# Development and Evaluation of a Wearable Device for Sleep Quality Assessment

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***Abstract*—*Objective:*** **In this study, a wearable actigraphy recording device with low sampling rate (1 Hz) for power saving and data reduction and a high accuracy wake-sleep scoring method for the assessment of sleep were developed.** ***Methods:*** **The developed actigraphy recorder was successfully applied to overnight recordings of 81 subjects with simultaneous polysomnography (PSG) measurements. The total length of recording reached 639.8 h. A wake-sleep scoring method based on the concept of movement density evaluation and adaptive windowing was proposed. Data from subjects with good ($N = 43$) and poor ($N = 16$) sleep efficiency (SE) in the range of 52.7–97.42% were used for testing. The Bland–Altman technique was used to evaluate the concordance of various sleep measurements between the manual PSG scoring and the proposed actigraphy method.** ***Results:*** **For wake-sleep staging, the average accuracy, sensitivity, specificity, and kappa coefficient of the proposed system were 92.16%, 95.02%, 71.30%, and 0.64, respectively. For the assessment of SE, the accuracy of classifying the subject with good or poor SE reached 91.53%. The mean biases of SE, sleep onset time, wake after sleep onset, and total sleep time were −0.95%, 0.74 min, 2.84 min, and −4.3 min, respectively.** ***Conclusion:*** **These experimental results demonstrate the robustness and reliability of our method using limited activity information to estimate wake-sleep stages during overnight recordings.** ***Significance:*** **The results suggest that the proposed wearable actigraphy system is practical for the in-home screening of objective sleep measurements and objective evaluation of sleep improvement after treatment.**

***Index Terms*—Actigraphy, objective sleep measurements, sleep efficiency (SE), wake-sleep scoring, wearable devices.**

Manuscript received December 3, 2015; revised March 18, 2016 and August 5, 2016; accepted September 12, 2016. Date of publication September 23, 2016; date of current version June 15, 2017. This work was supported in part by project grants from the National Science Council (Grant NSC 100-2410-H-006-025-MY3 and Grant NSC 103-2811-H-006-006) and in part by the Ministry of Science and Technology (Grant MOST 105-2221-E-006-221). *Asterisk indicates corresponding author.*

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Digital Object Identifier 10.1109/TBME.2016.2612938

## I. Introduction

SLEEP plays an important role in the daily activities of humans, and sleep disorders seriously affect quality of life. For example, insomnia promotes difficulty in initiating and/or maintaining sleep, followed by nonrestorative sleep, and it is associated with impairments of daytime functioning or significant distress [1]–[3]. To investigate the cause of insomnia and other sleep disorders, it is necessary to record/monitor the sleep of affected patients and analyze the recorded data.

Traditionally, a polysomnography (PSG) is used for sleep monitoring; this approach includes an electroencephalogram (EEG), electrooculogram (EOG), electrotromyogram (EMG), and electrocardiogram. The results of PSG measurement are well accepted in sleep studies. However, to conduct sleep monitoring, the subject must stay in a sleep laboratory and place electrodes on his/her head and body, with wires connecting the electrodes and expensive, bulky monitoring equipment. The inconvenience of the wires and the unfamiliar environment make the subjects feel uncomfortable, which could have an impact on the results of the sleep measurements. Therefore, PSG is not recommended for the clinical evaluation of insomnia unless another sleep disorder is suspected [4].

To solve this problem, several wireless portable PSG systems have been developed [5], [6]. However, these devices are still not self-applicable by a user at home. The design of sleep monitoring systems should consider the ease of use and the comfort of wearing the system. Over the past two decades, a type of sensor placement system [7], [8], actigraphy, has become a way to assess acceptable and an accessible tool in sleep research and sleep medicine. It has been recommended as an option but not as part of a standard insomnia research [4]. Several algorithms have also been proposed to automatically identify sleep and wake periods using actigraphy [9–15]. There are different commercial devices on the market, and each device has its own measurement characteristics and, therefore, requires appropriate sleep-wake scoring algorithms and validation studies.

Previous work has established the reliability and validity of actigraphy in sleep-wake detection, especially in normal populations of infants, children, and adults [16]–[20]. However, the validity of actigraphy in special populations, such as individuals with other sleep-related disorders, is more questionable [13], [14]. The most problematic validity issue is the low specificity of actigraphy in detecting wakefulness within sleep periods. Moreover, the actigraph recorder with lower sampling

rate for power saving and a high accuracy of the corresponding sleep-wake staging method based on less recorded data should be considered for the application of long-term sleep measurements.

In this study, a wrist actigraphy recorder, integrated with a microelectromechanical system (MEMS), a three-axis accelerometer, and a novel adaptive window-based sleep-wake staging algorithm, was developed for sleep measurement [21]. To develop and evaluate the wrist-watch actigraphy recorder as well as the sleep-wake staging algorithm, a total of 81 subjects, including 56 subjects with good sleep efficiency (SE) (SE $\geqq$ 85%) and 25 subjects with poor SE (SE $<$ 85%), were monitored and recorded by the PSG and the developed actigraphy recorder simultaneously for at least 8 h of sleep overnight. The overall agreement and the concordance of various sleep measurements between the manual PSG scoring and the proposed actigraphy method were evaluated. The aim of this study was to develop a hardware and software integration system that had good performance for both wake-sleep staging and assessment of sleep measurements with low data rates for long-term monitoring. Success of this study will benefit in-home screening of sleep measurements, insomnia diagnosis and as well as research, the objective evaluation of sleep improvement after treatment.

## II. Materials

### A. Subjects and Recordings

To develop and evaluate the proposed sleep-wake staging system, the PSG (Siesta 802 PSG, Compumedics, Inc.) and the developed actigraph recorder were mounted on each subject for simultaneous overnight recording. There were 81 participants recruited for our experiments (47 males and 34 females, ranging in age from 20 to 60 years), including 56 subjects with good SE and 25 subjects with poor SE. Each subject contributed a night's PSG recording for only one night (i.e., a total of 81 PSG recordings), and the total length of the recording data was 639.8 h. These measurements were approved by the internal review board of the National Cheng Kung University. Subjects were first recruited by online advertisements and announcements on notice boards at the National Cheng Kung University. Participants were required to refrain from any drugs/medication and limit caffeine use (no caffeine intake for at least 5–6 h prior to sleep laboratory visits). The all-night PSGs were recorded in the sleep laboratory at the cognitive institute of the National Cheng Kung University. There was no outside interference during data collection, and no medications were used to induce sleep.

