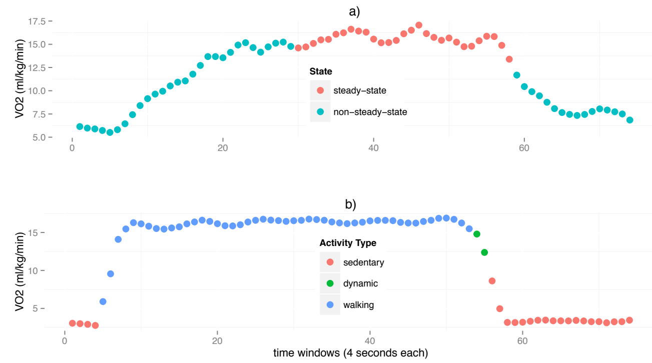

Fig. 1. Example of non-steady-state VO_2. a) Non-steady state reference VO_2. b) Predicted VO_2 as estimated by steady-state activity-specific models. In this work, non-steady state modelling is used combined with classic steady-state models to better estimate actual VO2.

Our approach combines detection of non-steady-state VO_2, activity-specific linear models and non-steady state transition-specific non-linear functions. Fig. 1 shows typical non-steady state dynamics in activities of daily living, such as transitions between sedentary activities (e.g. sitting or standing), walking and then sedentary again. Fig. 1.b shows color-coded activities as detected by an activity recognition system, while Fig. 1.a shows steady-state and non-steady-state-data. Non-steady-state VO_2 is present when the participant starts walking and when the participant stops walking. Fig. 1.a show measured VO_2 while Fig. 1.b shows VO_2 as predicted by state of the art activity specific models. Prediction models (Fig. 1.b) jump between one value to the other as soon as a new activity starts, while transitions shown in Fig. 1.a are much slower. Thus, a different modeling technique is required during non-steady-state.

A. Estimation Architecture

VO_2 predictions are generated by a sequence of steady-state and non-steady-state models (see, e.g. Fig. 2):

$$\dots W_1, V_1, W_2, V_2, W_1, V_3 \dots$$

where W_i are activity-specific models used when steady-state is detected and V_i are transition-specific non-steady-state models used when non-steady-state is detected. Each state W_i or V_i comprises t predictions based on the time spent in a specific activity or transition duration:

$$W_i = \{VO2_{SS_1}^{Wi}, \dots, VO2_{SS_t}^{Wi}\}$$
$$V_i = \{VO2_{NS_1}^{Vi}, \dots, VO2_{NS_t}^{Vi}\}$$

In the following sections, we describe W_i, V_i and model selection.

1) Activity-Specific Steady-State Models - W_i: W_i are composed of two parts: activity recognition and activity-specific multiple linear regression equations. Assuming n clusters of activities:

$$C = \{c_1, \dots, c_n\}, \forall c_i \in C, \quad \exists \quad W_i$$

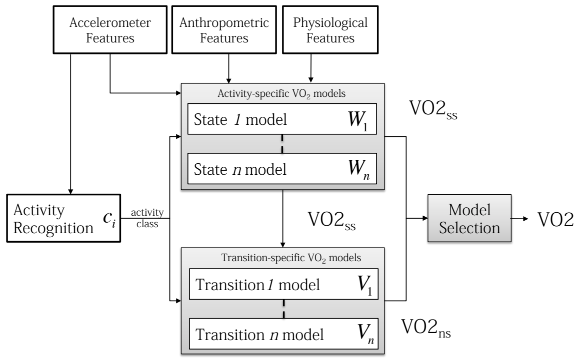

Fig. 2. Block diagram of out approach using activity-specific linear models and transition-specific non-linear functions to estimate VO2. Features are used for activity recognition and activity-specific VO_2 models. Activity recognition is used to select the proper activity-specific or transition-specific model.

