Activity Monitoring and Existing Algorithms Regarding Energy Expenditure Estimation: A Short Review

Florian Richert[1]
1 movisens GmbH, Karlsruhe, Germany

Figure 1: Move 3

Introduction

An important determinant of health is physical activity, which has been defined as "[…] any bodily movement produced by the contraction of skeletal muscle that increases energy expenditure (EE) above a basal level" (US Department of Health and Human Services, 2008). Insufficient activity increases the risk of developing several diseases, e.g. coronary heart diseases. To avoid such diseases, at least 30 min of moderate physical activity at five days a week has been recommended (Garber, et al., 2011). But to check the compliance of such recommendations is critical and with subjective methods impossible (Rosenbaum, 2012). Therefore objective methods are required. Additionally, physical activity can be classified qualitatively (sedentary behavior, locomotion, work), quantitatively (frequency, duration, intensity) and contextually (time, place, position, posture) (Butte, Ekelund, & Westerterp, 2012). In the past years a lot of research has been devoted to developing objective physical activity measurement-tools tools, e.g. wearable monitors. The golden standard to assess EE is doubly labeled water. But due to its large volume and the high costs involved, this method isn't applicable in everyday life situations.

Thus, a common method to assess physical activity is the estimation of EE using wearable monitors. But these measurement tools differ in recorded parameters and the data processing that follows. Therefore some devices are more and some are less appropriate for EE estimations. For instance, with pedometers it is difficult to measure the step length and thus the covered distance – both influencing factors on EE. In addition, vertical displacement and movement of the upper body are also missing from this data. Hence, pedometers are inappropriate for EE estimations. In contrast, a popular measurement tool for physical activity is an accelerometer. There are a lot of different approaches in processing raw data for EE estimation. This inconsistency results in several issues (saving and displaying raw data (mg) vs. Counts (John & Freedson, 2012; Welk, McClain, & Ainsworth, 2012); activity based model vs. linear regression model (Lyden, Kozey, Staudenmeyer, & Freedson, 2011); more precise EE estimation with additional sensors (Grams, Tegtbur, Kück, Gützlaff, Marschollek, & Kerling, 2011). These issues and existing technologies relating to accelerometry will be discussed in the following section.

Raw data vs. Counts

Accelerometers (E.g. activity sensor Move 3; c.f. Figure 1) come in a wide range with different approaches on how to process the raw acceleration data. Unfortunately, there is no standard for data processing and thus there are no standardized output variables. Hence, data processing

info@movisens.com

depends on the corresponding company. Several companies use an imaginary transformed variable called Counts, calculated from the raw acceleration data. Counts are generated during the data processing by filtering after the acceleration signal is recorded. The filter used depends on the company and thus this inconsistency makes it nearly impossible to compare different devices from different companies. Therefore it is recommended to capture and store data in a unique storage format, and then process the data to obtain information. Raw data as output variable – the unprocessed/unfiltered raw acceleration signal of each axis (direction: x, y, z; unit: mg) – are also favored (Hey, Anastasopoulou, & von Haaren, 2014; John & Freedson, 2012; Welk, McClain, & Ainsworth, 2012). Based on these suggestions, the movisens sensors (Move 3, EcgMove 3, LightMove 3 and edaMove) record and save the raw data from the triaxial acceleration signal. Thus it is also possible to recalculate parameters, e.g. EE, at a later date with new algorithms and new methods.

Linear regression vs. activity based models

Another problem estimating EE is that after filtering the raw data, a lot of devices use linear regression models. Single regression models are known to over- or underestimate EE due to the non-linear relationship between activity and EE. For example, additional load on the body (pulling, pushing,..) can't be measured (Hey, Anastasopoulou, & von Haaren, 2014). Thus no single regression model is appropriate to estimate EE and hence, the use of linear regression models is questionable (Butte, Ekelund, & Westerterp, 2012; Crouter, Churilla, & Basset Jr, 2006). It could be shown, that an activity-based regression model (c.f. Figure 2) is advantageous and more accurate (c.f. Figure 3) (Campbell, Crocker, & McKenzie, 2002). The sensors from movisens use a triaxial accelerometer for activity recognition. The acceleration data is classified into relevant activity classes before further processing. Afterwards the appropriate algorithm for the corresponding activity class is selected. This approach seems to be advantageous compared to other devices and results in a more accurate EE estimation than other devices (Anastasopoulou, Tubic, Schmidt, Neumann, Woll, & Härtel, 2014; Härtel, Gnam, Löffler, & Bös, 2011; Lyden, Kozey, Staudenmeyer, & Freedson, 2011).