The PSG recordings contained six EEG channels (C3-M2, C4-M1, F3-M2, F4-M1, P3-M1, and P4-M1, according to the international 10–20 standard system, with the M1 and M2 electrodes placed on the left and right ear lobes), two EOG channels (above the right and below the left outer canthus) and a chin electrotromyogram (EMG) channel. The sampling rate was 256 Hz with 16-bit resolution. The filter settings of the cutoff frequencies were 0.5–30 Hz for EEG/EOG and 5–100 Hz for EMG. The signals of C3-M2, C4-M1, two EOGs, and a chin EMG were used for manual scoring. The developed actigraphy recorder was worn on the subjects' left wrist. All 81 PSG sleep recordings were visually scored by a sleep specialist (who had over 800-h experience in PSG recording and scoring) using the Rechtschaffen and Kales (R&K) [22] rules with a 30-s interval (named an epoch). In this study, data from 13 subjects with good SE (SE $\geqq$ 85%) and nine subjects with poor SE (SE $<$ 85%) were used as the training data to develop the sleep-wake scoring algorithm, and data from the remaining subjects were used for performance evaluation.

TABLE I
Basic Subject Demographics Including Gender, Age, SEs, SOTs, WASOs, and TSTs

| | Group with good SE ($N = 56$) | Group with poor SE ($N = 25$) | Total ($N = 81$) |
|---|---|---|---|
| Gender (males /females) | 57%(32)/ 43%(24) | 60%(15)/ 40%(10) | 58%(47)/ 42%(34) |
| Age (mean ± sd) | 28.3 ± 3.74 | 28.76 ± 8.53 | 28.44 ± 5.81 |
| Sleep efficiency (mean ± SD (%)) | 92.62 ± 2.9 | 74.48 ± 8.76 | 87.02 ± 4.71 |
| Sleep onset time (mean ± SD (min.)) | 10.87 ± 9.6 | 30.22 ± 23.10 | 16.8 ± 13.77 |
| Wake after sleep onset (mean ± SD (min.)) | 27.44 ± 17.61 | 83.03 ± 47.78 | 44.6 ± 26.92 |
| Total sleep time (mean ± SD (min.)) | 417.54 ± 43.72 | 322.42 ± 67.39 | 388.18 ± 51.03 |

### B. Objective Sleep Measurements

Various objective sleep measurements, including SE, total sleep time (TST), sleep onset time (SOT), and wake after sleep onset (WASO), are commonly used to objectively represent a subject's sleep quality and they were also estimated by the proposed actigraphy method and compared to the results of manual PSG scorings.

The definitions of these objective sleep measurements are described as follows. We adopted start and end of the PSG recording time as lights off and lights on time. The time period from lights off to lights on was defined as time in bed (TIB). The TST was defined as the amount of actual sleep time during TIB. SE is the ratio of TST to TIB. In clinical diagnoses, people may have a bad night of sleep if their SE is lower than 85% [23]. Therefore, the accuracies of the proposed sleep-wake staging algorithm applied to the data from subjects with SE $\geqq$ 85 (defined as a good SE) and from subjects with SE $<$ 85 (defined as a poor SE) were provided and compared. SOT was defined as the length of time that it takes to accomplish the transition from full wakefulness to sleep. SOT was measured to examine whether a person was able to fall asleep quickly or not. WASO was defined as the total minutes of wakefulness recorded after sleep onset. WASO was used to determine if a person had difficulty in maintaining sleep after SOT. Table I presents the basic subject demographics, including gender, age, SEs, SOTs, WASOs, and TSTs (mean ± sd) obtained from the questionnaires and the manual PSG scorings.

## III. Automatic Sleep-Wake Staging Method

An automatic sleep-wake staging algorithm converting the accelerometer (ACC) signals to the sleep-wake index is an essential technique for a wearable actigraphy recording device.

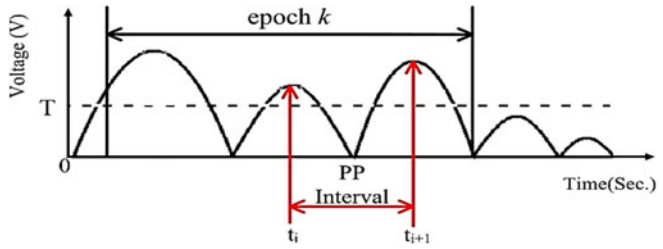


Fig. 1. Illustration of the peak-to-peak interval (PP interval).

The one-axis ACC signals were divided into a series of 30-s epochs (identical to PSG), and the proposed algorithm classified each epoch as a wake or sleep stage by analyzing the recordings.

### A. Feature Extraction

For each epoch, two features, the peak-to-peak interval and maximum magnitude, are extracted [21]. Peaks of the ACC signals with magnitudes higher than a threshold $T$ are first identified, and the minimal interval between two successive peaks is defined as a feature called the peak-to-peak interval (PP interval). The PP interval of epoch $k$, denoted as $PP_k$, can be calculated as follows:

$$PP_k = \begin{cases} \min \quad (t_{i+1} - t_t), & N \geq 3 \\ 0, \quad \text{otherwise} \end{cases} \tag{1}$$

where $t_i$ and $t_{i+1}$ denote the times of the $i$th and $(i+1)$th peaks (with magnitudes higher than $T$) in epoch $k$. $N$ denotes the number of peaks with magnitudes higher than $T$ in epoch $k$. Note that if there are fewer than three such peaks (i.e., $N < 3$) in an epoch, the peaks are treated as noise and discarded. Fig. 1 illustrates the definition of the PP interval. The threshold $T$ is used to remove the influences of small actions, which are usually caused by breathing or pulses. $T$ is set as the value of multiplying the standard deviation of the ACC signals in the training data by 0.1 and the value is 3.35 mg in this paper.

The maximum ACC magnitude in epoch $k$, denoted as $\text{Max}_k$, is calculated by

$$\text{Max}_k = \begin{cases} \max & \text{ACC}(t), t \in \text{epoch } k \text{ and } \text{ACC}(t) > T \\ 0, & \text{otherwise} \end{cases}. \tag{2}$$

The values of $PP_k$ and $\text{Max}_k$ are used to determine whether there are evident activities in epoch $k$, as shown in

$$\text{Activity\_PP}_\text{k} = \begin{cases} 1, & \text{PP}_\text{k} < 11 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$\text{Activity\_Max}_k = \begin{cases} 1, & \text{Max}_k \neq 0 \\ 0, & \text{Max}_k = 0 \end{cases}. \tag{4}$$

In (3), the subject is determined as having activities in epoch $k$ if $PP_k$ is smaller than a threshold, 11 s. Peaks with large PP intervals are treated as artifacts. The 11-s threshold was used because 99.5% of the $PP_k$ values were smaller than 11 s when the epochs were identified as awake in our training data.

