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Home sleep monitoring based on wrist movement data processing

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Abstract

In this paper, two original sleep monitoring algorithms, including threshold and k-means clustering algorithms are presented. All the proposed algorithms use only acceleration data acquired from the non-dominant wrist with a 3-axis accelerometer, allowing the detection of falling asleep and waking up and a classification into 4-sleep stages (“awake”, “light sleep”, “deep sleep” and “REM”). We validate the proposed methods by comparing them to the results of “Fitbit Charge 2” and “Withings Sleep Analyzer”. Based on wrist movement data collected during 10 nights of sleep of a volunteer, we can show that the algorithms obtain promising results that allow us to consider a new non-intrusive method for users and medical staff to follow the trend of sleep quality through long term monitoring. This longitudinal monitoring can help to detect abnormal changes in sleep that are usually a sign of a change in health status.

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Keywords: Sleep monitoring; wrist movement; threshold; k-means; home monitoring.

1. Introduction

With increasing social pressure and an aging population, more and more people are suffering from sleep problems. A good quality of sleep is an important factor in good health. It has been reported that sleep disorders are highly correlated with health deterioration¹. According to the AASM (American Academy of Sleep Medicine)², there are about 90 sleep disorders including insomnia (one third of population), sleep apnea syndrome (2% to 4%), restless legs syndrome (6%), narcolepsy (0.04%), sleep paralysis (6%), nocturnal terrors, the confusional arousals and nightmares (2.2% to 5%)³. Sleep disorders and sleep dysregulation can lead to medical consequences such as cardiovascular (arrhythmia, hypertension, stroke), metabolic (diabetes, obesity) and psychiatric disorders

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(depression, irritability, addictive behaviors)⁴. Poor sleep quality can affect physical and mental performance, judgment and mood, and is the main preventable factor leading to accidents⁵. Therefore, effective and continuous sleep monitoring is of great significance for understanding and follow-up of our health condition. In recent years, sleep stage classification has been a topic extensively studied as one of the most critical steps to effectively diagnose and treat sleep-related disorders. Obtaining the time spent in different sleep stages in the ordinary daily life environment is of great significance for research and commercial applications. For example, obtaining accurate sleep architecture may provide better information to guide behavioral changes and provide recommendations related to improving sleep⁶. PSG (Polysomnography) is today the gold standard for sleep monitoring and classification of sleep stages (R or REM for Rapid Eye Movement, N1 to N3 for Non-Rapid-Eye Movement and W for wake). However, it is very invasive, expensive and time-consuming to implement. It is therefore very difficult to use the PSG as a home and long-term sleep monitoring device.

As a result, many researchers and technicians have tried to develop simple and non-intrusive systems which overcome these issues. Guettari et al.⁷ adopt self-organizing map (SOM) algorithm—Kohonen to classify signal segments into three categories: deep/paradoxical sleep (R, N3), agitated and light sleep (N1, N2) and awake phase (W) based on the signal of body movements during sleep collected by a thermopile sensor. It evaluates their system in comparison with the PSG. Gu et al.⁸ use the conditional random field (CRF) model to classify the sleep phases into wake, light sleep, deep sleep and REM based on the features of signals from a microphone, accelerometer and light sensor. They use the result of Zeo, which is based on the EEG, as the ground truth. Chambon et al.⁹ use the softmax classifier to classify sleep stages into wake, N1, N2, N3 and REM based on the EEG (Electroencephalography), EOG (Electrooculography), ECG (Electrocardiography) and EMG (Electromyography) signal from the PSG. The reference of this work is the PSG records. Güneş et al.¹⁰ adopt K-means clustering as a feature weighting processing and then use k-nearest neighbors and decision tree as classifier to discriminate sleep stages into awake, REM, N1, N2, N3 based on the EEG signal. The results are compared to the PSG. In the study by Kalkbrenner et al.¹¹, a body sound microphone attached to the subject's neck to record tracheal body sounds is used in order to detect respiratory and heart beats and to extract cardiorespiratory features. An inertial measurement unit including an accelerometer and a gyroscope, attached to the chest belt, is used to record movement and sleep positions in order to extract movement features. Next, a linear discriminant (LD) classifier was used for the automated classification of sleep stages for Wake, REM, light sleep and deep sleep, compared to the PSG. For a more detailed overview of sleep monitoring systems, readers may refer to the review paper¹² published by our team.

