An Adaptable Inertial Sensor Fusion-Based Approach for Energy Expenditure Estimation

D. Schuldhaus[1], S. Dorn[1], H. Leutheuser[1], A. Tallner[2], J. Klucken[3] and B. M. Eskofier[1]

[1] Digital Sports Group, Pattern Recognition Lab, Department of Computer Science, University Erlangen-Nuremberg, Germany
[2] Institute of Sport Science and Sport, University Erlangen-Nuremberg, Germany
[3] Department of Molecular Neurology, University Hospital Erlangen, Germany

Abstract— **Using multiple inertial sensors for energy expenditure estimation provides a useful tool for the assessment of daily life activities. Due to the high variety of new upcoming sensor types and recommendations for sensor placement to assess physiological human body function, an adaptable inertial sensor fusion-based approach is mandatory. In this paper, two inertial body sensors, consisting of a triaxial accelerometer and a triaxial gyroscope, were placed on hip and ankle. Ten subjects performed two trials of running on a treadmill under three speed levels ([3.2, 4.8, 6.4] km/h). Each sensor source was separately subjected to preprocessing, feature extraction and regression. In the final step, *decision level fusion* was performed by averaging the predicted results. A mean absolute error of 0.50 MET was achieved against indirect calorimetry. The system allows an easy integration of new sensors without retraining the complete system. This is an advantage over commonly used *feature level fusion* approaches.**

Keywords— **Energy expenditure, inertial sensor, regression, decision level fusion, treadmill.**

I. INTRODUCTION

The World Health Organization states that the 4th leading risk factor for mortality is insufficient physical activity [1]. Several studies showed that physically active people have higher levels of health-related fitness and lower rates of various chronic diseases compared to physically inactive people [2].

The quantitative assessment of the physical activity during individual daily life is of major interest for an objective and quantitative monitoring of fitness. Fitness provides a measure for the health status and individual quality of life.

One commonly used assessment of physical activity is energy expenditure [3]. Energy expenditure can be measured by indirect calorimetry [4]. The approach estimates the expended energy from oxygen consumption and carbon dioxide production. Energy expenditure is mostly expressed in metabolic equivalent (MET). MET is considered as the ratio of work metabolic rate to a standard resting metabolic rate [3]. Although indirect calorimetry is accurate in measuring the expended energy under various conditions, the technical requirements impair the application for daily life physical activity measurement.

In recent years, small and lightweight wearable sensors like inertial measurement units were used to provide a reliable, unobtrusive and objective measurement of physical activity. Besides the classification of daily life activities [5], they are commonly applied in the field of energy expenditure estimation, which is shown in the following paragraphs.

In [6], a triaxial accelerometer was placed on the lower back. Eleven subjects performed sedentary activities and walked on a motor driven treadmill with different speed levels. The summed integral of the absolute value of each accelerometer signal was used as input for a linear regression. The model achieved a standard error of estimate of 0.70 W/kg.

In [7], a triaxial accelerometer and a triaxial gyroscope were placed on the hip. Eight subjects walked on a motor driven treadmill with different speed levels. The average integral of the mean-subtracted sensor output was used as feature for each of the six sensor axes. Bayesian linear regression was applied to estimate oxygen consumption and a root mean square prediction error of 35 ml/min was achieved.

In [8], two triaxial accelerometers were placed on hip and wrist. Furthermore, ventilation was measured by a sensor secured to the abdomen. Fifty subjects performed 13 activities of varying intensity. In total, 63 features in the time domain and frequency domain were computed. A Support Vector Machine was applied to identify the types of physical activity. In a second step, a Support Vector Regression model was built for each predefined groups of activities. All in all, the approach achieved a root mean square error of 0.54 MET using the two accelerometers and 0.42 MET using an additional ventilation sensor. For the activity group, which includes treadmill running with different speed and inclination levels, a mean absolute error of 0.36 MET was achieved.

In [6], only one sensor was used for the estimation of the expended energy. In [7, 8], the general applicability of using several sensor types and positions was shown to estimate the energy expenditure. In [7, 8], feature level fusion was

J. Goh (ed.), *The 15th International Conference on Biomedical Engineering*, IFMBE Proceedings 43,
DOI: 10.1007/978-3-319-02913-9_32, © Springer International Publishing Switzerland 2014

performed. In feature level fusion, features from different sensor axes are extracted and fused [9]. The final regression result is based on the fused features. If additional sensor types like magnetometer, or sensor positions like thigh, should be integrated into the regression system, the complete system has to be retrained. Due to the high variety of new upcoming sensor types and recommendations for sensor placement, an adaptable integration of new information into the estimation process is needed. In [10], a system was introduced for the classification of daily life activities, which used decision level fusion of different sensor locations for the integration of new information.