Typically, there are no frequent movements in all-night sleep. Therefore, according to the principle of the accelerometer, the stage will be classified as sleep when the power of the accelerometer signal is very small. Otherwise, the stage will be classified as awake. Although activities can be caused by sleep arousals, these activities are almost noncontinuous. To prevent the incorrect identification of the stage of an epoch due to sparse sleep-arousal activities, a windowing approach was used in the proposed sleep-wake staging algorithm. Specifically, for each epoch $k$, the corresponding window was a set of contiguous epochs, with epoch $k$ as the middle of this epoch set, and we defined the movement density (MD) of epoch $k$ as (5) and (6) shown at the bottom of this page, where $\text{MD}_k^{\text{PP}}$ and $\text{MD}_k^{\text{Max}}$ denote the MD based on the PP interval and the maximum ACC magnitude, respectively. The $w$ and $L$ denote the number of epochs in the window (i.e., the window size) and the total number of epochs in the ACC data, respectively.

$$\text{MD}_k^{Max} = \begin{cases} \left( \sum_{1}^{k+\lfloor w/2 \rfloor} \text{Activity\_Max}_i \right) / (w - \lfloor w/2 \rfloor + k), \text{when} & 1 \leq k \leq \lfloor w/2 \rfloor \\ \left( \sum_{k-\lfloor w/2 \rfloor}^{k+\lfloor w/2 \rfloor} \text{Activity\_Max}_i \right) / w, \text{when} & \lfloor w/2 \rfloor < k < L - \lfloor w/2 \rfloor \\ \left( \sum_{k-\lfloor w/2 \rfloor}^{L} \text{Activity\_Max}_i \right) / (w - \lfloor w/2 \rfloor + L - k), \text{when} & L - \lfloor w/2 \rfloor \leq k \leq L \end{cases} \tag{5}$$

and

$$\text{MD}_k^{\text{PP}} = \begin{cases} \left( \sum_{1}^{k+\lfloor w/2 \rfloor} \text{Activity\_}PP_i \right) / (w - \lfloor w/2 \rfloor + k), \text{when} & 1 \leq k \leq \lfloor w/2 \rfloor \\ \left( \sum_{k-\lfloor w/2 \rfloor}^{k+\lfloor w/2 \rfloor} \text{Activity\_}PP_i \right) / w, \text{when} & \lfloor w/2 \rfloor < k < L - \lfloor w/2 \rfloor \\ \left( \sum_{k-\lfloor w/2 \rfloor}^{L} \text{Activity\_}PP_i \right) / (w - \lfloor w/2 \rfloor + L - k), \text{when} & L - \lfloor w/2 \rfloor \leq k \leq L \end{cases} \tag{6}$$

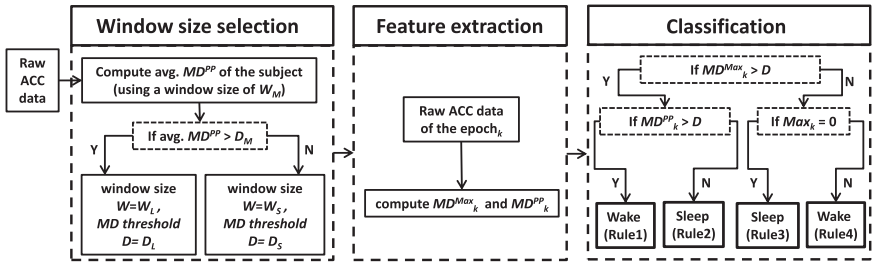


Fig. 2. Flowchart of the automatic sleep-wake staging algorithm.

From (5) and (6), the MD of an epoch is determined by the activity of that epoch and the neighboring epochs. An epoch with a larger MD will be more likely to be identified as awake. For the epoch at the beginning and the last $(\mathrm{w}-1)/2$ of the recording, the numbers of the previous and following neighbor epochs were less than $(\mathrm{w}-1)/2$, respectively, so only the available neighbor epochs were used to calculate the MD.

### B. Automatic Sleep-Wake Staging Algorithm

The automatic sleep-wake staging algorithm identifies the stage of each epoch as sleep or awake, mainly according to the MD of that epoch. Fig. 2 shows the flowchart of the proposed staging algorithm.

***1) Window Size Selection:*** The first step in Fig. 2 is to determine the window size $w$ for the calculation of (5) and (6). If the subjects have frequent movements (most of them with poor SE) during all-night sleep, making the window size is too small, it is easy to misclassify the sleep epochs with movement activities as wake stages. Increasing the window size can reduce such misclassifications. On the contrary, the subjects with good SE usually have relatively rare movements. Therefore, a small window size is more suitable for these subjects. The dual-window approach, which adopts suitable window sizes for the users according to their movement frequency, is the key strategy of the proposed method.

The MD estimated based on the PP interval, $\mathrm{MD}_k^{\mathrm{PP}}$, for each epoch is first calculated by (5) with a medium window size $w = W_m$. In this paper, $W_m$ was set as 25 (i.e., 25 30-s epochs). Then, the average $\mathrm{MD}_k^{\mathrm{PP}}$ denoted as $\mathrm{MD}^{\mathrm{PP}}$ was calculated. As shown in Fig. 2, a large $\mathrm{MD}^{\mathrm{PP}}$ (i.e., the value of $\mathrm{MD}^{\mathrm{PP}}$ was larger than a threshold $D_M$) indicates frequent movements or poor SE in the ACC recording, and a large window size $W_L$ is used for wake-sleep staging. Otherwise, a small window size $W_S$ is selected.

***2) Wake-Sleep staging:*** After window size selection and feature extraction, the final step of the proposed method is to classify each epoch as a wake or sleep stage based on the MD estimated based on the PP interval, $\mathrm{MD}_k^{\mathrm{PP}}$ and based on the maximum ACC magnitude, $\mathrm{MD}_k^{\mathrm{Max}}$ by (6) and (7). As shown in Fig. 2, there are four rules in our method:

*Rule 1:* if the $\mathrm{MD}_k^{\mathrm{Max}}$ is larger than the density threshold $D$, and the $\mathrm{MD}_k^{\mathrm{PP}}$ is also larger than $D$, the epoch $k$ is classified as awake.