In literature, most research adopts supervised machine learning methods that usually require large amounts of learning data to train the classifier and computation to implement the model. However, some works adopt unsupervised methods such as k-means clustering to achieve a sleep stage classification. It is generally based on signals directly related to sleep stages such as the EEG signal which is very intrusive and not easy to collect in home environment.

In this study, we try to use the proposed methods to detect the time of falling asleep and waking up, as well as the time spent in each sleep stage during sleep. This information will be used as important reference provided to users or medical staff to determine whether the sleep is healthy. We propose a threshold-based method and a k-means clustering method using only the acceleration data from a wrist-worn 3-axis accelerometer to achieve first detection of the falling asleep and waking up moments and a classification of sleep stages into four classes: awake, light sleep, deep sleep and REM. The results of the proposed methods will be compared to “Fitbit” and “Withings” devices, namely the “Fitbit Charge 2” and the “Withings Sleep Analyzer”. Both methods require a relatively smaller amount of computation¹³ which could make the implementation of the algorithm easier and more efficient for real-time applications. Moreover, acceleration data from a wrist sensor is very easy to collect. The subject only has to wear a small and lightweight watch like on his wrist, which is very suitable for home environment and long-term monitoring.

The rest of the paper is organized as follows: Section 2 presents the data acquisition and preprocessing method; Sections 3 and 4 describe the proposed “Threshold” method and “MK-means” method respectively; Section 5 presents experimental results to evaluate the performance of the proposed methods. Finally, Section 6 gives a conclusion and perspectives.

2. Data acquisition and preprocessing

2.1. The sensing device and settings

We use a smart module (Fig. 1) already designed in our team as a detection device. The smart module is an embedded system powered by a button battery (3V) whose basic components are: a NRF51822 microcontroller containing a 32-bit ARM Cortex M0 processor and a 256kB flash memory, a 2MB non-volatile FRAM memory for data backup during sleep, a low-power tri-axial accelerometer ADXL362. Programs are written in C using Keil μ Vision.

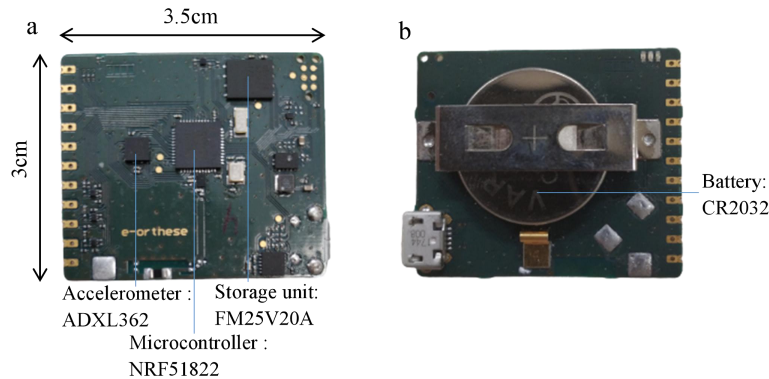


Fig. 1. Smart module-sensing device used. (a) Front side; (b) Back side.

ADXL362 accelerometer on smart module is adopted to acquire acceleration data in the experiment. The parameters of ADXL362 are: $-2g \sim 2g$ measurement range, 12.5 Hz output data rate (ODR) and 8 bits output resolution. Acceleration data is collected every second and stored in FRAM.

A study showed that the average activity of the dominant wrist was higher than for the non-dominant wrists for all behaviors¹⁴. For the physical activity model, a parametric statistical analysis showed significant differences ($p < 0.001$) in the 50th and 90th percentile of accelerations produced by dominant and non-dominant wrists¹⁵. It is therefore necessary to specify whether the device is worn on the dominant or non-dominant wrist in order to adapt the algorithm. In this study, we position the smart module on the non-dominant wrist, wearing it like a watch as shown in Fig. 2.

