

Proceedings

Development of Calorie Tracking Algorithm for Children and Comparison with Commercialized Product [†]

Yongwon Jang ^{*}, Dae-Sik Lee and Seunghwan Kim

Electronics and Telecommunications Research Institute in Korea, Daejeon 34129, Korea;
dslee@etri.re.kr (D.-S.L.); skim@etri.re.kr (S.K.)

^{*} Correspondence: yongwon@etri.re.kr; Tel.: +82-42-860-6071

[†] Presented at the Eurosensors 2017 Conference, Paris, France, 3–6 September 2017.

Published: 17 August 2017

Abstract: In this study, we developed an appropriate calorie tracking algorithm for children and compared it with the current commercial product. The results of the developed algorithm showed 94.2% accuracy in the classification of intermittent activities: sitting down, standing up, turning around and jumping; and 92.9% accuracy in the classification of continuous activities: walking, running, stair climbing, and jumping rope. This comparison shows that the developed algorithm outperforms the commercialized one and shows it is suitable for actual use of children. This study provides new activity monitor algorithm for children's self-management.

Keywords: calorie tracking algorithm; activity monitor; children; comparison with commercialized product

1. Introduction

Recently, there has been a significant increase in obesity and overweight worldwide [1]. Since obese children are more likely to become obese as they become adults, it is important to prevent and manage obesity and overweight during the early age [2]. It is very difficult to lose weight with one's own will and it is especially hard to find children with strong will, so physical activity monitors help children to prevent and manage obesity and overweight. Currently, there are many commercialized calorie tracking devices, however, there are no devices for children. Most commercialized calorimeters are wrist-worn type which are not suitable for children due to the restrictions of data input such as age, height, and body weights.

In this study, we developed an algorithm which can be applied to waist-worn activity monitor devices suitable for children. Because it is important to capture both calorie assessment data and the type of activities in order to fully understand the child's daily activities. To ensure an effective result we have designed an algorithm for physical activity classification and calorie consumption assessment.

2. Materials and Methods

2.1. Materials

2.1.1. Participants and Ethics in Experiment

To develop the physical activity monitor, we recruited total 136 boys and girls to conduct an activity protocol consisting of a series of physical activities. All participants were Korean elementary school students who are eight to twelve years old (mean = 10.8, sd = 1.1).

The obtained data from the participants was used to develop algorithms that categorize physical activity and evaluate the calories consumed by physical activity. The clinical process of data collection

was approved by the institutional review board, and the recruited children agreed to participate in written form.

2.1.2. Equipments

The participants of data acquisition experiment performed a series of physical activity protocols, including movements such as sitting down, standing up, walking, running, and so on. Between protocols, each participant had two measurement device set on their body. The first device was a portable metabolic monitoring device called an indirect calorimeter (K4b2, Cosmed, Italy) [3]. It was utilized as a reference device for measuring energy consumption. The second device is a measuring module of acceleration signals generated by the attendee's body movements. It has customized design for this study which consists of three modules: wrists, waist and ankle. The picture of subject who wears both portable metabolic monitoring device and accelerometer system at the same time. The waist module attaches to the pants and for the wrists and ankles it is attached using Velcro strips. Each acceleration module is composed with 3-axis acceleration sensor, micro controller, memory chip and etc.



Figure 1. The picture of subject who wears both portable metabolic monitoring device and accelerometer system at the same time. (a) The reference device, portable metabolic analyzer, K4b2. (b) The devised 3-axis accelerometer system which is composed of 3 part module, waist, wrist and ankle.

2.2. Methods

While their performing the several physical activities in protocol, both worn systems recorded activity data. The devised three parts of 3-axis accelerometer modules acquired acceleration signals data to classify the physical activity type, and the indirect calorimeter stored user's burned calorie data to assess the energy expenditure due to physical activities. We extracted various feature candidates from acceleration signal data for a machine learning method and the effective features were chosen by the determination of cross-correlation between feature candidates and targets.

For this algorithm study, we adopted Artificial Neural Network (ANN) method which is one of the supervised machine learning algorithm to attain physical activity classification. We extracted and selected features from the physical activity data and made input patterns of the ANN for classification. The ANN determines what kind of physical activity is detected based on the input pattern. The ANN is composed of input layer, hidden layer with tangent sigmoid transfer function, and output layer with softmax transfer function. The overall algorithm has three different ANNs. Each three network was designed for four intermittent physical activity, four continuous activity, and calorie consumption estimation. The hidden layer's nodes were determined by examining the best performance among the various numbers of nodes. All data patterns were shuffled randomly and divided into three groups, those were training, validation, and test group, with the ratio of 70:15:15, respectively. Like the previous research [4], scaled conjugate gradient algorithm was used in the data group training for fast supervised learning. After each training session, we provided data of the verification group to the training network to see if network performance improved. The performance of trained network is defined here as a cross-entropy. The repetition of training and validation

process continued until the performance of the verification process deteriorated six consecutive times. Then the training process was over to prevent overfitted network.