*Rule 2:* if the $\mathrm{MD}_k^{\mathrm{Max}}$ is larger than the density threshold $D$, and the $\mathrm{MD}_k^{\mathrm{PP}}$ is not larger than $D$, the epoch $k$ is classified as sleep.

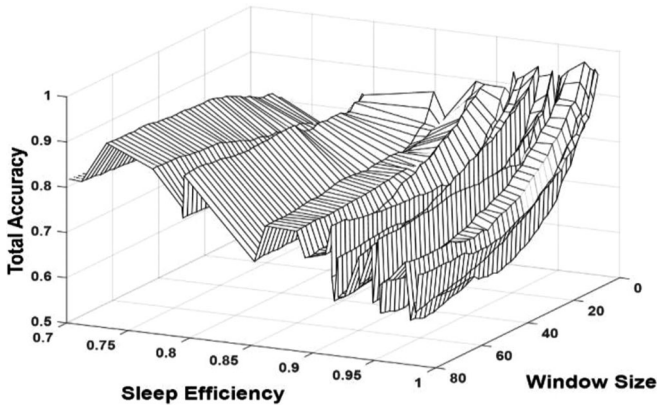


Fig. 3. Accuracy changes in utilizing various window sizes for the sleep-wake staging of data from subjects with different sleep efficiencies.

*Rule 3:* if the $\mathrm{MD}_k^{\mathrm{Max}}$ is not larger than the density threshold $D$, and the $\mathrm{Max}_k$ is 0, the epoch $k$ is classified as sleep.

*Rule 4:* if the $\mathrm{MD}_k^{\mathrm{Max}}$ is not larger than the density threshold $D$, and the $\mathrm{Max}_k$ is not 0, the epoch $k$ is classified as awake.

In the above rules 3 and 4, if the $\mathrm{MD}_k^{\mathrm{Max}}$ is not larger than $D$, the $\mathrm{Activity\_Max}_k$ is utilized to classify the epoch. The epoch $k$ is classified as sleep if the $\mathrm{Activity\_Max}_k$ is equal to zero. Otherwise, the epoch $k$ is classified as awake. It is noted that there are two density thresholds $D_L$ and $D_S$ designed for large and small windows, $W_L$ and $W_S$, respectively.

Fig. 3 illustrates an example of utilizing a fixed window size for the sleep-wake staging of the training data from subjects with good and poor SE. The accuracy is defined as the agreement between the developed wearable system and the manual scoring of PSG. The results show that increasing the window size leads to reducing the accuracy for subjects with good SE while increasing the accuracy for subjects with poor SE. This example shows the limitation of the fixed window approach and the motivation of the dual-window strategy proposed in this paper.

***3) Parameter Determination:*** The final step is to determine the window sizes $W_L$ and $W_S$ as well as the thresholds $D_M$, $D_L$, and $D_S$. Fig. 4 shows the distributions of the training data corresponding to average MD estimated based on PP interval, $\mathrm{MD}^{\mathrm{PP}}$ ($x$-axis) and the best window size with the highest accuracy ($y$-axis) for each all-nigh recording. It can be observed that the large window size perform better for the data with large $\mathrm{MD}^{\mathrm{PP}}$ and the small window size is suitable for the data with low $\mathrm{MD}^{\mathrm{PP}}$.

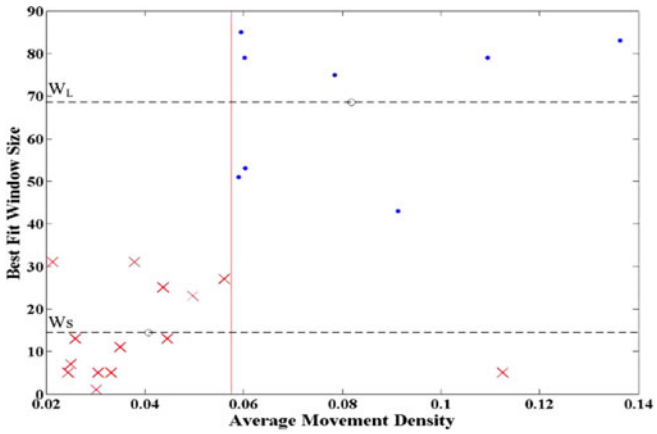


Fig. 4. Distributions of the training data corresponding to the average MD estimated based on PP interval, $MD^{PP}$ (*x*-axis) and the best window size with the highest accuracy (*y*-axis) for each all-night recording. The open circles are the centers of the two clusters determined by the K-means.

According to this observation, the K-means clustering [24] was utilized to analyze the data in Fig. 4, and these data were divided into two clusters: one for large window sizes and large $\mathrm{MD}^{\mathrm{PP}}$, (i.e., the dots) denoted by $C_L$, and the other for small window sizes and low $\mathrm{MD}^{\mathrm{PP}}$ (i.e., the crosses), denoted by $C_S$. The cluster centers of the large and small window clusters marked by two open circles were 69 and 15, so these two values were set as $W_L$ and $W_S$, respectively. The median MD threshold $D_M$ was set as 0.0575 because it could effectively separate these two clusters according to the distribution of the $\mathrm{MD}^{\mathrm{PP}}$ values for the training data.

Fig. 5(a) and 5(b) shows the distributions of $\mathrm{MD}^{\mathrm{PP}}$ values of sleep and wake epochs calculated with a large window size ($W_L$) and small window size ($W_S$) for the two subject clusters presented in Fig. 4. As shown in Fig. 5(a), $D_L$ is set as 0.1 because this value separates sleep/wake epochs well. The percentage of the sleep epochs (5209 epochs) whose $\mathrm{MD}^{\mathrm{PP}}$ values were smaller than 0.1 was 77.2%, and the percentage of the wake epochs (1399 epochs) whose $\mathrm{MD}^{\mathrm{PP}}$ values were larger than this value was 69.88%. In the determination of $D_S$, as shown in Fig. 5(b), it was not easy to choose a threshold to separate sleep and wake epochs effectively due to the similar distributions of $\mathrm{MD}^{\mathrm{PP}}$ for the sleep and wake epochs. In this paper, $D_S$ was set as 0.2 because it was applied to subjects with good sleep quality (i.e., with fewer wake epochs), and the percentage of the sleep epochs (11 670 epochs) whose $\mathrm{MD}^{\mathrm{PP}}$ values were smaller than this value was 98.67%. Although the $\mathrm{MD}^{\mathrm{PP}}$ values in 55.3% of the wake epochs were smaller than $D_S$, the number of those wake epochs was only 549, far smaller than the number of the sleep epochs whose $\mathrm{MD}^{\mathrm{PP}}$ values were smaller than $D_S$.