2.2. Reference devices

We adopt “Fitbit”¹⁶ and “Withings”¹⁷ as reference devices. The average of the results obtained by these two devices is used as a reference to evaluate the results of the proposed methods. The “Fitbit Charge 2” is a commercial device wrist-worn that has been compared to the gold standard PSG (polysomnography) and validated as promising in sleep stages and sleep-wake detection. It showed a sensitivity of 0.96 (accuracy to detect sleep), a specificity of 0.61 (accuracy to detect wake), an accuracy of 0.81 for the detection of N1+N2 sleep (“light sleep”), an accuracy of 0.49 for the detection of N3 sleep (“deep sleep”), and an accuracy of 0.74 for the detection of rapid-eye-movement (REM) sleep¹⁸. The “Withings Sleep Analyzer” is also a commercial device which is a sleep sensor under the mattress. It has been developed in collaboration with the sleep physicians at Hôpital Bécélère in Paris and the data obtained have been carefully compared with those obtained by polysomnography (PSG)¹⁷. During the whole night's sleep, the volunteer will be monitored simultaneously with our Smart Module, “Fitbit” and “Withings”. The implementation of the monitoring devices is shown in Fig. 2.

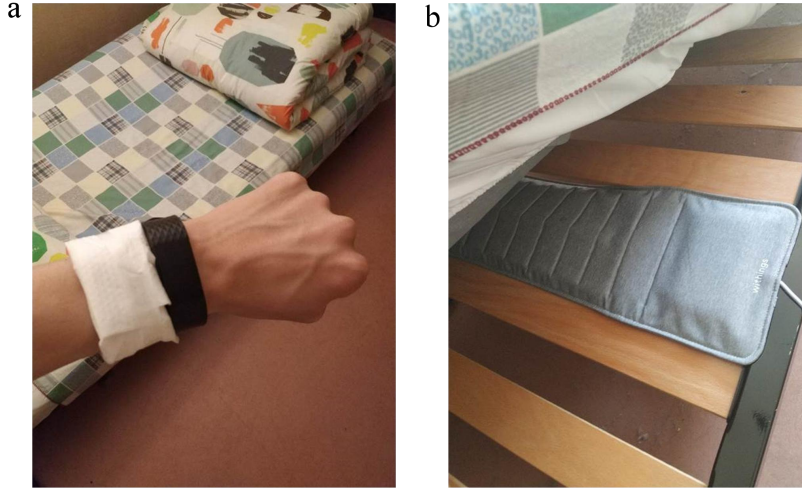


Fig. 2. Implementation of monitoring devices. (a) Smart module (packaged in a white strip) and “Fitbit”; (b) “Withings”.

2.3. Data preprocessing

With the acceleration values Ax , Ay , and Az , a corresponding movement level M_i for sample i will be calculated by equation (1), where N is the number of samples.

$$M_i = |Ax_{i+1} - Ax_i| + |Ay_{i+1} - Ay_i| + |Az_{i+1} - Az_i|, \quad i = 1, 2, 3, \dots, N-1 \quad (1)$$

The data of the night movement level are cut into 30-samples epochs, noted as S_j ($j = 1, 2, 3 \dots L$, where L is the total number of epochs for one night). Each epoch is the shortest unit for the further sleep stage classification, which has a duration of 30s, as in the Rechtschaffen and Kales Guidelines¹⁹. Using a sleep stage classification algorithm, each epoch will be classified as awake, light sleep, deep sleep and REM.

For each epoch, the movement levels of the 30 corresponding samples are summed to obtain an epoch movement level EM_j , as in equation (2).

$$EM_j = \sum_{k=1}^{30} M_{jk}, \quad j = 1, 2, 3, \dots, L \quad (2)$$

Where j is the index of epochs, L is the number of epochs.

As sleep is a constantly evolving process, it is necessary to associate the previous and following periods when analyzing the sleep state at a given time. Thus, for each epoch, 9 epochs are considered before and after it. A weighted PM value is defined (see equation (3)) to further facilitate sleep analysis.

$$PM_j = e^{-0.25}EM_{j-9} + e^{-0.5}EM_{j-8} + e^{-1}EM_{j-7} + e^{-0.25}EM_{j-6} + e^{-0.5}EM_{j-5} + e^{-1}EM_{j-4} + e^{-0.25}EM_{j-3} + e^{-0.5}EM_{j-2} + e^{-1}EM_{j-1} + e^0EM_j + e^{-1}EM_{j+1} + e^{-0.5}EM_{j+2} + e^{-0.25}EM_{j+3} + e^{-1}EM_{j+4} + e^{-0.5}EM_{j+5} + e^{-0.25}EM_{j+6} + e^{-1}EM_{j+7} + e^{-0.5}EM_{j+8} + e^{-0.25}EM_{j+9}, \quad j = 10, 11, 12, \dots, L-9 \quad (3)$$

