A 15-μA Metabolic Equivalents Monitoring System using Adaptive Acceleration Sampling and Normally Off Computing

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***Abstract*— This paper describes a low-power metabolic equivalents (METs) estimation method for monitoring physical activity. Long-term continuous METs monitoring can contribute to detection of non-communicable diseases. The proposed system consists of dedicated METs estimation hardware and a non-volatile CPU. A test is fabricated in a 130-nm CMOS with a ferroelectric capacitor process. Evaluation results show that the proposed system, which consists of the test chip and an accelerometer, requires about 15-μA on average.**

Keywords—acceleration; adaptive sampling; normally off computing; physical activity; metabolic equivalents; wearable

I. INTRODUCTION

Increasing medical costs related to the global prevalence of non-communicable diseases (NCDs) has come to be a severe issue worldwide. Reportedly, 38 million people die each year from NCDs, the four main types of which are diabetes, cancers, cardiovascular diseases, and chronic respiratory diseases.

Proper daily exercise and physical activity are important means of mitigating or forestalling NCDs. For efficient management of exercise, recording daily physical information and analyzing it in real time are important. Wearable devices are a convenient means for individuals to monitor and recognize physical activity (PA).

Because users presumably wear devices for a long time in their daily lives, the devices should be small, with low power consumption. Battery weight is a dominant characteristic of wearable devices. Therefore, this study was undertaken to develop a low-power device for use in long-term physical activity (PA) intensity estimation.

II. METABOLIC EQUIVALENTS ESTIMATION FOR PHYSICAL ACTIVITY MONITORING

This section introduces a PA estimation algorithm and method for reducing power consumption.

Metabolic equivalents (METs) values have been widely used as indicators to quantify PA intensity. The METs value is the amount of oxygen consumed at rest. In fact, 1 MET is expressed as follows [1].

$$1 \text{ MET} = 3.5 \text{ ml } O_2/\text{kg/min}$$

The amount of oxygen uptake at rest must be measured to obtain an accurate METs value. However, the method of gathering exhaled gases is too stressful to continue measurements over long periods. Therefore, the method of estimating METs values using a triaxial accelerometer has been developed as a less burdensome measurement method [2].

A. METs estimation algorithm

Recent studies have showed the METs estimating approaches using linear regressions, which are complex to develop on a hardware circuit. Carneiro et al. [3] compared two linear regressions models, one using speed, and the other using the feature root mean square(fRMS) of the magnitude of the triaxial accelerations. This supposes using the accelerometer of the smartphone, so does not focusing on hardware processing. Other study by Delgado-Gonzalo et al. [4] sets constant METs value at non-rhythmic activities such as resting situation, and use a multi-linear regression for walking and running situation. However, it does not exhibit much more detailed METs estimation. Mortazavi et al. [5] designed different regression model for each activity in exergaming, but this is also expecting for software processing. Thus, there are hardly METs estimation methods considering hardware processing.

Fig. 1 presents a flow chart of our proposed METs estimation method. First, the acceleration of each axis from the accelerometer is passed through a Butterworth filter (high-pass filter) with 0.7-Hz cut-off frequency to eliminate the acceleration of gravity. Next, the synthetic acceleration (vector magnitude: $\sqrt{x^2 + y^2 + z^2}$) is calculated from each high-pass filter output. Then METs is calculated from the average value of the synthetic acceleration in 10 s duration [2]. Here, ACC_i denotes the mean value of synthetic acceleration for the 10 s

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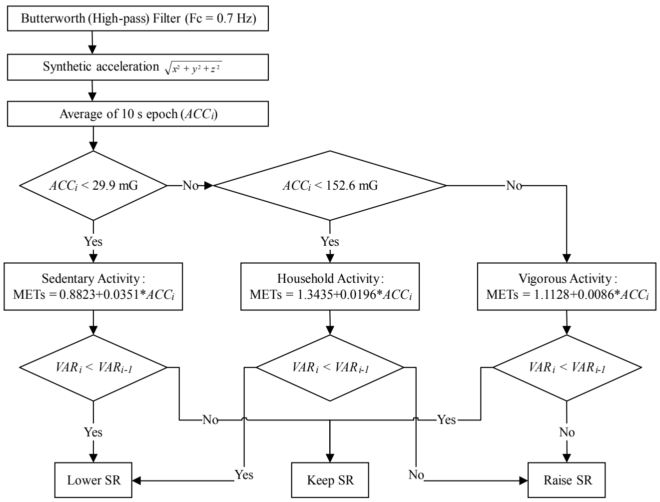


Fig. 1. Flow chart of proposed METs estimation algorithm.