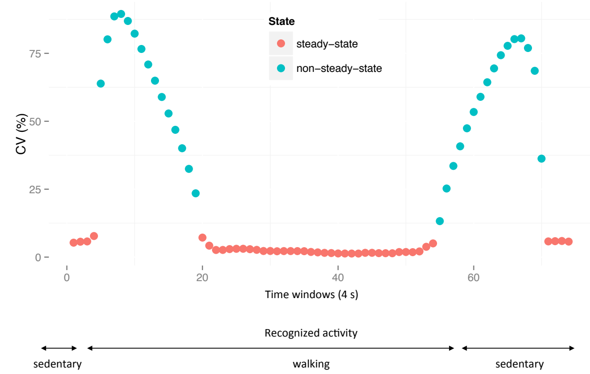

Fig. 3. Example waveform of the CV of the estimated VO_2 for a sequence of sedentary, walking and sedentary activities. *State* is non-steady when $CV > 15\%$. The CV captures transitions between activities as well as within activities, thus detecting non-steady-state VO_2.

where the parameters of the activity-specific model W_i are derived from VO_2 values for a specific cluster of activities c_i:

$$VO2_{SS}^{Wi} = X_{act_i}\beta_{act_i} + \epsilon \quad (1)$$

β is the vector of regression coefficients, and X_{act_i} is the vector of input features. Features are grouped into accelerometer, physiological and anthropometric features (see Fig. 2).

2) Transition-Specific Non-Steady-State models - V_i: We compare *linear*, *exponential* and *logistic* functions as V_i. Assuming r types of transitions:

$$Tr = \{tr_1, \ldots, tr_r\}, \forall tr_i \in Tr, \quad \exists \quad V_i$$

Linear functions: for a transition type V_i from steady-state W_j to steady-state W_k, a linear model is derived as follows:

$$VO2_{NS}^{Vi} = \alpha + \beta t + VO2_{SS}^{Wj} + \epsilon \quad (2)$$

where $VO2_{NS}^{Vi}$ are target VO_2 values during non-steady-state for the transition V_i, defined by transition-specific linear functions. The predictor t is the time elapsed since the transition started. $VO2_{SS}^{Wj}$ is the VO_2 of the steady-state before the transition (W_j). Parameters α and β are the slope and intercept of the linear model.

Logistic functions: for a transition type V_i, a non-linear model is derived as follows:

$$VO2_{NS}^{Vi} = \frac{\theta_1}{1 + exp^{-(\theta_2^{Vi} + \theta_3^{Vi} t)}} + VO2_{SS}^{Wj} + \epsilon \quad (3)$$

where $VO2_{NS}^{Vi}$ are target VO_2 values during non-steady-state for the transition V_i, defined by transition-specific logistic functions. The predictor t is the time elapsed since the transition started. $VO2_{SS}^{Wj}$ is the VO_2 of the steady-state before the transition (W_j). Transitions between activities of different type and intensity will have different dynamics [5], [17], thus require transition-specific functions. The parameter θ_1 is the asymptote of the logistic function, and can be automatically derived as the difference between the steady-state VO_2 before (W_j) and after (W_k) the transition:

$$\theta_1 = VO2_{SS}^{Wk} - VO2_{SS}^{Wj}. \quad (4)$$

Parameters θ_2^{Vi} and θ_3^{Vi} control the shape of the logistic curve (e.g the transition speed), and were determined by fitting for each transition type. Thus, θ_2^{Vi} and θ_3^{Vi} are transition-specific. The transition type (i.e. V_i) depends on the activities recognized by the activity recognition system during steady-states W_j and W_k.

Exponential functions: a transition model for a transition type V_i is derived as follows:

$$VO2_{NS}^{Vi} = \theta_1 - exp^{\alpha + \beta t} + VO2_{SS}^{Wj} + \epsilon \quad (5)$$

where $VO2_{NS}^{Vi}$ are target VO_2 values for the transition V_i, defined by transition-specific exponential functions. The predictor t is the time elapsed since the transition started. $VO2_{SS}^{Wj}$ is the VO_2 of the steady-state before the transition (W_j). The parameter θ_1 is the same as for the logistic function, indicating the asymptote of the exponential, and can be automatically derived as shown in Eq. 4.