3. Results

The physical activity monitor algorithm was developed based on artificial neural network which is one of the machine learning methods. It is capable to classify four types of intermittent activities and another four types of continuous activities. Tables 1 and 2 below shows the confusion matrices of intermittent and continuous physical activity classification result. As shown in Table 1, sitting, standing up, turning around, and jumping could be classified of an accuracy of 92.2%, 81.9%, 99.2% and 99.8% respectively. Overall accuracy was 95.3%. Table 2 shows the classification results of continuous activities such as walking, running, stairs climbing, and jumping rope. Each activity has an accuracy of 96.2%, 88.7%, 95.3%, and 90.6%, respectively. The overall accuracy is 93.0%.

Table 1. The result of classification for intermittent activities.

Network Output	Actual Activity (Target)			
	Sitting Down	Standing Up	Turning Around	Jumping
Sitting down	92.2%	13.0%	0.5%	0.2%
Standing up	5.5%	81.9%	0.3%	0.0%
Turning around	2.3%	4.9%	99.2%	0.0%
Jumping	0.0%	0.2%	0.1%	99.8%

* Overall accuracy is **95.3%**/* The sum of the column is 100%.

Table 2. The result of classification for continuous activities.

Network Output	Actual Activity (Target)			
	Walking	Running	Stairs Moving	Jumping Rope
Walking	96.2%	10.4%	0.0%	0.0%
Running	2.8%	88.7%	1.9%	1.9%
Stairs moving	0.9%	0.0%	95.3%	7.5%
Jumping rope	0.0%	0.9%	2.8%	90.6%

* Overall accuracy is **93.0%**/* The sum of the column is 100%.

The developed algorithm also provides the consumed calories for the four types of continuous physical activity. To demonstrate the validity of the developed algorithm, we compared it with the commercially available product, UP move™ (JAWBONE, USA). Thirty-one boys and girls who did not participate in the previous classification algorithm development session have participated for this experiment. They were equipped with an accelerometer device on their waist which was applied with the developed algorithm and a commercialized target device on their wrist. We compared the assessed calorie consumption results for walking fast and slow, running and jumping rope. Table 3 below shows that the developed algorithm outperforms the compared commercial product. Table 3 shows that the ratio of the result of developed algorithm to the reference value, that is β/α column, ranges 95.5% to 115.7%. On the other hand, the ratio of the result of commercialized product to the reference value, that is γ/α column, ranges 74.0% to 169.4%. These facts reveal that the commercialized product could not provide appropriate calorie estimation value to children and also imply that the dedicated device for children would be necessary.

Table 3. The result of comparison, developed algorithm VS UP move™ by JAWBONE.

Protocol	Item	Reference Value			Comparison with Commercialized Product							
		(K4b ² , Mean Value)			Result of Developed Algorithm				Result of UP Move™			
		¹ α	SD α	SD α / α	¹ β	² β / α	SD β	SD β / β	¹ γ	² γ / α	SD γ	SD γ / γ
	Walk slow	0.075	0.011	0.146	0.087	115.7%	0.043	0.494	0.127	169.4%	0.079	0.617
	Walk fast	0.093	0.017	0.183	0.090	97.3%	0.012	0.134	0.131	141.1%	0.079	0.605
	Run	0.157	0.025	0.157	0.150	95.5%	0.018	0.118	0.203	128.8%	0.203	0.699
	Jump rope	0.168	0.032	0.191	0.166	99.0%	0.051	0.307	0.124	74.0%	0.124	0.470

¹ The unit of α , β , γ is Cal/m/kg. ² Ratio to α (K4b²).

4. Discussion

The algorithm consists of three components: an intermittent activity classification, a continuous activity classification, and an evaluation of calorie consumption. These algorithmic components must be implemented with large algorithms for insertion into embedded systems. In addition, extraction and selected features should be minimized to reduce the load on signal processing while maintaining accuracy.

Table 3 shows the limit of the product that is commercialized. Commercialized products did not allow input age to be under 13 years old. The input range for height and weight was determined based on age 13 years or older. In the results of Table 3, the difference between the ratio of developed algorithm results to the reference value and the ratio of the value from the commercialized device to the reference value is clearly apparent. In some respects, differences can be created due to mismatches between participants and age inputs.

5. Conclusions

We developed three ANNs to classify the intermittent physical activities, the continuous physical activities, and the estimation of calorie consumption. Each network performed well and the overall accuracy was acceptable. The network developed for estimating calorie consumption was compared to commercialized devices and outperformed comparable devices.

The calorie consumption result of the developed algorithm was closer to the reference data from indirect calorimeter compared the result of the commercialized product.

Acknowledgments: This research was supported by the R&D Program for Society of the National Research Foundation (NRF) funded by the Ministry of Science, ICT & Future Planning(Grant number: NRF-2013M3C8A2A02078519).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. World Health Organization. Available online: <http://www.who.int/mediacentre/factsheets/fs311/en/> (accessed on 29 June 2017).
2. Serdula, M.K.; Ivery, D.; Coates, R.J.; Freedman, D.S.; Williamson, D.F.; Byers, T. Do Obese Children Become Obese Adults? A Review of the Literature. *Prev. Med.* **1993**, *22*, 167–177. doi:10.1006/pmed.1993.1014.
3. Cosmed Srl. Available online: <http://www.cosmed.it/en/products/cardio-pulmonary-exercise-testing/k4-b2-mobile-cpet> (accessed on 29 June 2017).
4. Møller, M.F. A scaled conjugate gradient algorithm for fast supervised learning. *Neural Netw.* **1993**, *6*, 525–533.



© 2017 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).