3. “Threshold” method

3.1. Step 1: Sleep and Awake discrimination

We note the threshold-based method as the “Threshold” method. Wrist movement can be considered as an indicator of wakefulness²⁰. The amount of wrist movement can therefore be a sign of sleep or awake. We define $T_{S/W}$ as a threshold for discriminating “Awake” from “Sleep” epochs, which is 1350 determined from observations and experimental tests. When the PM value of an epoch is greater than $T_{S/W}$, the epoch is classified as “Awake”. Otherwise, it is classified as “Sleep” and the discrimination process continues to refine the classification.

3.2. Detection of falling asleep and waking up

Based on “sleep” and “awake” detections using the threshold method described above, we have defined a falling asleep point and a waking up point corresponding respectively to the beginning and the end of a night sleep.

Once monitoring begins, if the “sleep” state lasts at least 5 minutes, the first point of the 5 minutes will be considered as the starting point of falling asleep, noted as asleep point. Starting from the end of recording and doing backward monitoring, if the “sleep” state lasts at least 5 minutes, it will be considered as the last “sleep” epoch. So the next epoch is considered as the starting point of the awakening, noted as awakening point. The epochs between asleep point and awakening point are defined as a sleep segment.

3.3. Step 2: Deep sleep, Light sleep and REM discrimination

As the lower movement level corresponds to the deep sleep state²¹, it is feasible to define a standard deviation threshold of several continuous PM values to distinguish deep sleep from light sleep and REM. For epochs first classified as “Sleep”, 6-epochs groups G are formed (representing 3-minute data). For each G , the standard deviation (SD) of the PM values is calculated. If SD is less than a threshold $T_{D/LR}$, the epochs in G are classified as “Deep sleep”. The $T_{D/LR}$ value is 49 derived from testing, observation and correction.

Light sleep and REM are characterized by relatively high and relatively low movement levels respectively. Thus, a new threshold on the PM value can be used to discriminate them. After the two previous steps, the remaining epochs noted as H can be classified as “Light sleep” or “REM”. To discriminate these two stages, a 560 value threshold $T_{L/R}$ is defined, derived from experimental observation and tests. When the PM of H is higher than $T_{L/R}$, it will be classified as “Light sleep” otherwise as “REM”.

3.4. Optimization processing

After obtaining the result of the sleep stages classification, some steps are necessary to optimize results:

- Modify all the epochs before falling asleep point to be “awake”.
- Modify all the epochs after awakening point to be “awake”.
- When ‘light sleep’ lasts no more than 1 minute and there is an “awake” state before and after, define this ‘light sleep’ period so that it is classified as ‘awake’.
- When “REM” lasts less than 1 minute and there is a ‘light sleep’ before and after, set this “REM” period as a ‘light sleep’ one.

4. “MK-means” method

4.1. K-means clustering

As a classical machine learning method, k-means clustering²² has been widely used in fields as diverse as image segmentation, data compression, wireless sensor network routing, data mining, etc. It is an efficient method for automatically classifying a dataset into k-groups based on the similarity of the features of each dataset.

For the k-means clustering algorithm, the selection of the initial cluster centers could significantly affect the final clustering result. As the initial clustering centers are randomly selected, the clustering result also has some uncertainty. During the experiments, we found that the final clustering results using randomly selected cluster centers usually do not change much, but in few cases the final clustering results were very far from each other, as also reported in²³. To prevent this issue, we repeat the same clustering procedure 10 times, and then determine the classification to which the epoch finally belongs by majority voting.

The k-means method is applied to sleep epochs to obtain a hypnogram containing “Awake”, “Light sleep”, “Deep sleep” and “REM”. The sleep epochs start from the time where we fall asleep until we wake up, which is detected by the “Threshold” method described in section 3. As far as we know, there are several works^{24,25,26} which adopt k-means method to classify sleep stages using the EEG signal, but none use the wrist movement signal.

4.2. Features extraction

A 2-dimension feature based on *PM* is used for k-means clustering. We directly use *PM* as the first dimension of the feature. All *PM*s are grouped sequentially, and each group contains 6 *PM* values. The standard deviation of the *PM* values in each group is used as the second dimension of the feature for the 6 corresponding epochs in the group. In other words, the second dimension of the feature for the 6 epochs in a group is the same, i.e. the standard deviation of the corresponding *PM* values.