The purpose of this paper is to introduce a generalized approach for energy expenditure estimation based on decision level fusion extending our findings in [10]. The system needs no complete retraining after adding new sensor types and positions.

II. METHODS

A. Data Acquisition

Two SHIMMER sensor nodes (Shimmer Research, Dublin, Ireland) were placed on the hip and ankle (Fig. 1). Each sensor node consisted of a triaxial accelerometer and a triaxial gyroscope. The range of the accelerometer was ±1.5 g on the hip and ±6 g on the ankle. The range of the gyroscope was ±500 °/s on the hip and ±2000 °/s on the ankle for 70 % of the subjects and ±500 °/s for 30 % of the subjects due to sensor problems. The sampling rate for all sensors was 204.8 Hz.

A study with ten healthy subjects (seven male and three female, age 49 ± 12 years, height 178 ± 10 cm, weight 80.7 ± 14.6 kg) was performed. All subjects gave written informed consent about their participation. Approval from the ethical committee was received (Re.-No. 181 12B, 24.07.2012, Medical Faculty, Friedrich-Alexander-University, Erlangen-Nuremberg, Germany).

In one trial, each subject had to run on a treadmill (hp-cosmos model mercury med 5.0, Traunstein, Germany) at three different speed levels ([3.2, 4.8, 6.4] km/h) The speed levels were chosen according to [11]. In a second trial, an oscillating treadmill was used imposing different levels of physical activity. Each speed level lasted six minutes according to [11]. Fig. 2 shows the angular velocity during running on a treadmill without oscillating for the speed levels [3.2, 6.4] km/h. For the expended energy, expressed in MET, the oxygen consumption was measured by a spirometry system and was divided by 3.5mL·kg^{-1} min^{-1} [4]. The sampling rate was 0.2 Hz. Table 1 shows the average mean, standard deviation and range of the measured expended energy.

B. Proposed Regression System

The proposed regression system is depicted in Fig. 3. Four sensor sources were defined: accelerometer on the hip (HP_A), gyroscope on the hip (HP_G), accelerometer on the ankle (AK_A) and gyroscope on the ankle (AK_G). Each sensor source was processed separately. The processing included preprocessing, feature extraction and regression. In the following sections, the details are described.

Table 1 Mean, standard deviation and range of measured expended energy [MET] by indirect calorimetry with respect to speed levels.

Speed level	MET (mean)	SD	Range
3.2 km/h	3.44	0.88	2.37-7.07
4.8 km/h	3.91	0.56	2.90-5.52
6.4 km/h	5.51	0.91	4.12-8.23

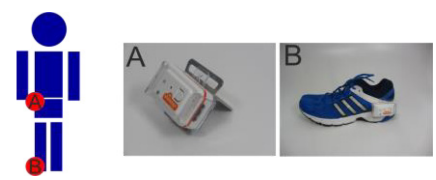

Fig. 1 SHIMMER placement on hip (A) and ankle (B).

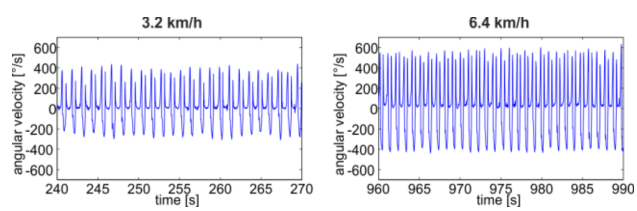

Fig. 2 Angular velocity during treadmill running at [3.2, 6.4] km/h.

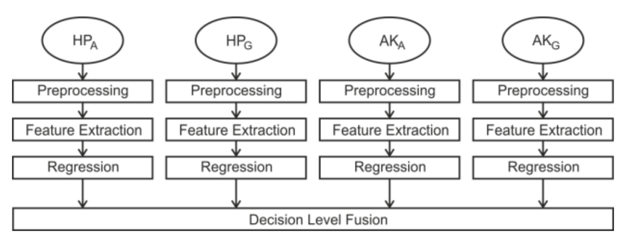

Fig. 3 Proposed regression system for the four sensor sources accelerometer on the hip (HP_A), gyroscope on the hip (HP_G), accelerometer on the ankle (AK_A) and gyroscope on the ankle (AK_G).

a) Preprocessing

Processing of the acquired inertial data and MET data was performed in non-overlapping sliding windows. The width of the windows was set to 30 seconds, which was proposed in [6, 8]. The corresponding ground truth MET values in each sliding window were averaged. Furthermore, only sliding windows with a steady metabolic state were considered. Therefore, only the final three minutes of the six-minute periods of exercise were used for further processing, which was proposed in [11].

