Aerobic Fitness Level Estimation Using Wearables

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Abstract

Background: Aerobic fitness level (AFL) is a parameter closely related to a person's overall health. The gold standard of measurement is currently using expensive laboratory equipment.

Aims: This study aimed to estimate AFL automatically using data measured with wearables.

Methods: AFL was estimated in 2D space. The first dimension is the exertion level, and the second is the body's response to the exertion. Exertion level was determined based on metabolic equivalent calculated for each classified activity using the data of speed and elevation. The activity classification is based on deep neural networks. The body's response estimation is based on heart rate calculated from ECG or PPG.

The test set contained 27 subjects. The reference was measured under laboratory conditions using the gold standard method. AFL classification by ACSM guidelines was used.

Results: AFL determined by our algorithm were 0.44±0.09, 0.50±0.10, 0.53±0.09, 0.58±0.15, and 0.70±0.07 for the reference classes very poor, poor, fair, good, and excellent, respectively. The correlation between the reference and determined values is 0.76.

Conclusion: Our method showed promising results and will be further developed.

1. Introduction

Aerobic fitness level (AFL), also called Cardiorespiratory fitness (CRF), is strongly correlated with an increased risk of all-cause mortality. Specifically, AFL is considered one of the best predictors of the two most common causes of death in developed countries - cardiovascular disease and cancer. [1]

According to conventional gold standard method, AFL is evaluated using the measured maximum oxygen consumption (VO2max) [2]. In previous works, many equations were proposed to determine AFL using the measured VO2max and other parameters such as age, gender, and weight [3], [4].

The disadvantage of the mentioned methods is the problematic measurement of VO2max. Accurate measurements can be done in the laboratory using breathing gas analysis. This measurement is time-consuming and requires expensive laboratory equipment.

In recent years, portable breath gas analysis masks have also been used to estimate AFL. With the help of this mask, it is possible to continuously measure oxygen consumption during movement and then predict the maximum oxygen consumption from these values [5]. However, this measurement still requires very obtrusive and expensive mask for breath gas analysis. In addition, the measured person usually has to perform a standardized measurement protocol.

The main objective of this article is to present a method for estimating AFL without the need for measurements using a mask to analyze oxygen consumption. Our method only needs GPS and accelerometer (ACC) data and continuously measured heart rate (HR) – obtained from electrocardiogram (ECG) or photoplethysmogram (PPG). All these quantities can be obtained by smartwatches commonly available in the population.

In addition, our method does not require the analyzed individual to perform a standardized protocol. AFL is continuously calculated for the measured subject during the activities which the subject performs during the day.

2. Method

The proposed method for estimating AFL is based on the automatic assessment of the intensity of the performed activity and the body's response to this activity (Figure 1). The activity's intensity is determined by user-independent parameters (chapter 2.3). Conversely, the body's response is determined according to the HR (chapter 2.5).

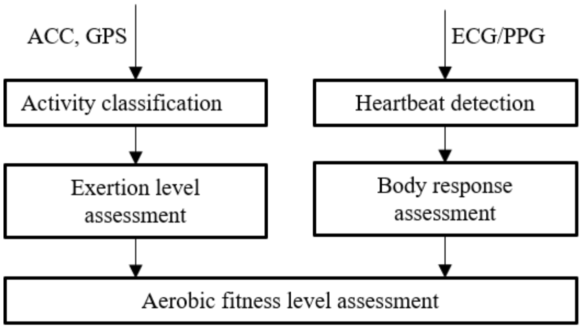

Figure 1. Block diagram of the proposed method.

2.1. Data

The performance of our algorithm was verified on a total of 27 subjects. The subjects performed a measurement consisting of rest, walking, running, and cycling phases. The signals were measured using five wearable devices (Table 1). ACC data were measured at 3 body's parts – wrist (Empatica), chest (Faros), and instep of the foot (BiosignalsPlux). Reference VO2 max and AFL were also measured for each subject in the laboratory.

Table 1. Measured signals.

Device	Measured signals	Sampling frequency [Hz]
Empatica E4	PPG, ACC	64, 32
Faros	ECG, ACC	1000, 100
BiosignalsPlux	ACC	1000
Mobile phone	GPS	
VO2Master	VO2	

2.2. Activity classification

Activity classification is performed based on signals from up to three triaxial ACCs (chapter 2.1). Currently, three different types of activities (walking, running, and cycling) and rest are supported by the proposed AI algorithm; other activities are not supported in this work.

The proposed multi-input neural network model is based on a combination of convolutional, recurrent, and fully connected layers. The activity is classified on the basis of an analysis of a 10-second data chunk. It contains raw data from ACCs mentioned above. From the raw data, features describing the signal in the static, time, and frequency domains are extracted.

The following feature groups are acquired by feature extraction (number of features):

- statistical (5),
- time-domain (3),
- frequency domain (12).

For each ACC axis, a total of 20 features are extracted from one data chunk. Together with the raw data, they are used as input to the proposed neural network model. This approach reduced confusion between activities like fast walking and running.