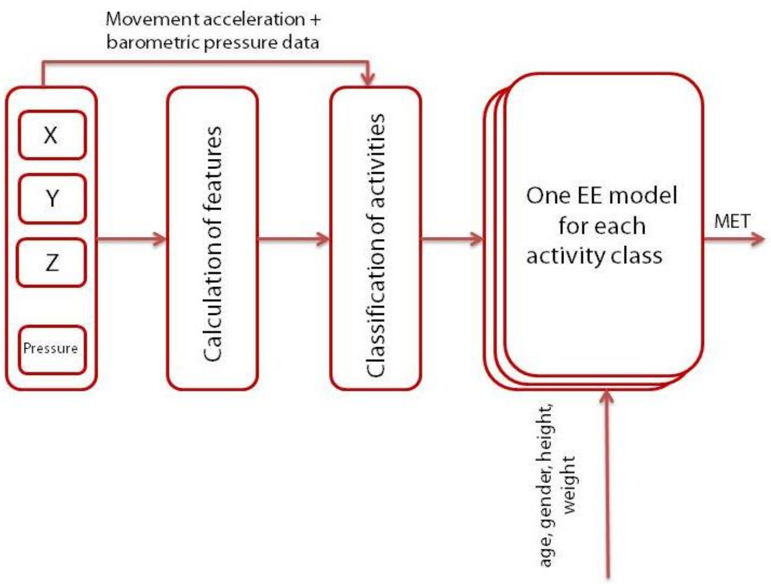

Figure 2: Schematic description of the activity based EE estimation

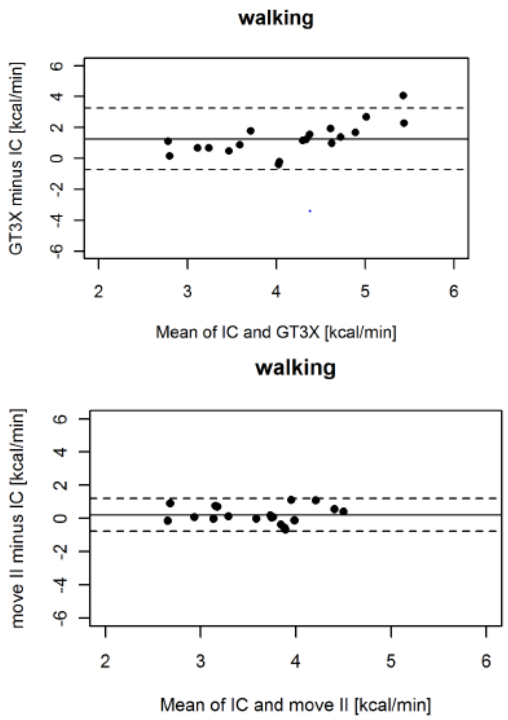

Figure 3: Predicting EE with a linear (top) and an activity based model (bottom) (source: Anastasopoulou et al., 2014)

Sensorfusion
To improve EE estimation, the movisens sensors include a barometric sensor to assess changes in altitude. The fault of most common accelerometers is that they are not precise in EE estimation for ascending/decending a slope or stairs. This problem results out of a similar walking pattern while walking on an incline/stair compared to walking on a flat surface (Anastasopoulou, Tubic, Schmidt, Neumann, Woll, & Härtel, 2014; Campbell, Crocker, & McKenzie, 2002). Including more sensors and thus generating more information about the inclination (flat vs. incline) and the movement in isolation lead to an improved EE estimation. This added barometric sensor improves the EE estimation accuracy significantly (Anastasopoulou, Härtel, Tubic, & Hey, 2014). For example the sensors from movisens were evaluated with a mean classification rate of 98.2%, whereas the smallest classification rate was noted for cycling (95.1%) (Anastasopoulou, Tansella, Stumpp, Shammas, & Hey, 2012). These accurate classifications of activity lead to an improved EE estimation. Sensor fusion is not only limited to barometric sensors. Every conceivable and helpful sensor could be linked to accelerometers. E.g. measuring of heart rate could improve EE estimation (Butte, Ekelund, & Westerterp, 2012).