b) Feature Extraction

Nine features were computed for each sensor axis. In order to characterize the signal distribution, the mean of the absolute signal amplitudes, the standard deviation, the 10th, 25th, 50th, 75th, 90th percentiles, minimum and maximum value were computed. This resulted in 27 features for each sensor source. In order to reduce the feature set, a sequential forward selection was performed [12].

c) Regression

The following regression algorithms were compared: Support Vector Regression (SVR) with polynomial kernel [13], classification and regression tree (CART) [14] and multiple linear regression (MLR) [15]. For performance assessment, the mean absolute error was computed with a leave-one-subject-out cross-validation. For further processing, the best regression algorithm for each sensor source was considered.

d) Decision Level Fusion

The predicted MET values of all four sensor sources were fused in the final step. In this case, the mean of all predicted MET values was taken as final predicted MET value.

III. Results

Table 2 shows the mean absolute error of the four sensor sources regarding the three compared regression algorithms SVR, CART and MLR. The best accuracy of 0.61 MET was achieved by HP_A and AK_G.

Table 3 shows the mean absolute error of the four sensor sources regarding the three speed levels.

Table 4 shows the mean absolute error of the energy expenditure estimation after the decision level fusion regarding the three speed levels. An overall mean error of 0.50 MET was achieved.

Table 2 Mean absolute errors [MET] regarding the four sensor sources. Best results are printed bold.

Algorithm	HP_A	HP_G	AK_A	AK_G
SVR	0.64±0.45	0.79±0.71	0.71±0.53	**0.61±0.41**
CART	**0.61±0.36**	0.96±0.72	0.71±0.51	0.67±0.50
MLR	0.77±0.58	0.79±0.71	**0.66±0.48**	0.85±0.46

Table 3 Mean absolute errors [MET] of four sensor sources regarding the three speed levels. Best results are printed bold.

Speed level	HP_A	HP_G	AK_A	AK_G
3.2 km/h	0.47±0.24	0.56±0.42	0.44±0.32	**0.40±0.25**
4.8 km/h	**0.57±0.29**	0.63±0.58	0.62±0.42	0.61±0.35
6.4 km/h	**0.79±0.72**	1.15±1.32	0.92±0.80	0.83±0.72

Table 4 Mean absolute errors [MET] after decision level fusion regarding the three speed levels.

Speed level	Error
3.2 km/h	0.37±0.24
4.8 km/h	0.51±0.35
6.4 km/h	0.62±0.49

IV. Discussion

In this paper, a generalized approach for energy expenditure estimation was proposed, in which additional sensor information can easily be integrated into the system using decision level fusion.

Regarding the mean absolute error of the four sensor sources and the three compared regression algorithms (Table 2), the two best accuracies were achieved by HP_A and AK_G with the algorithms CART and SVR, respectively. The reason in the case of HP_A might be that no significant rotational movements were present during treadmill running. This might change during daily life activities like vacuuming. The reason in the case of AK_G might be based on significant movements in the sagittal plane during treadmill running.

Regarding the mean absolute error of the four sensor sources and the three speed levels (Table 3), the best accuracy for speed level 3.2 km/h was achieved by AK_G. The best accuracy for speed levels 4.8 km/h and 6.4 km/h was achieved by HP_A. Thus, for higher intensity levels, the upper part of the body has more influence on the energy expenditure than the lower part [16].

Regarding the mean absolute error after decision level fusion (Table 4), it can be summarized that this reduced the error by 7.5 %, 10.5 % and 21.5 % regarding the speed levels 3.2 km/h, 4.8 km/h and 6.4 km/h, respectively. This indicates that fusing different sensor sources improves the energy expenditure estimation, especially for higher speed levels.

During data acquisition, the triaxial accelerometer often reached the saturation state, which might affect the regression. Thus, using an accelerometer with a higher range might improve the regression results.

The accuracy might be further improved by using different approaches in the decision level fusion. The predicted

MET values can e.g. be used as features for an additional regression procedure including a feature selection step. The feature selection might eliminate the sensor sources that are not suitable for the prediction of the energy expenditure.

In [8], a mean absolute error of 0.36 MET was achieved for moderate locomotion with two accelerometers and a ventilation sensor. This means an improvement of 28 % compared to the proposed system. Thus, by further integrating a ventilation sensor, the accuracy of the proposed system might improve. The ventilation sensor would be an additional sensor source, which can easily be integrated in the pipeline as an additional block (Fig. 3). A retraining of the complete system is not necessary. The idea of activity-dependent regression in [8] can also be integrated in the proposed system. For this purpose, the proposed system can be combined with the classification system described in [10], which also performed a sensor-dependent processing and decision level fusion.