In order to minimize overfitting, some regularization mechanisms were used, such as dropout layers, L1 and L2 regularization of selected neural layers, and data augmentation.

2.3. Exertion level assessment

The body's exertion was quantified using the metabolic equivalent of task (MET). MET was calculated according to activity type by one of the following equations [6], [7]:

$$MET_{walk} = \frac{0.1*v+1.8*v*inc}{3.5} + 1,$$

$$MET_{run} = \frac{0.2*v+0.9*v*inc}{3.5} + 1,$$

$$MET_{cycling} = \frac{1.163*watt}{0.24*weight} + 1,$$

where v and *inc* are speed and inclination coming from GPS data, and *watt* is cycling wattage – the power subject produces with legs to get the bike going. Cycling wattage was estimated based on multiple information about gear, cycling style, and external conditions. More detailed information is in [7], [8], [9].

For the resting phase, we assumed that MET starts to decrease asymptotically to 1 after the active part. In our work, we estimate this fact using the following exponential function:

$$MET_{rest} = (MET_{last} - 1)e^{-\lambda t} + 1,$$

where MET_{last} is currently the last known MET value before the rest phase starts, λ determines the steepness of the exponential decline and is empirically set to 0.035, and t expresses the duration of the rest phase.

Finally, we divided MET values into five exertion levels (Table 2), ranging from light activities (1), such as standing, to vigorous and heavy activities (5), such as intensive running or cycling.

Table 2. Conversion of MET values to exertion levels.

Exertion level	MET
1	< 2
2	2-4.5
3	4.5-7.5
4	7.5-11
5	> 11

2.4. Heartbeats detection

Heartbeats detection is used for the subsequent calculation of the HR, which is important for estimating the body's response.

A previously introduced QRS complex detector [10] was used to detect the heartbeats in the ECG. This is based on an ensemble of three detectors based on continuous wavelet transform, phasor transform, and Stockwell transform.

If no ECG signal is available, heartbeats were detected in the PPG signal. For heartbeats detection and HR calculation, the algorithm based on stationary wavelet transform was used. The PPG signals were decomposed into several frequency bands, the proper band where the heartbeats manifest the most was selected, and then the peaks were detected and HR calculated.

2.5. Body's response assessment

The body's response to exertion is evaluated using a modified Borg's scale (RPE) (Table 3). The evaluation is based on HR. The current HR is compared with the maximum HR, and the HR part of the body's response is classified into one of five classes.

Table 3. Modified Borg's scale (RPE) – conversion of HR to body's response levels.

Body's response	Current HR/max HR [%]
1	< 60
2	60-70
3	70-80
4	80-90
5	90-100

For the body's response evaluation, the maximum HR is necessary. It is calculated using the following equation:

$$HRmax = 220 - age.$$

If the age is unknown (not set by the user), a constant HRmax of 185 beats per minute (bpm) is used.

2.6. Aerobic fitness level assessment

The AFL assessment is done in two dimensions (Table 4). The first dimension is an exertion level (chapter 2.3.), and the second is a body's response to the exertion (chapter 2.5.). The AFL is classified into nine levels – critical, very poor, poor, low, normal, medium, high, expert, and excellent.

According to Table 4, AFL is evaluated continuously for each recorded activity. The resulting AFL is the median AFL during the measurement. If the recorded activity falls into at least 3 exertion levels, the AFL calculated during level 1 is not included in the median.

Table 4. Aerobic fitness level assessment.

		Exertion level				
		1	2	3	4	5
Body response	1	Normal	Medium	High	Expert	Excellent
	2	Low	Normal	Medium	High	Expert
	3	Poor	Low	Normal	Medium	High
	4	Very poor	Poor	Low	Normal	Medium
	5	Critical	Very poor	Poor	Low	Normal

The resulting AFL was converted to a number between zero and one for further comparison of the algorithm with reference. First, the determined AFL was assigned a number from zero (category critical) to eight (category excellent). The range from zero to one was then provided by dividing by eight.

3. Results

The activity classification accuracy of the proposed algorithm reached 97.90 % on the validation dataset and 92.90 % on the test dataset. The highest error rate on the test dataset was due to confusion between walking and running activities (3.57 %).

Table 5. Confusion matrix of the activity classification on the test dataset. Values in the table represent the number of 10-second segments.

		Predicted class			
		Rest	Walking	Running	Cycling
True class	Rest	65	0	6	0
	Walking	2	78	12	0
	Running	3	0	81	0
	Cycling	0	1	0	88

The MET estimation was validated by comparison with reference values measured with the VO2Master mask (Figure 3).

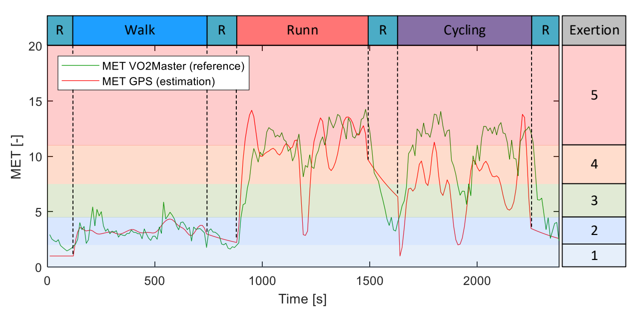

Figure 3. MET units estimation versus the VO2Master mask reference for one measurement; R is rest.