## IV. Actigraph Recorder

### A. Hardware Architecture

The hardware of the developed actigraph recorder includes a microcontroller unit (MCU) and an accelerometer, as shown in Fig. 6. There is a USB port to transmit the recordings to the host platform. Table II presents the dimension, weight, and current consumption of the developed actigraph recorder [21]. The current consumption was measured using the National Instruments USB-6009 data acquisition card. The recorder can support approximately 239.48 h of operation, and the recordings are stored in the internal flash memory (40 959 B) with a 1-Hz sampling rate and 10-bit resolution. This capacity is sufficient for overnight recording in the development phase. External storage can be added for future applications.

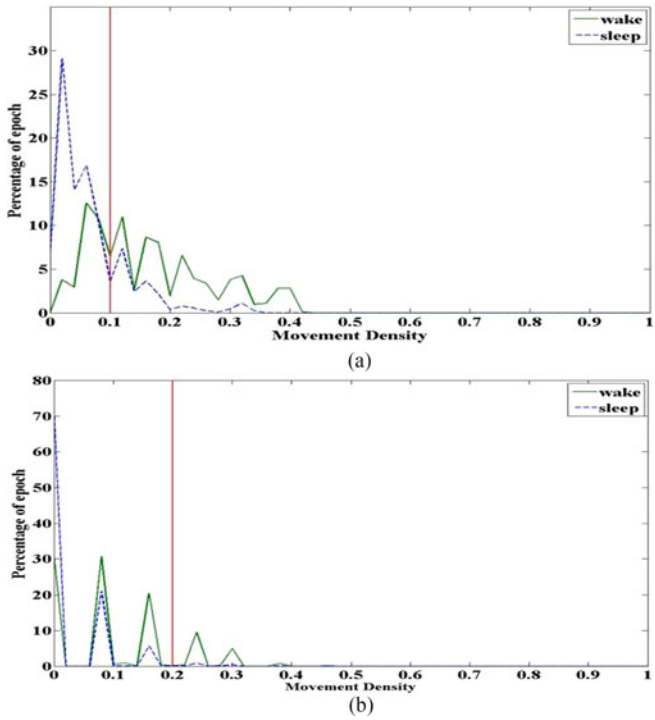


Fig. 5. Distributions of MD values of sleep and wake epochs calculated with the large window size: (a) and the small window size (b) for the two subject clusters presented in Fig. 4.

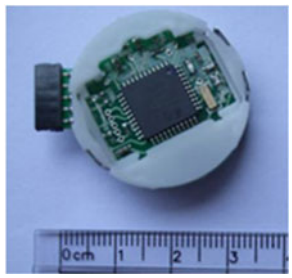

Fig. 6. Prototype of the actigraphy recorder.

TABLE II
Dimension, Weight and Current Consumption of the Actigraph Recorder

| | |
|---|---|
| Size of Circuit Board (mm × mm × mm) | 36 × 30 × 6 |
| Weight of Circuit Board (g) | 4.90 |
| Weight of Actigraph Recorder (g) | 32.53 |
| Average Current Consumption (mA) | 0.3758 |
| Battery Life (h) | 239.48 (3.0 V, 90 mAh) |

***1) Accelerometer:*** A three-axis accelerometer (ADXL 335, Analog Device, acceleration range of $\pm 3$ g and sensitivity of 3 mg) [25] is used in the actigraphy recorder. Generally, the acceleration range of the accelerometer in the recording of daily activities or wearable health monitoring is more than $\pm 5$ g [26]. Because frequent and large movements are rare in an all-night sleep, the acceleration range is set as $\pm 3$ g.

The recordings of the *Z*-axis accelerations are used in the automatic sleep-wake staging algorithm. The *Z*-axis gravity conversion voltage is approximately 550 mV. To detect wrist movements, the output signal of the accelerometer is high-pass filtered to remove the frequency range between DC and 0.5 Hz, the frequency range of gravity. Then, the signal is fed to the input of the analog-to-digital converter of the MCU.

***2) Microcontroller:*** The microcontroller, Microchip PIC18F46J50 [27], features low power consumption, high-speed CMOS flash memory, and a USB interface. For ACC data sampling, Timer 1 of the microcontroller is configured at 1 Hz as the sampling rate of a 10-bit analog-to-digital conversion (ADC) under a 1.25-V internal reference voltage. Considering the frequency of movements in all-night sleep, battery life, and the stored space for long-term sleep quality assessment, we set the sampling rate at 1 Hz. The sampled data are temporarily stored in a 3–B (1 bytes for data value, 2 bytes for time stamp) register of the microcontroller and then written to the on-chip flash memory before the next ADC.

### B. Software Organization

When the sleep recording procedure starts, the MCU obtains the date/time information from the real-time clock and calendar and then writes the information to the on-chip flash memory. When the ADC is performed, the 1-B sampled data are written to the flash memory. The sleep recording can be terminated by the user. The MCU is switched to the deep sleep mode upon termination of the sleep recording. Then, the recorded data can be uploaded to a host platform by connecting the actigraphy recorder to the USB port of the computer. The recorder is recognized as a removable storage device, and the recorded data can be accessed as regular files. In addition, a GUI program was developed with the MATLAB environment to implement the sleep-wake scoring algorithm presented in Section II.

## V. Evaluation and Results

There were 81 participants recruited in our experiments, including 56 subjects with good SE and 25 subjects with poor SE. The training data used to develop the sleep-wake scoring algorithm were randomly selected from the group with good SE ($N = 13$) and group with poor SE ($N = 9$), respectively. Data from the remaining subjects were used for performance evaluation. The testing data also contained subject groups with good ($N = 43$, SE $\geqq 85\%$, mean SE $= 92.62\% \pm 2.9\%$) and poor ($N = 16$, SE $< 85\%$, mean SE $= 74.48\% \pm 8.76\%$) SE to evaluate whether the proposed system could work well in both the subject groups.