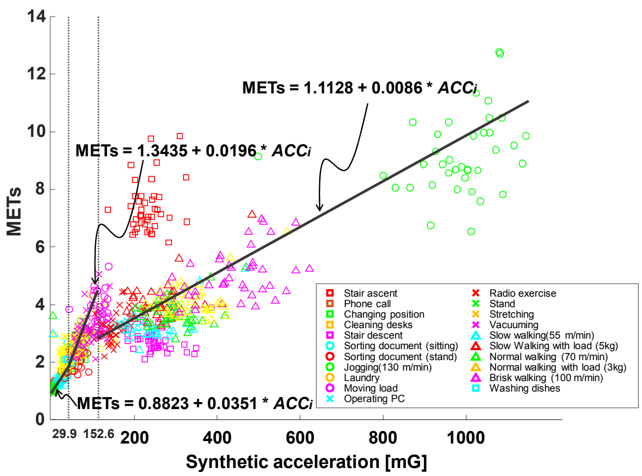


Fig. 2. Relation between measured synthetic acceleration and METs. METs is calculated from measured VCO_2.

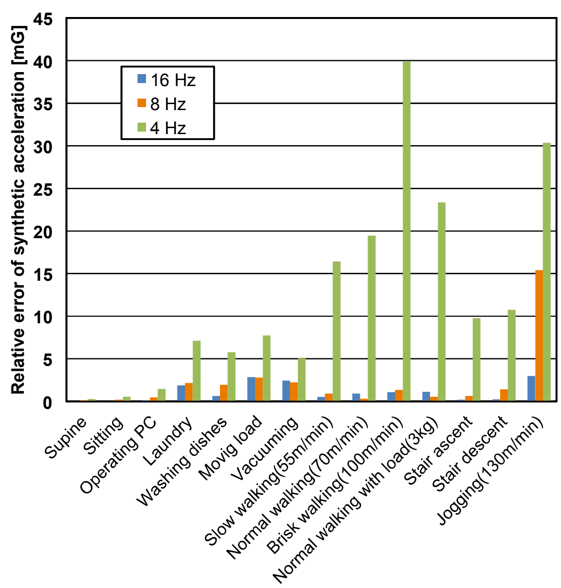


Fig. 3. Relative error of synthetic acceleration compared with 32-Hz fixed sampling rate in each activity.

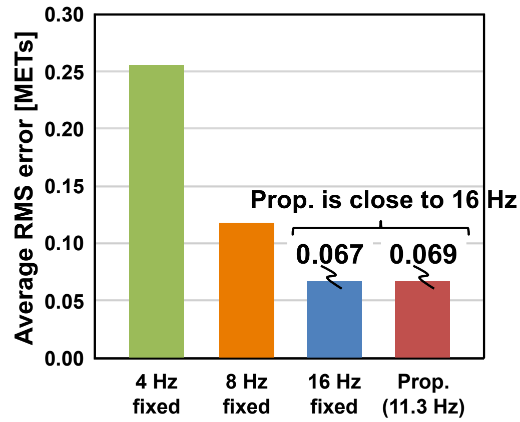


Fig.4. Average root-mean-squared error of METs with proposed algorithm and at fixed rates, compared with METs values at 32-Hz fixed rate. METs are calculated from 24-hour acceleration data of six subjects.

epoch. VAR_i denotes the variance of the synthetic acceleration in the same 10 s epoch [7].