Figure 4: Activity + ECG-Sensor (EcgMove 3 with chest belt)

This approach is realised in the EcgMove 3 (c.f. Figure 4), a sensor that combines the recording of activity and heart rate parameters such as heart rate or heart rate variability. The EcgMove 3 uses the heart rate for EE if a low activity is combined with a high heart rate. This might occure during “static” activities such as cycling or weight lifting. During such an activity nearly no acceleration signal can be recorded due to the fixed position of the accelerometer. Nevertheless this kind of activity comes along with a high EE and thus heart rate parameters seem to be a better pedictor for EE estimation.

(Interactive) Ambulatory Assessmet
Compared to questionnaires, activity sensors (accelerometers) provide the benefit of recording movement as the movement occurs. In contrast, forms come with a delay in recording of physical activity. Thus it has been stated that a sensor based system is advantageous to reduce systematic errors compared to traditionally timed forms (Rosenbaum, 2012). The recording of data during one’s everyday life is called ambulatory assessment (not limited to activity sensors – also feasible with forms e.g. on a smartphone). This advantage offers new research methods and could provide better insights into daily activities. Most sensors are very small and thus wearing

them in everyday life doesn't hinder participants. This approach makes it possible to check movement recommendations as described in the introduction. Using accelerometers offers insight into a wide range of topics for the research community. For instance the movisens sensors were used in a study to monitor patients with multiple sclerosis during their daily life. It was found that accelerometers can be used to capture changes in physical activity and walking ability and consequentially used for further interventions/training programs (Shammas, Zentek, von Haaren, Schlesinger, Hey, & Rashid, 2014). This demonstrates that using accelerometers could lead to changes in therapies or training and thus the quality of life in healthy and unhealthy people.

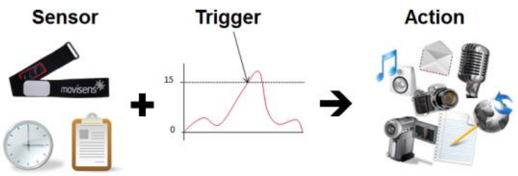

Figure 5: Schematically illustration of IAA

By using a combination of accelerometers and questionnaires, especially online on a smartphone, researchers can develop a better understanding of lifestyle through adding qualitative information to objective quantitative data. This approach is called Interactive Ambulatory Assessment (IAA) and allows the prompting of questionnaires during or a short time after a certain physical activity. A schematical illustration of IAA is depicted in Figure 5. This technique gives researchers the possibility to gain new insights into the psycho-physiological construct. Monitoring behavior or activity with forms popping up at random times, situations or contexts comes along with the issue that the accurate point of activity probably won't be assessed. Thus Ebner-Priemer, Koudela, Mutz, & Kanning (2013) conducted a study to increase the number of questionnaires filled out during active periods in everyday life. By linking an activity sensor to a mobile device and using the activity to trigger the questionnaires, they reached a higher compliance during active periods. As this method is relatively new in the research community, the number of studies is so far limited. But the first studies were already conducted, utilising among other things the equipment of movisens (sensors + software movisensXS) (Walter, et al., 2013).

Conclusion

The algorithms of the movisens sensors try to eliminate all known issues regarding EE estimation and activity recording that have been stated for other devices (saving and displaying raw data (mg) instead of Counts; activity-based model instead of linear regression model; more precise EE estimation with additional sensors (acceleration + barometric sensor + skin temperature) instead of only one acceleration sensor). Thus we can deduce that the movisens sensors are the most precise mobile sensors available on the market. Additionally, combining these sensors with the Experience Sampling platform movisensXS for Interactive Ambulatory Assessment will lead to new insights and offers new opportunities for researchers to gain previously unobtainable insights in to the psycho-physiological construct.

References

Anastasopoulou, P., Härtel, S., Tubic, M., & Hey, S. (2014). Using Support Vector Regression for Assessing Human Energy Expenditure Using a Triaxial Accelerometer and a Barometer. *International Conference on Wireless Mobile Communication and Healthcare*, pp. 106-113.

Anastasopoulou, P., Tansella, M., Stumpp, J., Shammas, L., & Hey, S. (2012). Classification of Human Physical Activity and Energy Expenditure Estimation by Accelerometry and Barometry. *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE, 2012*, pp. 6451-6454.