TABLE III
Performance of the Proposed Method in Wake-Sleep Recording

| Testing group | Accuracy (%) | Sensitivity (%) | Specificity (%) | kappa |
|---|---|---|---|---|
| Total | 92.16 | 95.02 | 71.30 | 0.64 |
| SE $\geqq$ 85 | 94.93 | 96.70 | 72.73 | 0.65 |
| SE $<$ 85 | 84.36 | 89.17 | 70.13 | 0.59 |

### A. Performance of Wake-Sleep Staging

Several performance indices, such as the accuracy, sensitivity, and specificity [28], were calculated to evaluate the performance of the proposed algorithm in wake-sleep staging. They are defined as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{7}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{8}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{9}$$

where TP, TN, FP, and FN represent the true positive, true negative, false positive, and false negative, respectively. In this paper, accuracy represents the overall agreement of the actigraphy analysis by the proposed algorithm and the manual PSG scorings. Sensitivity is defined as the proportion of manually scored "sleep" epochs that were rated as "sleep" with our proposed method. Specificity is defined as the proportion of manually scored "wake" epochs that were rated as "wake" with our proposed method.

In addition, Cohen's kappa coefficient ($\kappa$) [29] was calculated to assess the robustness of our system. $\kappa$ is a statistical measure of the inter-rater agreement among two or more raters; it is usually thought to be a more robust measure than simple percent agreement calculations because $\kappa$ accounts for agreements that occur by chance. The kappa statistic is a better measure of the scoring performance than the simple percentage of epoch-by-epoch scoring agreement [30].

Table III shows the performance of the proposed method in wake-sleep scoring. The average accuracy of the proposed method in all testing subjects is 92.16%. The sensitivities can achieve 96.70% and 89.17% for subject groups with good and poor SE, respectively. The specificity was higher than 70% for both subject groups. For $\kappa$, the proposed method could achieve 0.65 and 0.59 for subject groups with good and poor SE, respectively. The averaged $\kappa$ of all testing subjects was 0.64. The kappa values within 0.41–0.60 indicated moderate agreement and those within 0.61–0.80 indicated substantial agreement. These experimental results demonstrate the robustness and reliability of our method using limited activity information to estimate wake-sleep stages during overnight recordings.

### B. Assessment of Objective Sleep Measurements

The goal of actigraph analysis is to indirectly estimate the user's sleep measurements conveniently and easily. Therefore, in addition to wake-sleep stage classification, the assessment of

TABLE IV
COMPARISONS OF THE MANUAL PSG SCORING AND THE PROPOSED ACTIGRAPHY METHOD ON VARIOUS OBJECTIVE SLEEP MEASUREMENTS

| | SE (%) | SOT (min) | WASO (min) | TST (min) |
|---|---|---|---|---|
| Expert | 87.7 ± 9.6 | 15.4 ± 22.2 | 39.7 ± 40.2 | 396.1 ± 64.1 |
| Our method | 86.8 ± 10 | 16.1 ± 16.7 | 42.5 ± 39.9 | 391.7 ± 66.2 |
| MAE | 4.36 | 11.1 | 16.6 | 19.3 |
| *P* value | 0.19 | 0.77 | 0.43 | 0.18 |
| ICC | 0.84 | 0.53 | 0.75 | 0.93 |

*The *P* value is from the paired t-test.

objective sleep measurements should be considered and evaluated. In this paper, four common objective sleep measurements, including SE, SOT, WASO, and TST, were estimated by the proposed actigraphy method and compared with the results of manual PSG scorings [31]. The mean ± SD of these data are presented and statistical analysis was also performed to evaluate the results of the expert and the proposed method using a paired *t*-test. A $p$ value $<0.05$ was considered statistically significant.

In addition, the mean absolute error (MAE) and the intraclass correlation coefficient (ICC) [32] were also calculated to measure the agreements of the expert and the proposed method with respect to these sleep measurements. The MAE measures the average magnitude of the errors in a set of forecasts, without considering their direction. ICC represents agreements between two or more raters or evaluation methods in the same set. ICC can be interpreted as follows: 0–0.2 indicates poor agreement; 0.3–0.4 indicates fair agreement; 0.5–0.6 indicates moderate agreement; 0.7–0.8 indicates strong agreement; and $>0.8$ indicates almost perfect agreement. In this study, the ICC was calculated based on ICC (2, 1) [32] (i.e., a two-way ANOVA, model 2, and individual).

Table IV shows the comparisons of the manual PSG scoring and the proposed actigraphy method on various sleep measurements. No significant differences were found between sleep measurements from the manual PSG scoring and the proposed actigraphy method. The MAEs of SE, SOT, WASO, and TST are 4.36%, 11.1 min, 16.6 min, and 19.3 min, respectively. The high ICCs ($>0.75$) may also suggest generally strong agreement between the manual and the automatic measurements of various sleep measurements except for SOT. These results demonstrate that the sleep measurements of the testing subjects reported by the proposed actigraphy method are very close to the results of manual PSG scoring.

The Bland–Altman technique [33] is an another useful technique that plots the difference between actigraphy and manual PSG scoring against their means, and this technique is often used to determine whether the actigraph over- or underestimates each sleep measurement [34]. This measure was also included in this study.

Fig. 7 presents the Bland–Altman graphs for SE, SOT, WASO, and TST ($N = 59$). One representative graph is displayed for each sleep measure index. The difference was plotted against the average of actigraphy (ACT) and manual PSG scoring (PSG) for SE, SOT, WASO, and TST, respectively. The mean bias is represented as the mean difference between the actigraphy and manual PSG scoring, with a positive mean bias representing an actigraphy overestimation and a negative mean bias representing an actigraphy underestimation. Upper and lower limits based on 95% confidence intervals were used to determine the significance of the mean difference. To observe the performance differences of the proposed system between subjects with good and poor SE for estimation of various sleep measurements, the circles and crosses in Fig. 7 represent the subjects with good SE and poor SE, respectively.

The mean biases of SE, SOT, WASO, and TST were −0.95%, 0.74 min, 2.84 min, and −4.3 min, respectively. The results of the Bland–Altman technique demonstrated that the sleep measurements between the manual PSG scoring and the proposed actigraphy method were very close with high concordance on average. According to the SD values, the actigraphy method had better performance in estimating SE and TST. Moreover, the differences over the 95% confidence intervals all belonged to subjects with poor SE. Due to the limitation of analyzing body movements to indirectly estimate the user's sleep measurements, if the subject's movement during sleep were unusual (e.g., with low SE), SOT and WASO may not be able to be accurately reported with the actigraphy method, and further examinations are required.

Fig. 8 shows comparisons of subject-by-subject sleep measurements estimated by the proposed actigraphy method and the results of manual PSG scoring. The circles and crosses represent the subjects with good and poor SE, respectively. The root mean square errors (RMSEs) between the estimation of the proposed actigraphy method and the manual PSG scoring for various objective sleep measurements was also calculated. The RMSE is a quadratic scoring rule that measures the average magnitude of the error. The RMSEs of SE, SOT, WASO, and TST were 5.48%, 19 min, 27.4 min, and 24.6 min, respectively. The accuracy of classifying a subject as having good or poor sleep based on the estimated SE as higher or lower than 85% reached 91.53%. Furthermore, the distributions of SE and TST were very close to the diagonal, which indicated the proposed actigrphy method had good performance in estimating SE and TST. However, some large errors were observed in SOT and WASO for subjects with low SE. This phenomenon was consistent with Fig. 7.

