A Difference-Based Data Compression for Daily Activity Signals and Its Realization in an Embedded System

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Abstract - —*This paper presents a difference-based data compression algorithm for daily activity signals and its realization in an embedded system. Because daily activity signals have little variances between consecutive data samples, the proposed data compression algorithm compresses a sequence of digital numbers of daily activity signals into an initial value followed by a sequence of difference values. The proposed data compression algorithm had been realized in an embedded system. The realization of the proposed data compression algorithm utilized little hardware resources; only one buffer, one subtraction, one look-up table, and one encoding procedure were utilized. The effectiveness of the proposed data compression algorithm was validated by two experiments. For 11 different daily activities, the average data compression rates for the wrist sensor and ankle sensor were 58.16% and 52.50% respectively. For 24-hour daily activity signals, the data compression rates for the wrist sensor and the ankle sensor were 35.37% and 31.97% respectively.*

Keywords: Data compression; Accelerometer; Daily Activity

1 Introduction

Importance of daily activity monitoring has been gaining much attention in recent years due to the healthy activity styles could help us to increase our fitness levels, improve our health conditions, and prevent diseases [1]. Owing to the advances in the embedded system and sensing technology, accelerometer-based activity monitor were employed in the studies regarding to the quantification of daily activities such as sleep-wake period detection [2]-[4], daily activity detection [5]-[6], energy expenditure [7]-[8], and gait analysis [9]-[11]. From the aforementioned literature, the effectiveness of using accelerometer-based activity monitor has been validated. However, to widely promote the accelerometer-based activity monitor in the commercial market, there are still some technical problems needs to be solved. Hanson *et al.* concluded that the wireless communication, power saving, and data storage are the key factors of widespread adoptions of wearable sensors such as accelerometer-based activity monitor [12]. The issue of data storage became notable in the accelerometer-based activity monitor because large amount of data collected from accelerometer. For example, the data rate will reach up to 720bps and 62.2MB per day when it continuously works at 30Hz sample rate and 8 bits precision by 3 axes. The large amount of data causes the problem of high storage space requirement and high energy consumption. In our literature survey, the data compression of daily activity acceleration can be categorized into the implementing in the embedded system and simulating in the computer. In the field of implementing the data compression algorithms in the embedded system, Tanaka *et al.* employed Golomb-Rice coding in the data compression and reported that the compression rate is typically 30% [13]. Reinhardt *et al.* implemented run-length encoding (RLE) and adaptive Huffman coding (AHC) in an embedded system with tiny OS. Reinhardt *et al.* concluded that applying data compression may allow saving energy, even if additional microcontroller operations are required [14]. In the field of simulating data compression algorithms in the computer, Chen *et al.* employed wavelet transform and adaptive differential pulse code modulation (ADPCM) to compress running and sprinting data sets. The data compression rate in Chen *et al.*'s study is around 40%~50% [6]. Yang *et al.* examined the performance of the state of art compression scheme: the compressed sensing (C-S) framework. The experimental results showed that the C-S framework could effectively reduce the amount of data [14]. Although the state-of-art data compression algorithms such as the wavelet and the C-S compression can provide satisfactory data compression results, to implement those data compression algorithms in an embedded system is a problem due to the limited computing power of the embedded systems. Therefore, this paper aims at developing a hardware-friendly data compression algorithm for daily activity signals that can be easily implemented in the embedded system.

The rest of this paper is organized as follows. In Section 2, we present the hardware platform employed in our daily activity acceleration collection and data compression. In Section 3, the proposed data compression algorithm for daily activity signals is introduced. The results of simulation and hardware implementation of the proposed data compression algorithm are reported in Section 4. Finally, conclusions are given in Section 5.

2 iHelath daily acceleration sensor

A portable embedded system which is responsible for collecting signals and executing data compression called "iHealth daily acceleration sensor" is introduced in this section. The iHealth daily activity acceleration sensor is responsible for collecting signals and executing data compression algorithm in our study. The hardware block diagram of the iHealth daily acceleration sensor is shown in Fig. 1. The hardware consists of a microcontroller (PIC24FJ64GA002), a triaxial accelerometer (MMA7455L), a flash memory (MX25L128), a wireless RF transceiver (Nordic nRF24L01+), a Bluetooth® module (BTM-162), and a power management IC (LTC4063). The sampling rate of the iHealth daily acceleration sensor is 30Hz (f_s = 30Hz), and the signals data are stored in a flash memory with an 8-bit format (Sensitivity: ±8g). The circuit size of the iHealth daily acceleration sensor is 32mm × 30mm × 5mm. The circuit board of the iHealth daily acceleration sensor is enclosed by a case which can be worn on subjects' wrists and ankles to collect the daily activity signals.