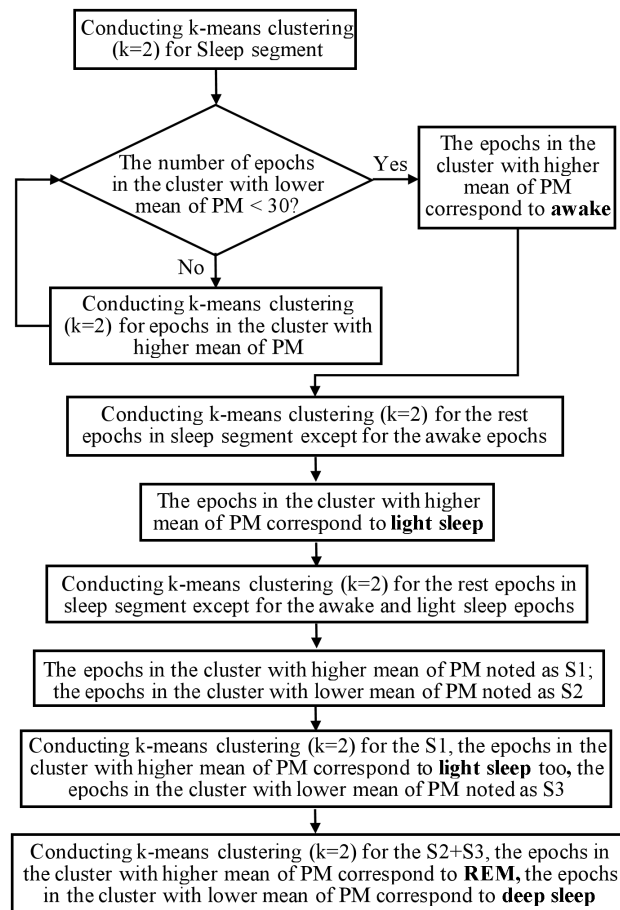


Fig. 3. Flow chart of MK-means method.

4.3. Sleep stages clustering

The overall procedure of this clustering method includes multiple iterations of k-means clustering with $k=2$, noted as “MK-means”. Fig. 3 shows the detailed process of the proposed “MK-means” method.

5. Experiment results

5.1. Experimental setup

One adult male without subjective sleep complaints was recruited for the tests. He is 28 years old and has a BMI (body mass index) of 18.3. A total of 10 overnights sleep data acquired in real conditions were tested using four sleep stage classification methods: two commercial products including “Fitbit” and “Withings”, two proposed methods including the “Threshold” method and “MK-means” method. Both the “Threshold” method and the “MK-means” method are implemented solely based on wrist movement data. The proposed algorithms are all implemented on the same computer with “Intel i7-2600 CPU @ 3.40GHz, 8GB RAM” on “MATLAB R2011b”.

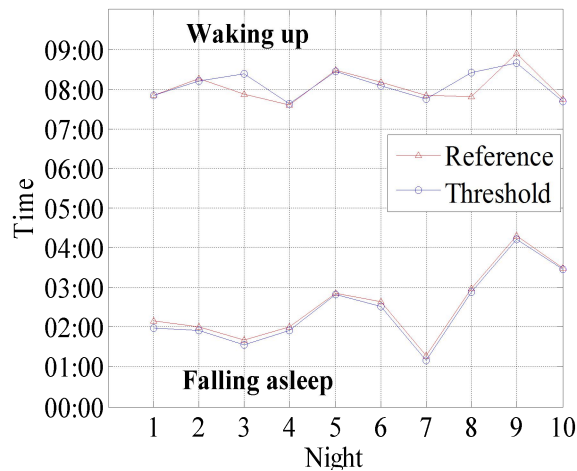


Fig. 4. Time of falling asleep and waking up obtained by reference and “Threshold” method.

5.2. Falling asleep and waking up detection

The detection of falling asleep and waking up is only achieved by the “Threshold” method. The mean value of “Fitbit” and “Withings” for the moments of falling asleep and waking up is adopted as reference. Over 10 nights, the absolute values of the time difference between the “Threshold” method and the reference for falling asleep time is 5.6 ± 2.4 min, and for waking up time is 10.3 ± 12.4 min. The 10 nights’ falling asleep and waking up time obtained by the reference and the “Threshold” method are shown in Fig. 4. As can be seen, the time difference for falling asleep is always very small. For the waking up time, most of them are very close to the reference. A relatively significant deviation appears during two nights (3 and 8), respectively 30 and 35 min.