Fig. 2 shows the relation of the measured METs and acceleration of 42 volunteer participants. The participants performed 23 distinct activities including a rest position. The METs value is estimated accurately from VO_2 and VCO_2 using Weir's equation [6]. All procedures involving human subjects were approved by an ethical committee. These measurements were taken according to the guidelines laid down in the Declaration of Helsinki. As presented in Fig. 2, three METs estimated equations were used because the suitable METs equation depends on the range of the synthetic acceleration.

B. Adaptive Sampling

Although the conventional method [2] used a fixed sampling rate of 32 Hz, it entails constant power consumption. In our previous work [7], we proposed an adaptive acceleration sampling method to reduce the average power consumption without degrading the estimation accuracy. In this work, we implemented this algorithm as dedicated hardware for METs estimation.

If the PA intensity is low, the lower sampling rate is acceptable, as depicted in Fig. 3. This result indicates that a 16-Hz fixed sampling rate can achieve less than 5-mG relative error compared with 32-Hz sampling rate. In this paper, we consider the results at 32 Hz as reference values whenever we calculate relative errors. 5-mG error is sufficient for METs estimation. The 8-Hz sampling rate has the same accuracy without jogging. When the subject is in a resting condition, a 4-Hz sampling rate is sufficient. According to this result, we introduced the adaptive sampling rate to reduce the average sampling rate.

As presented in Fig. 1, the sampling rate is chosen automatically according to the past synthetic acceleration. The values of ACC_i, VAR_i, and VAR_{i-1} determine whether the system raises, lowers, or maintains the sampling rate for the subsequent 10 s. The threshold is determined by the measurement value of the acceleration and the METs, which are presented in Fig. 2.

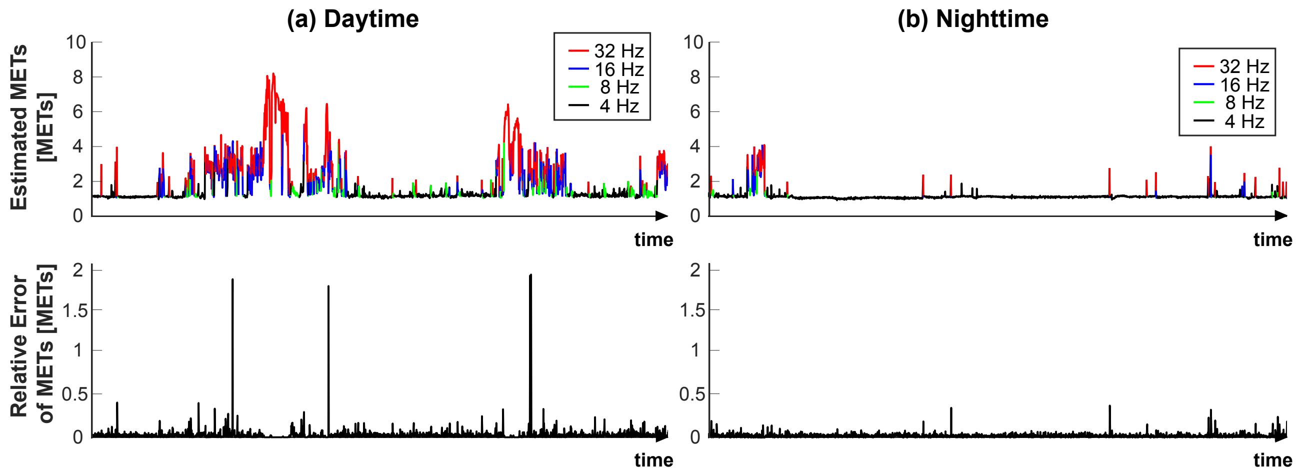


Fig. 5. Estimated METs and relative error from long-term measured acceleration using adaptive sampling: (a) in daytime and (b) at nighttime.