The experimental results demonstrate that the proposed system could work well in wake-sleep scoring. The average accuracy, sensitivity, specificity, and $\kappa$ of the proposed system with 59 testing data for wake-sleep staging were 92.16%, 95.02%, 71.30%, and 0.64, respectively. For the assessment of various sleep measurements, the mean bias of SE was less than 1%, and the mean biases of SOT, WASO, and TST were all less than 5 min. Because the actigraphy recorder is a fast and easy approach for objective sleep measurement, the fundamental requirement is to distinguish the subjects with poor SE from subjects with good SE. The accuracy of identifying a subject as having good or poor SE by the proposed system reached 91.53% (54/59). For the subjects with low SE, accurate SOT and WASO may possible with the actigraphy and further investigation is required.

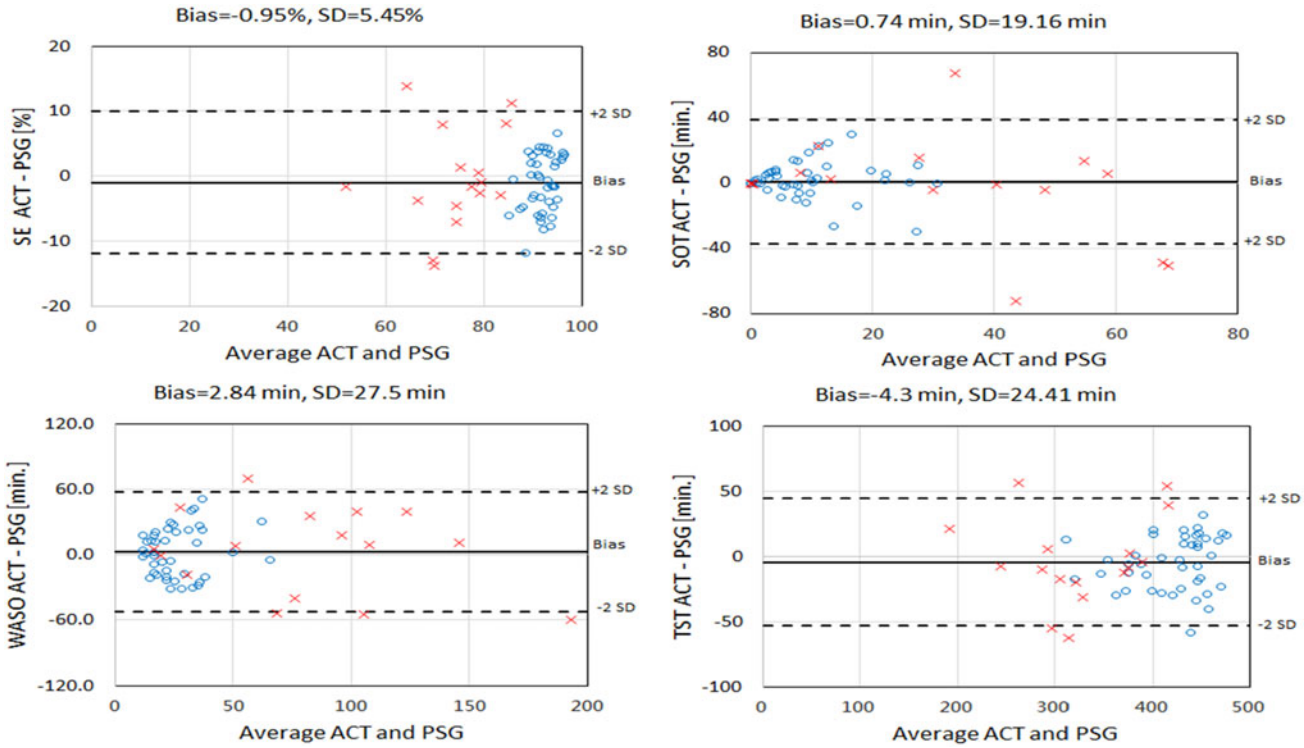


Fig. 7. Bland–Altman graphs for SE, SOT, WASO, and TST, respectively ($N = 59$). Plotted difference against average of ACT and PSG for SE, SOT, WASO, and TST, with 95% limits of agreement. One representative graph is displayed for each sleep measure index. Mean bias and standard deviation between the two measurements are presented. The circles and crosses represent the subjects with good SE and subjects with poor SE, respectively. A positive mean bias representing an actigraphy overestimation and a negative mean bias representing an actigraphy underestimation.

## VI. Discussion

Wearable devices for the evaluation of sleep constitute a practical direction in the development of health monitoring systems. A wrist actigraphy recorder, integrated with a MEMS, a three-axis accelerometer and a novel adaptive window-based sleep-wake staging algorithm, was developed for sleep measurement. Data that were collected from subject groups with good and poor SE were included to evaluate whether the proposed system could work well in both good and poor SE groups. Various objective sleep measurements, including SE, TST, SOT, and WASO were estimated by the proposed actigraphy method and compared to the results of manual PSG scorings to demonstrate the robustness and reliability of our method.

In addition to healthy individuals, the validity of actigraphy in special populations (e.g., individuals with sleep problems or poor SE) is more questionable [13]. A total of 639.8 h of all-night recording data from 56 subjects with good SE and 25 subjects with poor SE were included in this study. The average accuracy of the proposed method applied to the data from subject groups with good ($N = 43$) and poor SE ($N = 16$) was higher than 92%. Based on the dual-window approach used to adopt a suitable window size for the user according to his/her movement frequency, the detection rate of wake stages (specificity) reached 71.30% using the proposed method for the subjects with a wide range of sleep efficiencies (52.7–97.42%).

In the assessment of sleep measurements, the ICCs between the proposed method and the manual PSG scorings in estimating SE, SOT, WASO, and TST were 0.84, 0.53, 0.75, and 0.93, respectively. The results indicate strong agreement ($>0.6$) between the proposed method and manual PSG scoring of the sleep measurements, except for the SOT. For concordance estimation with the Bland–Altman technique, the mean biases corresponding to SE, SOT, WASO, and TST were $-0.95\%$, 0.74 min, 2.84 min, and $-4.3$ min, respectively. The accuracy of classifying the subject as having good or poor sleep based on the estimated SE was 91.53%. These results demonstrated that the proposed wearable actigraphy system has excellent potential for collecting in-home sleep measurements.