5.3. Cumulative duration of each sleep stage

The cumulative duration of each sleep stage is calculated for the “Fitbit”, “Withings”, “Threshold” and “MK-means” methods. We take the mean value of “Fitbit” and “Withings” for the cumulative duration of each sleep stage as a reference. Table 1 shows the mean \pm SD of the cumulative duration of each sleep stage obtained by reference, “Threshold” method and “MK-means” method. To check whether there is a statistically significant difference between the “Threshold” method and the reference or between the “MK-means” method and the reference with

regard to the cumulative duration of each sleep stage, we compute p-values for Pearson's correlation using a Student's t-distribution for a transformation of the correlation. The p-value is the probability of obtaining test results at least as extreme as the results actually observed, under the assumption that the null hypothesis is correct²⁷. Generally, it is considered that there is no statistically significant difference when $p < 0.05$ ²⁸. As shown in Table 1, only the cumulative duration of REM detected by the “MK-means” method shows a statistically significant difference with the reference. The cumulative duration of the REM by the “MK-means” method is slightly overestimated.

Table 1. Measures of the cumulative duration of each sleep stage between the reference and proposed methods.

Cumulative duration of each sleep stage (min)		Awake	Light	Deep	REM
Reference	Mean±SD	21.5±5.1	181.5±29.9	68.6±20.9	58.7±21.2
	Mean±SD	30±20.3	181.0±45.5	68.8±26.3	59.8±23.0
Threshold method	p-value	0.30	0.35	0.52	0.10
	Mean±SD	8.6±4.7	172.2±53.4	82.6±39.5	75.2±20.6
MK-means method	p-value	0.51	0.70	0.47	0.03

Bland-Altman plots were used to evaluate the agreement of the two proposed methods with reference to the detected cumulative duration of each sleep stage. As shown in Fig. 5 and Fig. 6, only one point in one of the sub-pictures (Fig. 5c) falls outside the range of the dotted line. This means that only the deep sleep duration estimated by the “Threshold” method for only one night is out the 95% agreement limit. It reveals good concordance between the two proposed methods and the reference.

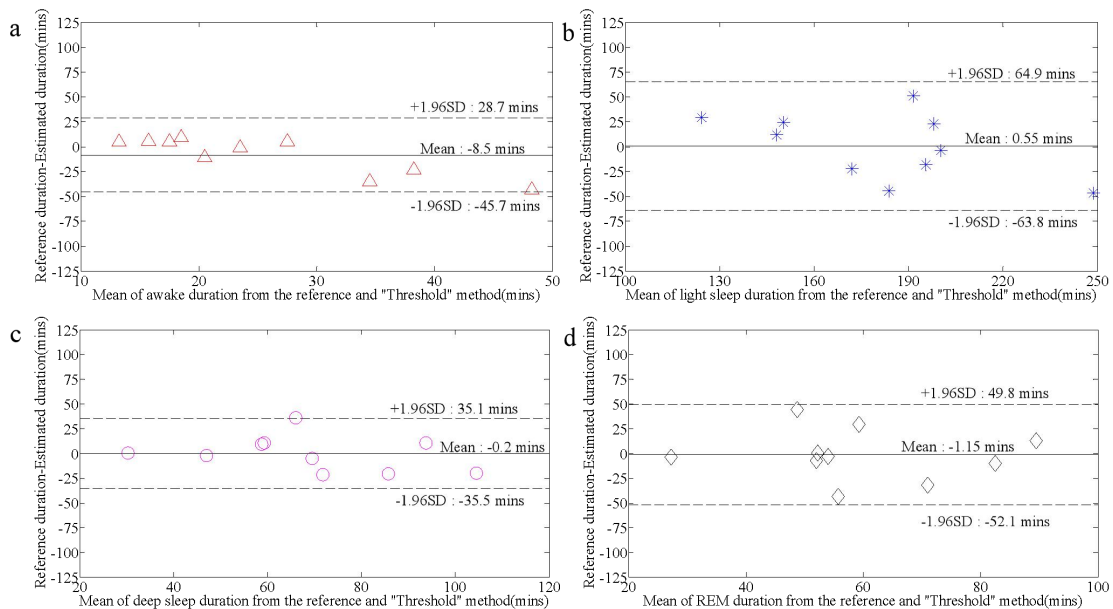


Fig. 5. A Bland-Altman agreement plot for four sleep stages determined by the “Threshold” method. (a) awake; (b) light sleep; (c) deep sleep; (d) REM.