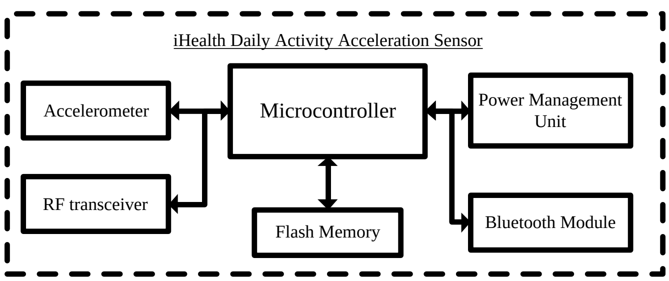

Fig. 1. Block Diagram of iHealth daily acceleration sensor

3 Difference-based data compression algorithm for daily activity signals

In this section, the proposed difference-based data compression algorithm for daily activity signals will be introduced. We will first analyze the characteristics of daily activity signals in Subsection 3.1. In Subsection 3.2, a block diagram of the proposed data compression algorithm will be introduced to explain the detailed procedures. The realization of the differenced-based data compression algorithm for daily activity signals is explained in Subsection 3.3.

3.1 Characteristics of daily activity signals

Daily activities can generate signals during the movement and can be collected by accelerometers. Commercial accelerometers commonly use number of bits to represent the signals they generate in an interval. For example, the sensor described in section 2 generates signals in an 8-bit format to represent signals in an interval (±2g, ±4g or ±8g, user-specified).

The characteristics of daily activity signals are associated with the types of activities. Daily activities can be categorized into four levels: sedentary, light, moderate and vigorous [16]. Signals of the four levels of daily activities exhibit various characteristics, having little variance in sedentary and light activities while varying a lot in moderate and severe activities. However, sedentary and light activities account for the main proportion of a day. Therefore, the proposed difference-based data compression algorithm aims at using less data to represent the sedentary/light daily activities, and further reduce the data size of all-day activity signals.

Table I. Percentage of the Successive data difference smaller than 1 unit in all-day Activity signals

Sensor Placement	**Axis**	**Successive Data Difference (bit)**	**Percentage (%)**
Wrist	*x*-axis	0	55.14
		1	14.33
		-1	14.32
	y-axis	0	61.24
		1	13.26
		-1	13.27
	z-axis	0	58.26
		1	14.82
		-1	14.87
Average (Wrist)		**0**	**58.35**
		1	**14.14**
		-1	**14.15**
Ankle	*x*-axis	0	69.96
		1	9.76
		-1	9.78
	y-axis	0	71.06
		1	9.76
		-1	9.59
	z-axis	0	66.64
		1	12.36
		-1	12.32
Average (Ankle)		**0**	**69.22**
		1	**10.62**
		-1	**10.56**

3.2 Difference-based data compression algorithm

Based on the characteristics observed in all-day activity signals, Table I reveals the percentage of successive data difference in 0, +1, -1 is 58.35%, 14.14% and 14.15% respectively (sensor worn on the wrist), and those on the ankle were 69.22%, 10.62% and 10.56% respectively.

In order to achieve the goal of data compression, we proposed a difference-based data compression algorithm of daily activity signals. Originally, a series of signals are represented by a sequence of digital numbers (8-bit digital number in our study). In the proposed algorithm, a sequence of digital numbers is transformed into an initial value followed a sequence of difference values. Based on the statistical analysis in Table I, the data difference of 0, 1, and -1 accounted for 86.64% and 90.41% in the wrist and the ankle for all-day data respectively. The proposed data compression algorithm uses digital number $(11)_2$, $(10)_2$, $(01)_2$ to denote the successive difference in 0, 1, and -1 respectively. When the data difference greater or smaller than 1 bit, the difference-based data compression algorithm will give a digital number

$(00)_2$, and then we have to put the original value of the acceleration data behind the digital number $(00)_2$. Block diagram of and one example of the proposed difference-based data compression algorithm are shown in Table II and Table III.

3.3 Embedded System Realization of the Difference-based Data Compression Algorithm for Daily Activity Signals

The proposed difference-based data compression algorithm for daily activity signals had been realized as a firmware program in the hardware platform mentioned in the Section 2. The proposed data compression algorithm utilized little hardware resource in the embedded system; only one buffer, one subtraction, one look-up table, and one encoding procedure were utilized.