3) Model Selection: Non-steady-state is detected using the CV of the predicted VO_2 over the last minute of data, according to a preselected threshold:

$$CV_{VO2_{SS}} = \frac{\sigma_{VO2_{SS}}}{\mu_{VO2_{SS}}} \quad (6)$$

where $\sigma_{VO2_{SS}}$ and $\mu_{VO2_{SS}}$ are the standard deviation and mean of a 60 s sliding window of predicted VO_2 values. Non-steady-state is detected if $CV_{VO2_{SS}} > CV_{Thres}$, where CV_{Thres} was set to 15%. Fig. 3 shows the CV for the predicted VO_2 data. CV can be used to locate non-steady-states, such as when activity intensity changes, thus even when there is no transition between two activities.

IV. Evaluation Study

A. Participants and Data Acquisition

Participants were 22 (17 male, 5 female), mean age $30.4 \pm 5.7\ years$, mean weight $71.2 \pm 12.4\ kg$, mean height $1.76 \pm 0.09\ m$, mean BMI $23.0 \pm 2.8\ kg/m^2$. Imec's IRB approved the study. Each participant signed an informed consent form. The sensor platform used was the ECG Necklace, a wearable sensor acquiring one lead ECG data at 256 Hz, and three-axial accelerometer data at 32 Hz. Activity type was annotated manually by experimenter. Breath-by-breath data were collected using the Cosmed $K4b^2$ indirect calorimeter. We interpolated calorimeter data at 0.25 Hz to align it with the ECG Necklace data, and applied a moving average with window size 4 elements to reduce high frequency noise.

B. Experiment Design

Participants reported at the lab after refraining from drinking, eating and smoking in the two hours before the experiment. Activities were grouped into six clusters to be used for activity classification. The six clusters were lying (*lying down*), sedentary (*sitting, standing, desk work, reading, writing, PC work*), dynamic (*stacking groceries, washing dishes, cleaning, sweeping, vacuuming*), walking (*treadmill flat at 3,4,5,6 km/h, inclined 3-5%, 3-5 km/h*), biking (*cycle ergometer, low medium and high resistance level*), running (*treadmill 7,8,9, and 10 km/h*). Activities were carried out for a period of at least 4 minutes, with the exception of running (1 to 4 minutes). All transitions were manually annotated.

C. Statistics and Performance Measure

Models were derived using leave-one-participant-out cross validation. The same training set, consisting of data from all participants but one, was used to perform feature selection, activity recognition, activity-specific VO_2 estimation and transition-specific VO_2 estimation models. The data from the remaining participant was used for validation. This procedure was repeated *n (n = number of participants)* times, and results were averaged. All parameters used in transition-specific functions were determined in the same way, no data used for model building was used for model evaluation. Performance of the activity recognition models was evaluated using the class-normalized accuracy. Results for VO_2 estimates are reported in terms of Root-mean-square error (RMSE), where the outcome variable was VO_2 in ml/kg/min. Paired t-tests were used to compare RMSE between models.

V. Implementation

A. Features Extraction and Selection

Features extracted from the sensors' raw data were used to derive activity recognition and VO_2 estimation models. Activity recognition was performed to classify the six activity clusters introduced in Section IV-B. Accelerometer data were segmented in 4 s windows, band-pass filtered between 0.1 and 10 Hz, to isolate the dynamic component caused by body motion, and low-pass filtered at 1 Hz, to isolate the static component, due to gravity. Feature selection for activity type recognition was based on mutual information. The final feature set included: *mean of the absolute signal*, *inter-quartile range*, *median*, *variance*, *main frequency peak*, *low and high frequency band signal power*. Feature selection for VO_2 estimation was based on how much variation in VO_2 each feature could explain within one cluster. The process was automated using linear forward selection.

B. Activity Recognition

We selected a time window of 4 s, which is short enough to detect short breaks in sedentary time, and long enough to capture the repetitive patterns of some activities (e.g. walking or running). Given the positive results in past research on activity recognition, we selected Support Vector Machines (SVMs) as classifiers. For the SVMs, we used a polynomial kernel with degree 5 (λ = 10, C = 1).

C. Activity-Specific Steady-State Models - W_i

Within one activity cluster, VO_2 can be estimated using features representative of VO_2 changes within the activity cluster [3], [1]. We used the *mean of the absolute signal* to model changes in intensity within an activity, together with HR. Anthropometrics features (*body weight* and *resting metabolic rate (RMR)*, estimated with the Harris-Benedict formula) were added depending on the activity cluster.