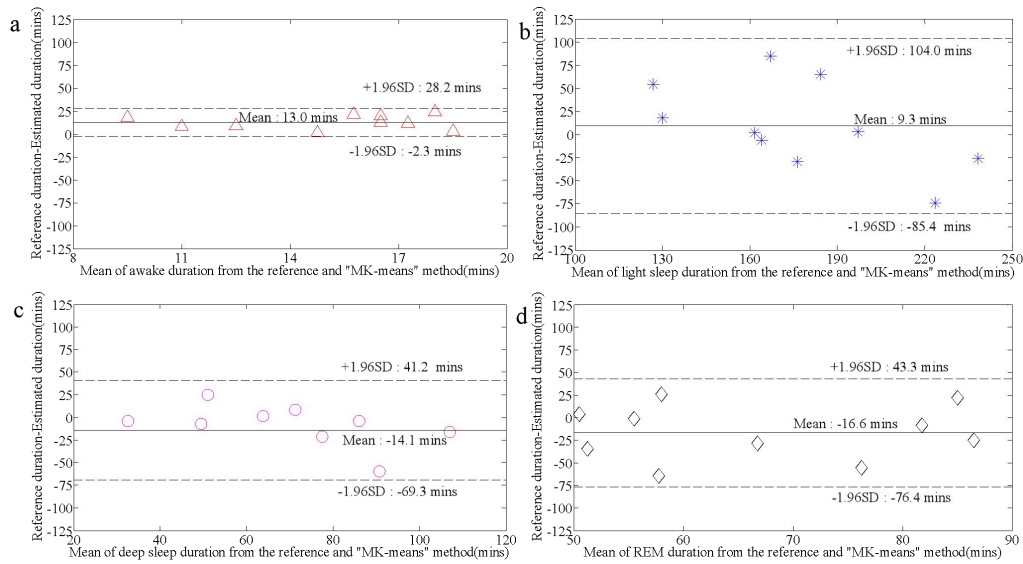


Fig. 6. A Bland-Altman agreement plot for four sleep stages determined by the “MK-means” method. (a) awake; (b) light sleep; (c) deep sleep; (d) REM.

The “MK-means” method gives no results out the 95% agreement limit. However, it should be noted that, compared to the reference, the results obtained by the “Threshold” method in the estimation of light sleep, deep sleep and REM duration show a deviation significantly lower (the points are closer to the $x=0$ line in the ordinate direction) than the “MK-means” method. Nevertheless, we still believe that the clustering method has advantages over the threshold method. We think that the method implemented by clustering is more versatile than the method implemented by simply using fixed thresholds. We assume that the “Threshold method” using adjusted thresholds for an individual may perform very good performances in long-term sleep monitoring for that person. These conjectures need to be verified by recruiting more volunteers to conduct many experiments. This is also our next work.

6. Conclusion

In this study, we propose two sleep monitoring algorithms based only on wrist movements acquired by a 3-axis accelerometer. The proposed algorithms include a “Threshold” method and a “MK-means” method. The “Threshold method” uses three thresholds to achieve falling asleep and waking up detection and provides classification into four sleep stages (“awake”, “light sleep”, “deep sleep” and “REM”). The “MK-means” method also achieves classification into four sleep stages. The commercial products “Fitbit” and “Withings” are used as a reference device to validate the proposed methods. Experimental data are acquired from 10 overnights sleep of a volunteer. For the detection of falling asleep and waking up time, the proposed method shows a deviation of 5.6 ± 2.4 mins and 10.3 ± 12.4 mins respectively compared to the reference. For the detection of cumulative duration of each sleep stage, a p-value is calculated. The results show that only the “MK-means” method slightly overestimated the cumulative duration of REM. Meanwhile, Bland-Altman's plots also show that both methods are in good agreement with the reference. Although good results were obtained in this primary study, tests with more volunteers and validation using a gold standard such as the PSG are necessary. This work is ongoing.

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