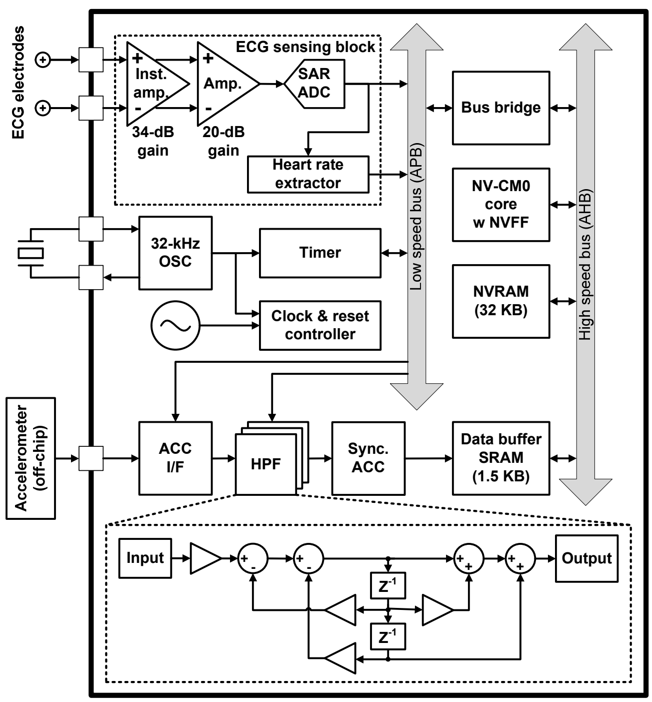
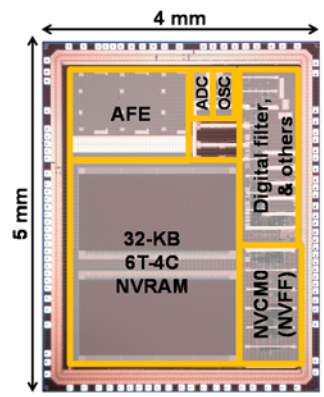


Fig. 6. Block diagram of the proposed METs estimation device.



Technology		0.13 μm CMOS
Supply voltage		1.2 V (AFE, ADC, Logic, Mem.)
		3.0 V (32.768-kHz OSC, I/O)
Chip area		4x5 mm²
Frequency		24 MHz (for processor)
		32 kHz (for other blocks)
Processor		32-bit Cortex M0 (with NVFF)
On chip memory		32-KByte 6T-4C NVRAM
AFE	Gain	54 dB
	Bandwidth	700 Hz
	CMRR	73 dB
ADC	Resolution	8 bit
	Current	0.23 μA@128 S/s, 1.0 μA@1 kS/s

Fig. 7. Test chip micrograph and specifications.

This algorithm is evaluated using long-term measurement data. For the experiment, six participants (ages 21–25 yr; 4 men, 2 women) spent a day wearing the triaxial accelerometer at the waist. For these measurements, the resolution of the measured acceleration is 10 bit.

To evaluate the accuracy, the METs value is calculated from measurements using the proposed adaptive sampling rate and fixed rates. Fig. 4 portrays the evaluation results of root mean squared (RMS) error. Here, the METs estimation result with a 32-Hz fixed sampling rate is used as the reference value. This result demonstrates that the proposed algorithm achieves almost identical RMS error compared with the 16-Hz fixed sampling rate, although the average sampling rate of the proposed method is only 11.3 Hz. In the proposed method, the usage rates of the sampling rates at 32 Hz, 16 Hz, 8 Hz, and 4 Hz are, respectively, 17.1%, 13.4%, 21.4%, and 48.1%.

Fig. 5 portrays examples of METs estimation results obtained using adaptive sampling from long-term (24 hours) continuous measured acceleration data in daily life. The sampling rate decreased when the physical activity was low, especially at nighttime.

III. Hardware Implementation

A. Architecture

To implement METs estimation with the adaptive sampling algorithm into a small and low-power sensor device, we introduced a non-volatile CPU [8]. The non-volatile CPU, which consists of a non-volatile memory and a non-volatile flip-flop based on a ferroelectric capacitor, can retain data of memory and registers, when its power source is gated. The power gating is an effective power reduction approach for biosignal monitoring because the biosignal including acceleration has very low frequency compared with CPU. Generally, the active rate of the CPU is less than 0.1 % in this application.