D. Non-Steady-State Detection

The CV over one minute windows was computed to locate non-steady-state segments of data. When the CV was higher than CV_{Thres}, a new non-steady-state transition was detected. CV_{Thres} was derived from previous literature on detection of non-steady-state VO_2, and empirically cross-validated on our dataset, since no definition of non-steady-state is widely accepted [10]. Once a non-steady-state transition V_i was detected between two steady-states W_j and W_k, the system compared the steady-state VO_2 levels and enables the non-steady-state models only if the difference in VO_2 was greater than a threshold. This filter avoids activating the non-steady-state models for transitions that are too small or short.

E. Transition-Specific Non-Steady-State models - V_i

Transition-specific non-steady-state models V_i were developed for the most common transitions. More specifically, logistic functions were derived by fitting the parameters θ_2 and θ_3 while linear and exponential functions were derived by fitting the parameters α and β of the respective models, for the following transitions: *sedentary to walking* (SW), *walking to sedentary* (WS), *sedentary to dynamic/household* (SD), *dynamic/household to sedentary* (DS), *walking fast to walking slow* (WWDOWN), *walking slow to walking fast* (WWUP). Data used for model development was not used for validation.

VI. Results

We report results for activity recognition, activity-specific steady-state models, non-steady-state detection and transition-specific non-steady-state models, together with summary statistics on the specific transitions considered in this work. An example of the proposed method applied to a transition between sedentary behavior and walking is shown in Fig. 4.

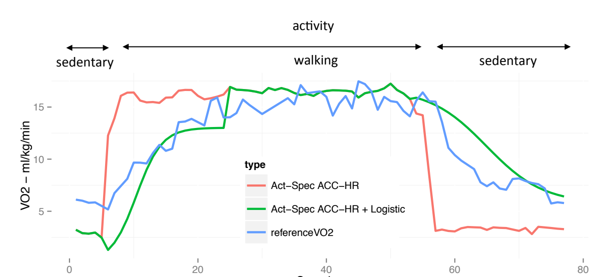

Fig. 4. Example of the results obtained when combining activity-specific steady state models and transition-specific non-stead-state models (Act-Spec ACC-HR + Logistic), as proposed by our method, for a transition between *sedentary* to *walking* and *walking* to *sedentary*. Act-Spec ACC-HR show the inability of steady-state models to predict VO_2 accurately during transitions.

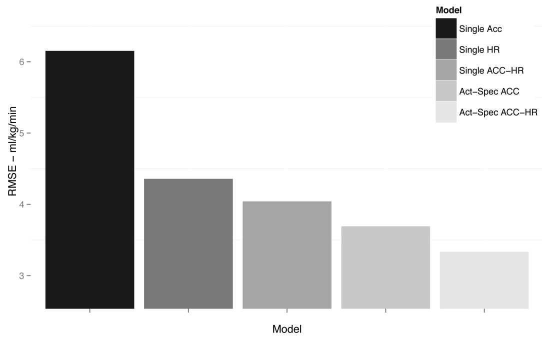

Fig. 5. RMSE for VO_2 estimation using different sensing modalities and methods for steady-state data. Activity-specific (Act-Spec) models outperform all others, combined accelerometer and heart rate (ACC-HR) data improves performance compared to accelerometer (ACC) or heart rate (HR) only.

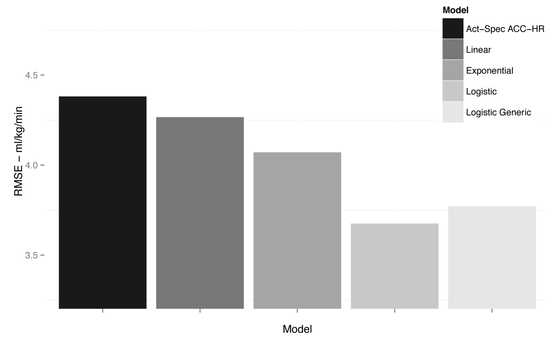

Fig. 6. RMSE for VO_2 estimation using different methods for non-steady-state data. While standard activity-specific models that combine acc and HR (Act-Spec ACC+HR) perform better than other models during steady-state (see Fig .5), they offer poor performance during transitions. Linear, exponential and logistic functions progressively reduce RMSE, with logistic functions providing the lowest errors. *Logistic Generic* refers to logistic functions were parameters did not vary depending on the transition type.