The accuracy of MET estimation was validated on a total of 20 volunteers (those with available VO2Master mask). Measurements were taken simultaneously with the VO2Master mask and subjects completed approximately 40 minutes of measurement. The measurement protocol included walking, running, and cycling phases alternated with a short rest period. The accuracy of the MET unit estimation in each phase as well as the accuracy of the overall measurement averaged over 20 volunteers can be seen in Table 6.

Table 6. MET unit estimation accuracy for the different activity; mean error is the estimate minus reference value.

Activity	Mean error	Mean absolute error
Rest	-0.32 ± 1.26	0.86
Walking	-1.10 ± 0.94	1.11
Running	0.70 ± 1.14	0.26
Cycling	-1.10 ± 1.42	1.41
Overall	-0.48 ± 0.97	0.67

The method for AFL estimation was validated by comparison with reference values calculated according to the equations given by ACSM Cardiorespiratory fitness classification guidelines [3]. The VO2max for calculating the reference AFL was measured in a laboratory.

A comparison of the determined and reference AFL groups is in Table 7. Our AFL values are calculated as the mean and standard deviation of the AFL of individuals belonging to the same reference AFL category.

Table 7. Reference and estimated values of AFL.

Reference AFL#	Estimated AFL#	Number of subjects
Very poor	0.44 ± 0.09	2
Poor	0.50 ± 0.10	4
Fair	0.53 ± 0.09	8
Good	0.58 ± 0.15	8
Excellent	0.7 ± 0.07	5
Superior	-	0

The reference categories do not correspond to our categories in Table 4. Therefore, we converted our verbal ratings into numbers for comparison (see chapter 2.6)

The correlation between the reference and estimated AFL values is 0.76. Reference values were converted to numbers from one (very poor) to five (excellent) to calculate the correlation.

5. Conclusion

We presented a method for automatic AFL estimation. Our results correlate with AFL determined in laboratory conditions using exhaled gas analysis, which is the gold standard method. In contrast, our method only needs continuously sensed HR and movement data from GPS and ACC. All these quantities can be obtained using devices widespread in the population, such as smartwatches.

Acknowledgments

This article is a result of the NextPerception project 876487/8A20007 (www.nextperception.eu), which is jointly funded by the European Commission and national funding agencies under the ECSEL joint undertaking.

References

[1] M. Imboden, M. Harber, M. Whaley, et al, “Cardiorespiratory Fitness and Mortality in Healthy Men and Women,” *J Am Coll Cardiol*, vol. 72, no. 19, pp. 2283–2292, Nov. 2018.

[2] V. Doijad, P. H. Kamble, and A. D. Surdi, “Effect of Yogic Exercises on Aerobic Capacity (Vo2 Max),” *International Journal of Physiology*, no.1, pp. 47–50, 2013.

[3] American College of Sports Medicine, “ACSM’s Guidelines for Exercise Testing and Prescription,” *Wolters Kluwer*, vol. 10, 2018.

[4] L. A. Kaminsky, R. Arena, and J. Myers, “Reference Standards for Cardiorespiratory Fitness Measured With Cardiopulmonary Exercise Testing: Data From the Fitness Registry and the Importance of Exercise National Database”, *Mayo Clinic Proceedings*, vol. 90, no. 11, pp. 1515–1523, 2015.

[5] A. H. K. Montoye, J. D. Vondrasek, and J. B. Hancock, “Validity and Reliability of the VO2 Master Pro for Oxygen Consumption and Ventilation Assessment”, *Int J Exerc Sci*, vol. 13, no. 4, Sep. 2020.

[6] American College of Sports Medicine, “ACSM' Metabolic Calculations Handbook,” *Lippincott W. and W.*, 2007.

[7] D. Meyer, G. Kloss, and V. Senner, “What is Slowing Me Down? Estimation of Rolling Resistances During Cycling,” *Procedia Engineering*, vol. 147, pp. 526-531, 2016.

[8] W. M. Bertucci, S. Rogier, and R. F. Reiser, “Evaluation of Aerodynamic and Rolling Resistances in Mountain-Bike Field Conditions,” *Journal of Sports Sciences*, vol. 31, no. 14, pp. 1606-1613, 2013.

[9] W. J. Steyn, and J. Warnich, “Comparison of Tyre Rolling Resistance for Different Mountain Bike Tyre Diameters and Surface Conditions,” *South Afr. J. Res. Sport Phys. Educ. Recreation*, Vol. 36 No. 2, pp. 179-193, 2014.

[10] L. Smital, L. Marsanova, R. Smisek, et al., “Robust QRS Detection Using Combination of Three Independent Methods,” *Computing in Cardiology*, vol. 47, 2020.

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