Fig. 6 presents a block diagram representing the proposed device. As described in Section II, the sampling rate of the

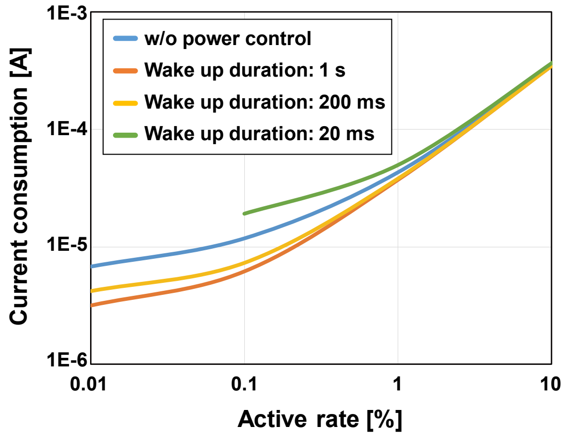


Fig. 8. Current consunption of non-volatile CPU.

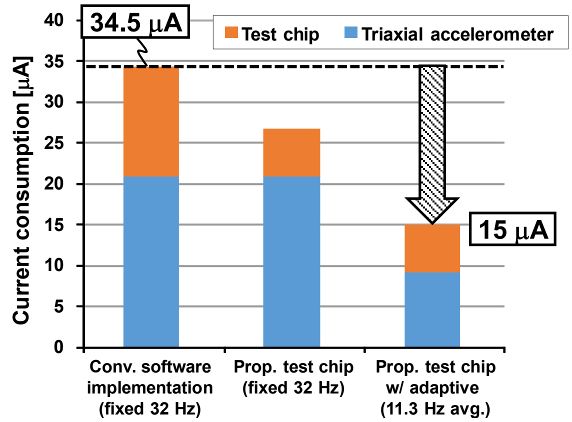


Fig. 9. System-level total current consumption.

accelerometer can be reduced using the adaptive sampling method. Furthermore, we implemented this algorithm as dedicated hardware to reduce the power consumption. In our implementation, the high-pass filter, the synthetic acceleration block, and data buffer are implemented as hardware. The data buffer is connected to a high speed bus (AHB). An interrupt signal is generated from a timer to wake up the CPU every 10 s. The CPU calculates the METs value from 10 s epoch data. Then, the next sampling rate and filter coefficients are decided by the CPU. The registers of the accelerometer interface are updated. For the rest of the time, the CPU is in a deep sleep state. Its power source is gated.

These normally off computing approaches also contribute to minimization of the active rate. The implementation result shows that the active rate of CPU is reduced from 2.65% to 0.08%. The estimated overhead of digital circuits is less than 1 μA.

B. Implementation result

To demonstrate the performance of the proposed system, a test chip was fabricated in a 130-nm CMOS with a ferroelectric capacitor process. Fig. 7 presents a chip micrograph and specifications.

Fig. 8 shows the measured current consumption of the non-volatile CPU. As presented in Fig. 8, both the active rate and the duration of wake up time contribute to power dissipation. In other words, signal processing should be merged as much as possible to reduce the CPU power. The dedicated METs estimation hardware and data buffer contribute respectively to reduction of the active rate and to increased wake up duration.

Fig. 9 shows the total power consumption of the proposed system, which consists of the test chip and an accelerometer (KX022; Kionix Inc.). When the entire METs estimation algorithm is implemented in the software, the total power consumption is 34.5 μA, on average. The measurement result shows that this power dissipation can be reduced to 15 μA on average using the adaptive sampling algorithm and its hardware implementation.

IV. Conclusion

We proposed a low-power METs estimation system. In the conventional implementation, the accelerometer and the CPU block require large amounts of power. The active power consumption of the accelerometer is reduced using the adaptive sampling method. Furthermore, we implemented the METs estimation algorithm as dedicated hardware to reduce the active power consumption of the CPU. In addition, a non-volatile CPU is used to reduce the stand-by power consumption.

Because the frequency range of the biosignal is sufficiently low compared with the operating frequency of the CPU, normally off computing using non-volatile circuit is effective for overall power reduction. The test chip is fabricated in a 130-nm process. Evaluation results calculated from measured acceleration in daily life show that the proposed system consumes about 15-μA on average.

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