A. Activity Recognition

Activity recognition accuracy was 94% on average across all participants using the validation procedure detailed in Sec. IV-C. More specifically, accuracy was 100% for *lying down*, 96% for *sedentary*, 81% for *dynamic/household*, 99% for *walking*, 91% for *biking* and 98% for *running*.

B. Activity-Specific Steady-State Models

RMSE for activity-specific steady-state VO_2 estimation models using combined accelerometer and HR data was 3.5 ml/kg/min. More specifically, RMSE was 1.16 ml/kg/min for *lying down*, 1.75 ml/kg/min for *sedentary*, 3.93 ml/kg/min for *walking*, 4.55 ml/kg/min for *dynamic/household*, 4.24 ml/kg/min for *biking* and 5.81 ml/kg/min for *running*. Similarly to what was reported in literature for EE estimation models, activity-specific VO_2 estimation models combining accelerometer and HR data outperformed single regression models relying on accelerometer only (46% RMSE reduction, $p = 4e^{-11} < \alpha$), HR only (23% RMSE reduction, $p = 0.0002 < \alpha$), combined accelerometer and HR data (17% RMSE reduction, $p = 0.001 < \alpha$) and activity-specific estimation models relying on accelerometer data only (10% RMSE reduction, $p = 0.002 < \alpha$). Fig. 5 provides an overview.

C. Non-Steady-State Detection

221 transitions were analyzed in total (45 SW, 28 WS, 42 SD, 53 DS, 39 WWUP, 14 WWDOWN). 85% of all transitions were correctly identified by the transition detection system. Transition detection was more accurate for transitions between *sedentary* to *walking* activities (98%) and for transitions between *walking* to *sedentary* activities (100%). Transition detection accuracy dropped to 78% and 84% for transitions between *sedentary* to *dynamic/household* and *dynamic/household* to *sedentary* respectively. Transitions in VO_2 within activities (e.g. following changes in walking speed or inclination), that were smaller than 1 ml/kg/min were not considered. All other within activities transitions were correctly identified (100%).

D. Transition Types

There was a significant relation between transition time and VO_2 change between the *starting* and *target* activities during a transition (correlation coefficient $r = 0.68$, $p = 0.0015 < \alpha$). VO_2 difference between the *starting* and *target* activities during a transition was 6.40 ml/kg/min for SW, 9.25 ml/kg/min for WS, 7.47 ml/kg/min for SD, 7.46 ml/kg/min for DS, 4.38 ml/kg/min for $WWUP$ and 5.80 ml/kg/min for $WWDOWN$. Average transition duration was 97 s for SW, 108 s for WS, 88 s for SD, 98 s for DS, 87 s for $WWUP$ and 125 s for $WWDOWN$. VO_2 estimation error for steady-state models during transitions involving *sedentary* and $household$ activities was 4.62 ml/kg/min (SD) and 4.50 ml/kg/min (DS), even though error during steady-state was only 1.75 ml/kg/min for *sedentary* and 4.55 ml/kg/min for $household$. VO_2 estimation error for steady-state models during transitions involving *sedentary* and *walking* activities was 5.63 ml/kg/min (SW) and 4.23 ml/kg/min (WS), even though error during steady-state was only 1.75 ml/kg/min for *sedentary* and 3.93 ml/kg/min for *walking*.

E. Transition-Specific Non-Steady-State models

Fig. 6 shows VO_2 RMSE during transitions for the best performing steady-state models (i.e. activity-specific models combining accelerometer and HR data) and non-steady-state models. VO_2 RMSE during transitions for steady-state models was 4.38 ml/kg/min. Linear models reduced RMSE to 4.27 ml/kg/min (3% RMSE reduction, $p = 0.5 > \alpha$), exponential functions to 4.07 ml/kg/min (7% RMSE reduction, $p = 0.2 > \alpha$), and logistic functions to 3.68 ml/kg/min (16% RMSE reduction, $p = 0.0007 < \alpha$). Thus, logistic functions were the best performing non-steady-state models for activities transitions. For comparison, we evaluated logistic functions were parameters were not fitted to specific transitions, but were held constant for all transitions, denoted as *Logistic Generic* in Fig. 6 and Table I. Logistic generic results were VO_2 RMSE of 3.77 ml/kg/min (14% RMSE reduction, $p = 0.002 < \alpha$).