To reduce the data storage space and to record representative activities during sleep, the acceleration range was set as $\pm 3$ g and the $Z$-axis accelerations of the accelerometer were recorded for analysis. Because frequent and large movements are rare during all-night sleep, which differs from daily activities, the sampling rate was set as 1 Hz. Due to the low sampling rate for power and storage saving, a scoring method based on the concept of MD estimation with adaptive windowing instead of traditional single-window-size activity magnitude threshold [6]–[9] was proposed.

Because actigraphy is an indirect sleep quality assessment approach, some limitations should be addressed. It can identify sleep-wake stages but cannot accurately provide more information about sleep stages (e.g., light sleep, deep sleep, and rapid eye movement). If the subject's movement activities during sleep are unusual, the accuracy of actigraphy scoring is affected. It was observed that the actigraphy method has worse performance in estimating SOT and WASO compared to estimating

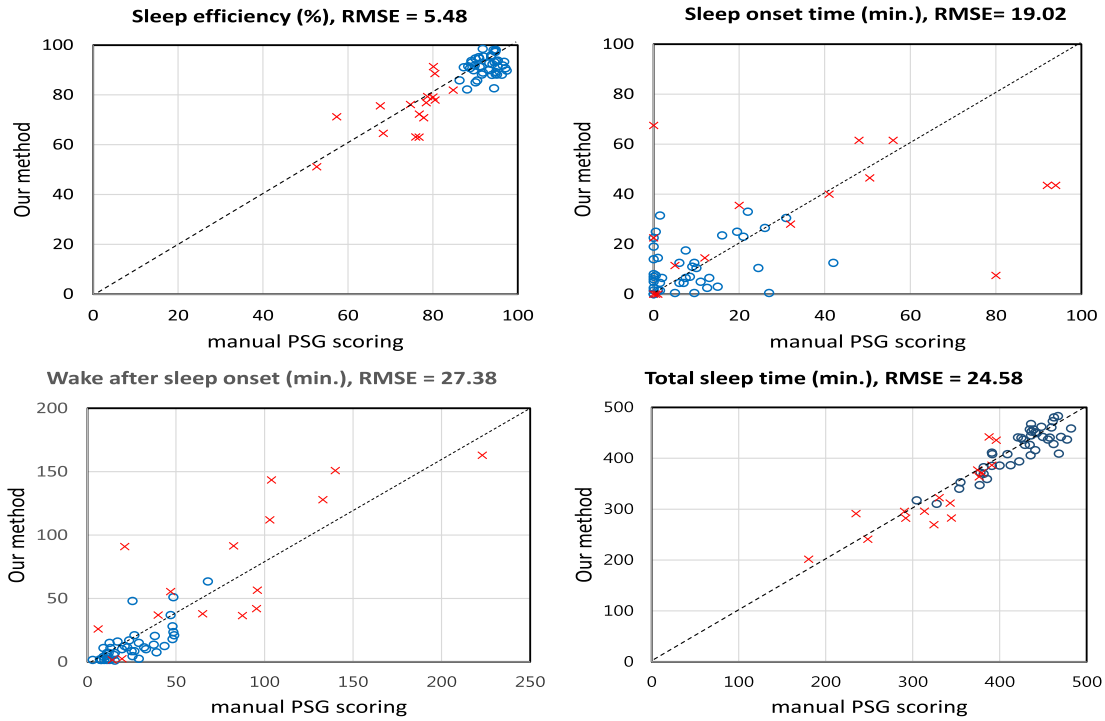


Fig. 8. Comparisons of subject-by-subject objective sleep measurements estimated by the proposed method and the manual PSG scoring. The circles and crosses represent the subjects with good SE and subjects with poor SE, respectively. RMSE = root mean square error.

SE and TST due to the limitations of the actigraphy-based sleep-wake staging algorithm. The subject may have uncontrollable or involuntary body movements in the sleep period so that the epoch can be misclassified as a wake stage. The subject may also have a long quiet-wake interval (i.e., the variability of movement is zero in the wake stage). Therefore, this quiet-wake period could be easily misclassified as sleep. According to the Bland–Altman graphs (see Fig. 7) and comparisons of subject-by-subject sleep measurements (see Fig. 8), some large errors were observed in SOT and WASO for subjects with low SE. Three subjects in our testing group had longer quiet-wake times (more than 80 min, refer to Fig. 8); therefore, the estimations of SOT for these three subjects exhibited more errors than for the other subjects. The experimental results showed that accurate SOT and WASO for subjects with low SE may not be possible to achieve with actigraphy and further investigations are required.

Finally, another limitation of this study was the young average age (under 30 years old) of the testing group. Older subjects need to be included and analyzed in future research. Moreover, the best window size and the MD of sleep/wake status in other subject groups, such as patients with attention deficit hyperactivity disorder [35] or mild cognitive impairment [36], should be considered in future research.

## VII. Conclusion

In this study, a wearable actigraphy recording device and a corresponding sleep quality evaluation program were developed and integrated. Data from subjects with good ($N = 43$) and poor ($N = 16$) SE in the range of 52.7–97.42% were used for testing. For wake-sleep staging, the average accuracy, sensitivity, specificity, and $\kappa$ of the proposed system were 92.16%, 95.02%, 71.30%, and 0.64, respectively. For assessment of sleep measurements, the accuracy of classifying the subject as having good or poor SE reached 91.53%. The mean biases of SE, SOT, WASO, and TST were −0.95%, 0.74 min, 2.84 min, and −4.3 min, respectively. The experimental results demonstrated that the developed hardware and software integration system had good performance for determining both wake-sleep staging and assessing SE and TST measurements with low data rates for long-term monitoring. The limitation of actigraphy in estimating SOT and WASO was also discussed. The results suggest that the proposed wearable actigraphy system is workable solution for in-home screening of an individual's SE and TST. It is also a convenient and quantitative approach for the evaluation of sleep improvement after treatment.

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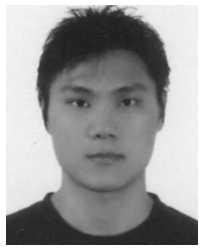

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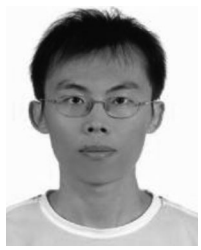

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