Anastasopoulou, P., Tubic, M., Schmidt, S., Neumann, R., Woll, A., & Härtel, S. (2014). Validation and Comparison of Two Methods to Assess Human Energy Expenditure during Free-Living Activities. *PLoS ONE, 9*(2), p. e90606.

Butte, N. F., Ekelund, U., & Westerterp, K. R. (2012). Assessing Physical Activity Using Wearable Monitors: Measures of Physical Activity. *Medicine & Science in Sports & Exercise, 44*(1 Suppl 1), pp. S5-S12.

Campbell, K. L., Crocker, P. R., & McKenzie, D. C. (2002). Field evaluation of energy expenditure in women using Tritrac accelerometers. *Medicine &*

Science in Sports & Exercise, 34(10), pp. 1667-1674.

Crouter, S. E., Churilla, J. R., & Basset Jr, D. R. (2006). Estimating energy expenditure using accelerometers. *European Journal of Applied Physiology, 98*(6), pp. 601-612.

Ebner-Priemer, U. W., Koudela, S., Mutz, G., & Kanning, M. (2013). Interactive multimodal ambulatory monitoring to investigate the association between physical activity and affect. *Frontiers in Psychology, 3*, p. 596.

Garber, C. E., Blissmer, B., Deschenes, M. R., Franklin, B. A., Lamonte, M. J., Lee, I. M., et al. (2011). American College of Sports Medicine position stand. Quantity and quality of exercise for developing and maintaining cardiorespiratory, musculoskeletal, and neuromotor fitness in apparently healthy adults: guidance for prescribing exercise. *Medicine & Science in Sports & Exercise, 43*(7), pp. 1334-1359.

Grams, L., Tegtbur, U., Kück, M., Gützlaff, E., Marschollek, M., & Kerling, A. (2011). Energieumsatzmessungen unter kontrollierten Bedingungen : Vergleich von Accelerometer, Multisensorsystem und mobiler Spiroergometrie. *Deutsche Zeitschrift für Sportmedizin, 62*(6), pp. 160-165.

Härtel, S., Gnam, J.-P., Löffler, S., & Bös, K. (2011). Estimation of energy expenditure using accelerometers and activity-based energy models—validation of a new device. *European Review of Aging and Physical Activity, 8*(2), pp. 109-114.

Hey, S., Anastasopoulou, P., & von Haaren, B. (2014). Erfassung körperlicher Aktivität mittels Akzelerometrie – Möglichkeiten und Grenzen aus technischer Sicht. *Bewegungstherapie und Gesundheitssport, 30*(2), pp. 73-78.

John, D., & Freedson, P. (2012). ActiGraph and Actical Physical Activity Monitors: A Peek under the Hood. *Medicine & Science in Sports & Exercise, 44*(1 Suppl 1), pp. S86-S89.

Lyden, K., Kozey, S. L., Staudenmeyer, J. W., & Freedson, P. S. (2011). A comprehensive evaluation of commonly used accelerometer energy expenditure and MET prediction equations. *European Journal of Applied Physiology, 111*(2), pp. 187-201.

Rosenbaum, D. (2012). Aktuelle Messverfahren zur objektiven Erfassung körperlicher Aktivitäten unter besonderer Berücksichtigung der Schrittzahlmessung. *Bundesgesundheitsblatt - Gesundheitsforschung - Gesundheitsschutz, 55*(1), pp. 88-95.

Shammas, L., Zentek, T., von Haaren, B., Schlesinger, S., Hey, S., & Rashid, A. (2014). Home-based system for physical activity monitoring in patients with multiple sclerosis (Pilot study). *BioMedical Engineering OnLine, 13*(10), pp. 1-15.

US Department of Health and Human Services. (2008). *Physical Activity Guidelines for Americans.* Washington D.C.: U.S. Department of Health and Human Services.

Walter, K., von Haaren, B., Löffler, S., Härtel, S., Jansen, C.-P., Werner, C., et al. (2013). Acute and medium term effects of a 10-week running intervention on mood state in apprentices. *Frontiers in Psychology, 4*, pp. 1-10.

Welk, G. J., McClain, J., & Ainsworth, B. E. (2012). Protocols for evaluating equivalency of accelerometry-based activity monitors. *Medicine & Science in Sports & Exercise, 44*(1 Suppl 1), pp. S39-S49.