TABLE I
VO_2 RMSE FOR TRANSITIONS MODELS CONSIDERING PERFECT TRANSITION DETECTION (ML/KG/MIN)

Transition	Activity-Specific	Linear	Exponential	Logistic	Logistic Generic
Sedentary to walking (SW)	5.42 ± 1.46	5.79 ± 1.86	4.67 ± 3.18	4.27 ± 2.20	4.94 ± 2.40
Walking to sedentary (WS)	3.84 ± 1.12	4.10 ± 1.62	3.26 ± 2.60	2.43 ± 1.59	2.48 ± 1.33
Sedentary to dynamic (SD)	4.28 ± 1.25	3.81 ± 1.54	4.07 ± 1.99	3.30 ± 1.29	3.29 ± 1.36
Dynamic to sedentary (DS)	4.20 ± 1.48	3.17 ± 1.43	3.32 ± 1.28	3.57 ± 1.31	3.42 ± 1.23
Walking slow to fast (WWUP)	4.10 ± 2.06	4.97 ± 2.43	3.15 ± 1.79	4.05 ± 2.10	4.06 ± 2.10
Walking fast to slow (WWDOWN)	4.03 ± 2.17	3.69 ± 2.32	4.87 ± 3.01	4.4 ± 2.28	3.95 ± 2.14
Mean	**4.38 ± 0.80**	**4.27 ± 1.05**	**4.07 ± 1.28**	**3.68 ± 1.10**	**3.77 ± 1.03**

VII. DISCUSSION

In this paper we introduced a method to estimate VO_2 during ADLs. Our method combines non-steady-state detection and transition-specific VO_2 estimation non-linear equations.

It is misleading to assume that EE can be derived from VO_2 alone. Proper modeling of non-steady-state transitions is important since both anaerobic and aerobic EE result in heat production, which is the true EE. However, only aerobic EE results in VO_2 consumption. To tackle non-steady-state VO_2 estimation, we proposed a method to locate periods of non-steady-state VO_2 using the CV over the predicted VO_2 level. Our results showed that the CV can be used for detecting transitions between and within activities. Then, we showed that modeling non-steady-state transitions using non-linear logistic functions for individual transition types could reduce VO_2 estimation error by 16%.

A. Activity Recognition and Transition Detection

In previous research both unsupervised and supervised methods for activity recognition were proposed in the context of VO_2 estimation, with supervised methods providing better results [18]. For this reason, we opted for supervised methods typically able to provide good accuracy on big clusters of activities as confirmed by our results, where 94% average accuracy was obtained in leave-one-participant-out validation design. Transition detection was highly accurate for all transitions including the *walking* activity ($98-100\%$). However, transition detection was less accurate for transitions involving *dynamic/household* activities ($78-84\%$), since these activities are both more difficult to recognize and highly variable in VO_2. In literature, several approaches have been proposed to detect transitions between activities [19], [20]. Detecting transitions based on the CV of the predicted VO_2 provides the advantage to detect not only transitions between activities, but also changes in intensity within the same activity (e.g. walking at a lower speed). Various definitions of steady-state have been reported [10]. Some researchers defined steady state as 5 consecutive 1-minutes intervals where O_2 consumption changes by less than 10%. However this definition resulted from assessments of basal metabolic rate and is not directly applicable to free living conditions, where we are interested in detecting much shorter transitions. Our analysis shows that one minute windows and a slightly less strict CV (i.e. 15%), are a good trade-off for non-steady-state and transitions detection.

B. Transition-Specific Non-Steady-State Models

Our analysis focused on *sedentary*, *dynamic/household* and *walking* activities, since our objective is to improve VO_2 estimation in common transitions during ADLs, where current methods lack proper modeling.