In summary, the proposed system showed the general applicability in predicting the energy expenditure during running on a treadmill. Furthermore, additional sensor sources can easily be integrated into the system. This adaptable integration is mandatory due to the high variety of new upcoming sensor types and recommendations for sensor placement.

V. Conclusion

Fusion of different sensor sources is often used in the estimation of energy expenditure. In this paper, triaxial accelerometers and gyroscopes were placed on hip and ankle, defining four sensor sources. Preprocessing, feature extraction and regression were separately performed for each sensor source. In the final step, decision level fusion was performed by taking the mean of all predicted MET values of the sensor sources. The proposed system reached a mean absolute error of 0.50 MET. It allows an easy integration of new sensors without retraining the complete system.

In the future, additional sensors can be integrated in the regression system, e.g. ventilation or electrocardiogram sensors. Furthermore, the regression system can be evaluated during daily life activities.

The proposed regression system can deliver a quantitative assessment of the physical activity in order to monitor the health status and to provide feedback about the individual quality of life. The feedback can motivate physically inactive people to be more active. This leads to lower rates of various chronic diseases, which should be one major goal for the future.

Acknowledgment

This work was supported by the Bavarian Ministry for Economic Affairs, Infrastructure, Transport and Technology and the European fund for regional development. Furthermore it was supported by the Bavarian research foundation. Shoes were provided by the adidas AG. The study was further supported by the Institute of Sport Science and Sport.

References

1. World Health Organization. Global Strategy on Diet, Physical Activity and Health. [cited 2013 August 19th]; Available from: http://www.who.int/dietphysicalactivity/pa/en/index.html.
2. Physical Activity Guidelines Advisory Committee (2008). Physical Activity Guidelines Advisory Committee Report 2008, Washington, DC.
3. Warren J M, Ekelund U, Besson H et al. (2010). Assessment of physical activity - a review of methodologies with reference to epidemilogical research: a report of the exercise physiology section of the European Association of Cardiovascular Prevention and Rehabilitation. Eur J Cardiovasc Prev Rehabil. 17(2):. 127-139.
4. Valanou E M, Bamia C, Trichopoulou A (2006). Methodology of physical-activity and energy-expenditure assessment: a review. Journal of Public Health 14(2): 58-65.
5. Leutheuser H, Schuldhaus D, Eskofier B M (2013), Hierarchical, Multi-Sensor Based Classification of Daily Life Activities: Comparison with State-of-the-art Algorithms Using a Benchmark Dataset. PLoS ONE. doi:10.1371/journal.pone.0013636.
6. Bouten C V, Westerterp K R, Verduin M (1994). Assessment of energy expenditure for physical activity using triaxial accelerometer. Med Sci Sports Exerc 26(12): 1516-1523.
7. Vathsangam H, Emken B A, Schroeder E T et al. (2010). Energy Estimation of Treadmill Walking using On-body Accelerometers and Gyroscopes. 32nd Annual International Conference of the IEEE EMBS, Buenos Aires, Argentina, 2010, pp 6497-6501.
8. Liu S, Gao R X, John D et al. (2012). Multisensor data fusion for physical activity assessment. IEEE Trans Biomed Eng 59(3): 687-696.
9. Hall D L, Llinas J (1997). An Introduction to Multisensor Data Fusion. Proceedings of IEEE 85(1): 6-23.
10. Schuldhaus D, Leutheuser H, Eskofier B M (2013). Classification of Daily Life Activities by Decision Level Fusion of Inertial Sensor Data, 8th International Conference on Body Area Networks, Boston, MA, 2013, accepted for publication.
11. Motl R W, Snook E M, Agiovlasitis S et al. (2009). Calibration of accelerometer output for ambulatory adults with multiple sclerosis. Arch Phys Med Rehabil 90: 1778-1784.
12. Theodoridis S, Koutroumbas K (2008). Pattern Recognition. Academic Press, San Diego, CA.
13. Smola A J, Schölkopf B (2004). A tutorial on support vector regression. Stat Comput 14: 199-222.
14. Breiman L (1984). Classification and regression trees. Chapman & Hall, London.
15. Montgomery D (2010). Applied statistics and probability for engineers. Wiley, Hoboken, NJ.
16. Heil D P (2006). Predicting Activity Energy Expenditure Using the Actical Activity Monitor. Res Q Exerc Sport 77(1): 64-80.