Table II. Definitions of the operation code in the proposed data compression scheme

d_i	Relations	O_i = OP + INF
0	Current acceleration is equal to previous acceleration	$(11)_2$
1	Current acceleration is greater than previous acceleration in 1 unit	$(10)_2$
-1	Current acceleration is greater than previous acceleration in 1 unit	$(01)_2$
Else	Current acceleration is greater or smaller than previous acceleration in more than 1 unit	$(00)_2 + a_i$

Table III. An example of the proposed difference-based data compression algorithm

i	a_i	d_i	O_i = OP + INF
1	$(00000000)_2$	0	$(11)_2$
2	$(00000001)_2$	1	$(10)_2$
3	$(00000010)_2$	1	$(10)_2$
4	$(00000010)_2$	0	$(11)_2$
5	$(11111010)_2$	Else	$(00)_2 + (11111010)_2$
6	$(11111001)_2$	-1	$(01)_2$
7	$(00000000)_2$	Else	$(00)_2 + (00000000)_2$
8	$(00000001)_2$	1	$(10)_2$
9	$(00000001)_2$	0	$(11)_2$
10	$(11111001)_2$	Else	$(00)_2 + (11111001)_2$

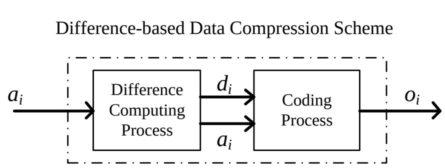

Fig. 2. Block diagram of the difference-based data compression algorithm

4 Experimental results

The effectiveness of the proposed difference-based data compression algorithm was evaluated in two different experiments. The first experiment was to examine the data compression rate in 11 different activities. The second experiment was to evaluate the data compression rate of the signals from subjects in a 24-hour period. The data compression rate in our experiment is defined as (1).

$$\text{Recogtion Rate} = \frac{\text{Compressed Size}}{\text{Original Size}} \times 100\% \qquad (1)$$

4.1 Data compression rate of daily activity accelerations

In our first experiment, the effectiveness of the proposed data compression algorithm for daily activity signals was examined. Total 18 subjects participated in this experiment; they were asked to collect their daily activity signals. All subjects were asked to conduct 11 different types of daily activities. During the experiment, the subjects were asked to wear two acceleration sensors mentioned in Section II. After all subjects performed the assigned daily activities, the signals were processed by the proposed differenced-based data compression algorithm. The data compression rates of different daily activities are shown in Table IV. There were two different data compression rate corresponding to the signals measured by the wrist activities and ankle activities. For the 11 daily activities, the data compression rates ranged from 25.07% to 101.63% for the wrist sensor, and 25.23% to 111.38% for the ankle sensor. The average data compression rate of 11 daily activities was 58.16% (wrist) and 52.50% (ankles). The results showed that the proposed data compression algorithm achieved a satisfactory performance in the sedentary and light level activities, such as sit and walking, whereas yielded a poor performance in the moderate and severe level activities, such as walking downstairs and running. However, the proposed data compression algorithm still improves the data compression rate of 24-hour daily activity signals since sedentary and light activities are accounted for most of the day.

4.2 Data Compression Rate in Daily Condition

In addition to compute the data compression rates of the 11 daily activities, we also asked the subjects to wear the acceleration sensors and did their daily activities as usual to examine the effectiveness of the proposed data compression algorithm in the daily condition. The signals were processed by the proposed data compression algorithm in the embedded system and the results are shown in Table V. The average data compression rate is 35.37%/31.97% in the wrist/ankle sensor respectively.

TABLE IV. Data compression rate of different activities

Activity Types	Data Compression Rate (%)	
	Wrist	**Ankle**
Sit	25.07	25.66
Washing Dishes	46.45	25.23
House Work	67.03	26.49
Cleaning Tables	50.88	43.38
Walking	55.73	93.82
Vacumming	61.41	32.59
Mopping	69.05	30.21
Upstairs	46.82	68.56
Downstairs	69.21	94.98
Running	101.63	111.38
Bicycling	46.45	25.23
Average Data Compression Rate	**58.16**	**52.50**

TABLE V. Data compression rate of 24-hour daily activity signals

Subject	Data Compression Rate (%)	
	Wrist	**Ankle**
Average of Data Compression Rate	35.37	31.97

5 Conclusions and future works

Development of a difference-based data compression algorithm for daily activity signals its realization in the embedded system was proposed in this paper. Originally, a series of signals is represented by a sequence of digital numbers (8-bit digital number in our study). In our difference-based data compression algorithm, a sequence of digital numbers is transformed into an initial value followed by a sequence of difference values. The proposed data compression algorithm had been realized in the embedded system and only utilized little hardware resource. The effectiveness of the proposed data compression algorithm was validated by two experiments. For the 11 daily activities, the average data compression rates for the wrist sensor and ankle sensor were 58.16% and 52.50% respectively. For the 24-hour daily activity signals, the data compression rates for the wrist sensor and the ankle sensor were 35.37% and 31.97% respectively. The existing drawback in the data compression of moderate and severe daily activity signals will be further investigated in our future work.