Thus, we have not considered transitions during intense activities (e.g. biking or running), which are less frequent in daily life and well studied in literature. The ADLs considered are characterized by similar levels of VO_2 for both the *starting* and *target* activity of a transition. Thus, the VO_2 change during a transition and the time required to reach steady state are similar. While parameters differ between transitions, and transition-specific logistic functions provided the best results, generic logistic functions which do not vary parameters based on the transition were sufficient to significantly reduce RMSE compared to steady-state models (14% RMSE reduction, $p = 0.002 < \alpha$). Logistic functions were proposed in literature to model HR recovery after intense exercise [21], due to the ability to model different dose-response relationships between two relatively stable levels. While we applied this technique to model transitory oxygen uptake during ADLs, the methodology could be extended to other physiological parameters undergoing similar changes. For comparison, we also fitted linear and exponential functions, as previously reported in literature [16]. However we found suboptimal results compared to logistic functions.

Another advantage of the proposed technique is that at runtime VO_2 estimations during transitions are only dependent on the previously fitted parameters and on the parameter θ_1, representing the difference in VO_2 between the *starting* and the *target* activity. Thus, these models could be applied to systems based on accelerometers only, and do not depend on other predictors or sensing modalities.

Performance of non-steady-state VO_2 models should be assessed outside of the lab [22]. However, there is currently no unobtrusive reference system that is able to measure breath-by-breath VO_2 in unconstrained settings. Only by using indirect calorimetry and supervised settings we can record data, which allows us to analyze how non-steady-state models can improve VO_2 estimations during transitions. In our evaluation protocol, we could not elicitate abrupt VO_2 changes within one activity, e.g. when changing the treadmill speed and inclination level, there was a gradual change, which could last up to 30 seconds. Hence, it was difficult to even collect representative data that could benefit from non-steady-state modeling within an activity (e.g. walking at different speeds) and the VO_2

estimation did not provide improvements over the steady-state. A set of thirty activities of varying intensities was used in this study and further work could extend the set, for example including activities involving carrying loads. However, we believe that the lifestyle activities used here are representative and relevant to assess VO_2 estimation in non-stationary daily life conditions. The generalized method proposed in this work is able to model abrupt within-activity changes in VO_2 without modifications to the model, since it detects transitions relying on the CV, instead of the activity type. While it is not feasible for us to robustly detect activities such as carrying a weight using a wearable sensor on the chest, the use of HR partially solves the problem. Carrying a load would create higher strain, thus raise HR, which is used in the estimation models, and therefore result in higher predicted VO_2. In this work, CV changes were shown to even indicate intensity changes within the same activity confirming the method's sensitivity. By properly modeling VO_2 during transitions and locating periods of non-steady-state, we quantified VO_2 for aerobic dynamics during the onset of exercise, as well as during ADLs characterized by short duration, with 16% error reduction compared to current methods.

References

[1] M. Altini, J. Penders, and O. Amft, "Personalizing energy expenditure estimation using a cardiorespiratory fitness predicate," in *Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2013 7th International Conference on*. IEEE, 2013, pp. 65–72.

[2] A. G. Bonomi, "Improving assessment of daily energy expenditure by identifying types of physical activity with a single accelerometer." *Journal of Applied Physiology*, vol. 107, no. 3, pp. 655–661, 2009. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/19556460

[3] E. Tapia, "Using machine learning for real-time activity recognition and estimation of energy expenditure," in *PhD thesis, MIT*, 2008.

[4] C. B. Scott, "Contribution of anaerobic energy expenditure to whole body thermogenesis," *Nutr Metab*, vol. 2, pp. 14–23, 2005.

[5] K. Wasserman, A. L. Van Kessel, and G. G. Burton, "Interaction of physiological mechanisms during exercise," *J Appl Physiol*, vol. 22, no. 1, pp. 71–85, 1967.

[6] K. R. Short and D. A. Sedlock, "Excess postexercise oxygen consumption and recovery rate in trained and untrained subjects," *Journal of Applied Physiology*, vol. 83, no. 1, pp. 153–159, 1997.

[7] S. W. Su, L. Wang, B. G. Celler, and A. V. Savkin, "Oxygen uptake estimation in humans during exercise using a hammerstein model," *Annals of biomedical engineering*, vol. 35, no. 11, pp. 1898–1906, 2007.

[8] S. W. Su, B. G. Celler, A. V. Savkin, H. T. Nguyen, T. M. Cheng, Y. Guo, and L. Wang, "Transient and steady state estimation of human oxygen uptake based on noninvasive portable sensor measurements," *Medical & biological engineering & computing*, vol. 47, no. 10, pp. 1111–1117, 2009.

[9] M. S. Orendurff, J. A. Schoen, G. C. Bernatz, A. D. Segal, and G. K. Klute, "How humans walk: bout duration, steps per bout, and rest duration," *J Rehabil Res Dev*, vol. 45, no. 7, pp. 1077–89, 2008.

[10] M. M. Reeves, P. S. Davies, J. Bauer, and D. Battistutta, "Reducing the time period of steady state does not affect the accuracy of energy expenditure measurements by indirect calorimetry," *Journal of Applied Physiology*, vol. 97, no. 1, pp. 130–134, 2004.

[11] J. Wang, S. J. Redmond, M. Voleno, M. R. Narayanan, N. Wang, S. Cerutti, and N. H. Lovell, "Energy expenditure estimation during normal ambulation using triaxial accelerometry and barometric pressure," *Physiological measurement*, vol. 33, no. 11, pp. 1811–1830, 2012.

[12] T. Yoshida and B. J. Whipp, "Dynamic asymmetries of cardiac output transients in response to muscular exercise in man." *The Journal of Physiology*, vol. 480, no. Pt 2, pp. 355–359, 1994.

[13] J. Smolander, T. Juuti, M.-L. Kinnunen, K. Laine, V. Louhevaara, K. Männikkö, and H. Rusko, "A new heart rate variability-based method for the estimation of oxygen consumption without individual laboratory calibration: application example on postal workers," *Applied Ergonomics*, vol. 39, no. 3, pp. 325–331, 2008.

[14] A. Pulkkinen, J. Kettunen, K. Martinmäki, S. Saalasti, and H. Rusko, "On–and off dynamics and respiration rate enhance the accuracy of heart rate based vo2 estimation," in *Proceedings of the ACSM Congress, Indianapolis, Abstract*, vol. 36, 2004.

[15] L. R. Dugas, L. van der Merwe, H. Odendaal, T. D. Noakes, and E. V. Lambert, "A novel energy expenditure prediction equation for intermittent physical activity." *Medicine and Science in Sports and Exercise*, vol. 37, no. 12, pp. 2154–2161, 2005.

[16] F.-C. Chuang, Y.-T. C. Yang, and J.-S. Wang, "Accelerometer-based energy expenditure estimation methods and performance comparison," in *2nd International Conference on Advances in Computer Science and Engineering (CSE 2013)*. Atlantis Press, 2013, pp. 99–103.

[17] E. Børsheim and R. Bahr, "Effect of exercise intensity, duration and mode on post-exercise oxygen consumption," *Sports Medicine*, vol. 33, no. 14, pp. 1037–1060, 2003.

[18] S. Chen, J. Lach, O. Amft, M. Altini, and J. Penders, "Unsupervised activity clustering to estimate energy expenditure with a single body sensor," in *Body Sensor Networks (BSN), 2013 IEEE International Conference on*. IEEE, 2013, pp. 1–6.

[19] R. Ali, L. Atallah, B. Lo, and G.-Z. Yang, "Detection and analysis of transitional activity in manifold space," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 16, no. 1, pp. 119–128, 2012.

[20] C. Zhu and W. Sheng, "Recognizing human daily activity using a single inertial sensor," in *Intelligent Control and Automation (WCICA), 2010 8th World Congress on*. IEEE, 2010, pp. 282–287.

[21] N. Christenfeld, L. M. Glynn, and W. Gerin, "On the reliable assessment of cardiovascular recovery: An application of curve-fitting techniques," *Psychophysiology*, vol. 37, no. 4, pp. 543–550, 2000.

[22] L. Bouarfa, L. Atallah, R. M. Kwasnicki, C. Pettitt, G. Frost, and G.-Z. Yang, "Predicting free-living energy expenditure using a miniaturized ear-worn sensor: An evaluation against doubly labelled water," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 2, pp. 566–575, 2014.

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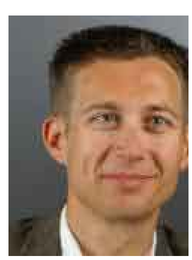

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