6 References

[1] http://www.americanheart.org/presenter.jhtml?identifier=4563

[2] M. Enomoto, T. Endo, K. Suenaga, N. Miura, Y. Nakano, S. Kohtoh, Y. Taguchi, S. Aritake, S. Higuchi, and M. Matsuura, “Newly developed waist actigraphy and its sleep/wake scoring algorithm”; Sleep and Biological Rhythms, vol. 7, 17—22, 2009.

[3] J. Tilmanne, J. Urbain, M. V. Kothare, A. V. Wouwer, and S. V. Kothare, “Algorithms for sleep-wake identification using actigraphy: a comparative study and new results”; Journal of Sleep Research, vol. 18, 85—98, 2009.

[4] P. Dürr, W. Karlen, J. Guignard, C. Mattiussi, and D. Floreano, “Evolutionary selection of features for neural sleep/wake discrimination”; Journal of Artificial Evolution and Applications, vol. 2009, 1—9, 2009.

[5] Y. P. Chen, J. Y. Yang, S. N. Liou, G. Y. Lee, and J. S. Wang, “Online classifier construction algorithm for human motion detection using an accelerometer”; Applied Mathematics and Computation, vol. 205, 849—860, 2008.

[6] J. Y. Yang, J. S. Wang and Y. P. Chen, “Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers”; Pattern Recognition Letters, vol. 29, 2213—2220, 2008.

[7] M. P. Rothney, E. V. Schaefer, M. M. Neumann, L. Choi, K. Y. Chen, “Validity of physical activity intensity predictions by Actigraph, Actical, and RT3 Accelerometers”; Obesity Society, vol. 16, 1946—1952, 2008.

[8] S. E. Crouter, J. R. Churilla, D. R. Bassett Jr, “Estimating energy expenditure using accelerometers”; Eur. Journal of Applied Physiology, vol. 98, 601—612, 2006.

[9] A. Salarian, H. Russmann, F. J. G. Vingerhoets, C. Dehollain, Y. Blanc, P. R. Burkhard, and K. Aminian, “Gait assessment in Parkinson’s disease: toward an ambulatory system for long-term monitoring”; IEEE Transactions on Biomedical Engineering, vol. 51, 1434—1443, 2004.

[10] M. S. Angelo, M. Chiara, S. Sergio, and C. Filippo, “Assessment of walking features from foot inertial sensing”; IEEE Transactions on Biomedical Engineering, vol. 51, 486—494, 2005.

[11] H. K. Lee, J. You, S. P. Cho, S. J. Hwang, D. R. Lee, Y. H. Kim, and K. J. Lee, “Computational methods to detect step events for normal and pathological gait evaluation using accelerometer”; Electronics Letters, vol. 46, 1185—1187, 2010.

[12] M. A. Hanson, H. C. Powell Jr., A. T. Barth, K. Ringgenberg, B. H. Calhoun, J. H. Aylor, and J. Lach, “Body area sensor networks: challenges and opportunities”; Computer, vol. 42, 58—65, 2009.

[13] T. Tanaka, S. Yamashita, K. Aiki, H. Kuriyama, and K. Yano, “Life Microscope: Continuous daily-activity recording system with tiny wireless sensor”; in Proc. Networked Sensing Systems, 162—165, 2008.

[14] Andreas Reinhardt, Delphine Christin, Matthias Hollick, Ralf Steinmetz, “On the energy efficiency of lossless data compression in wireless sensor networks”; in Proc. of the 4th IEEE International orkshop on Practical Issues in Building Sensor Network Applications, 873—880, 2009.

[15] S. Yang and M. Gerla, “Energy-efficient accelerometer data transfer for human body movement studies”; in 2010 IEEE Int. Conf. on Sensor Networks, Ubiquitous, and Trustworthy Computing, 304—311, 2010.

[16] B. E. Ainsworth, W. L. Haskell, M. C. Whitt, W. L. Irwin, A. M. Swartz, S. J. Strath, W. L. O'Brien, D. R. Bassett, K. H. Schmitz, P. O. Emplaincourt, D. R. Jacobs, A. S. Leon, “Compendium of physical activities: an update of activity codes and MET intensities”; Medicine and Science in Sports and Exercise, vol. 32, S498—504, 2000.