IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received March 10, 2020, accepted April 2, 2020, date of publication April 7, 2020, date of current version April 23, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2986397

A Short-Time Insomnia Detection System Based on Sleep EOG With RCMSE Analysis

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This work was supported by the Ministry of Science and Technology of Taiwan under Grant MOST 108-2221-E-035 -064 and Grant 109-2634-F-006-013. It was carried out at the AI Biomedical Research Center, Tainan, Taiwan.

ABSTRACT *Objective:* Currently, the prevalence of insomnia in 30% of the population in the word. To diagnose sleep issues, all-night polysomnography is usually taken from the patients, and the recordings are scored by a clinical staff. Nevertheless, manual sleep scoring and diagnosis are time consuming and subjective. In this study, a short-time insomnia detection system based on single-channel sleep EOG with refined composite multiscale entropy (RCMSE) analysis was proposed, and the performance of the proposed system was assessed with the manual scoring based on polysomnography. *Methods:* The sleep data from 32 subjects were used to develop and evaluate the proposed system; one half was healthy individual and the other half was insomnia patient. The corresponding RCMSE was computed from the short time single-channel sleep EOG (<30 min). Then, the mean values of their RCMSEs were computed. Finally, the mean values were used as input to an SVM classifier for insomnia detection. *Results:* 16 subjects were used to train a classifier; one half was healthy individual and the other half was insomnia patient; and the others were used to test. The averaged accuracy, sensitivity, specificity, kappa coefficient, and F_1 score of the proposed system were 89.31%, 96.63%, 82.00%, 0.79, and 90.04%, respectively. *Conclusion:* Our results showed that RCMSE is a useful and representative feature for short-time insomnia detection. In addition, the proposed method has high accuracy and is good homecare applicability because a single-channel sleep EOG is used. *Significance:* In the future, we can integrate the proposed system with an EOG eye mask and portable PSG system for sleep quality assessment or insomnia screening in the home environment.

INDEX TERMS Short-time insomnia detection, refine composite multiscale entropy, single-channel sleep EOG, support vector machine.

I. INTRODUCTION

Sleep takes approximately one-third of human live. A good sleep can help us getting the body to work right again, improved learning ability, physical development, emotional regulation, and good quality of life in human physiology [1]. However, the prevalence of insomnia symptoms without restrictive criteria is approximately 33% in the general population [2]. In the United States of America, 50-70 million people suffer from sleep disorders: among them, 30% of patients suffer from insomnia and 10% from chronic insomnia.

Insomnia is defined as chronic when it has persisted for at least three months at a frequency of at least three times per week. When the disorder meets the symptom criteria but has persisted for less than three months, it is considered short-term insomnia [3]. To diagnose insomnia, the physician may first execute a physical exam to look for signs of medical problems that may be related to insomnia and ask some sleep-related questions, such as sleep-wake pattern and daytime sleepiness. In addition, the physician may ask a subject to keep a sleep diary with the actigraphy for a couple of weeks. If the cause of insomnia is not clear, the subject should spend one or two night at a sleep center diagnosing another sleep disorder using polysomnography (PSG), such as sleep apnea.

PSG recordings, which including electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), and other physiological signals are usually obtained from patients and scored by a well-trained clinical staff. According to AASM rules [4], the sleep stages could be divided into

The associate editor coordinating the review of this manuscript and approving it for publication was Rajeeb Dey.

wakefulness (Wake), non-rapid eye movement (Non-REM; stages 1-3), and rapid eye movement (REM). Then, patient hypnograms (all-night sleep stages of the patient) are delivered to a physician for further analysis. However, sleep stage scoring is expensive because of the manpower shortage and because the demand for diagnosing sleep disorders exceeds the supply. Moreover, manual sleep scoring and diagnosis is a time consuming and subjective process, and the conventional polysomnography which uses many wires to connect instrument to patient is often a problem that leads to sleep disturbance. In general, people will experience the ''first-night effect,'' which often interferes with sleep quality, if they sleep in hospitals or sleep centers [5].

Currently, there is extensive ongoing research to develop an automatic sleep stage scoring system based on multi- or single-channel, including using decision tree [6], [7], machine learning [8]–[10], and deep learning [11]–[13], but the automatic sleep disorder detection proposed to date is primarily used for ''sleep apnea,'' and little research is devoted to insomnia detection. Insomnia detection often uses several features of the all-night sleep stages or a certain sleep stage to detect insomnia [14]–[17]. Although the overall accuracy of insomnia detection is more than 85%, it is still necessary to record all-night multi-channel PSG signal and manually score sleep stages.

Entropy was used to analyze the complexity of the biosignal in previous study [18]. For example, entropy was utilized to classify the sleep stage, assess the depth of anesthesia, detect epilepsy or analyze heart rate variability, etc. Moreover, multiscale entropy (MSE), a new signal analysis method, had been proposed [19], [20] to estimate the complexity associated with the long-range temporal correlation of a time series. Instead of a single scale, MSE calculates the sample entropy of a time series over multiple temporal scales. MSE had been applied in sleep field [21], [22]. Liang *et al.* [21], [22] computed MSE of EEG and EOG, and then used their MSE to develop the automatically sleep stage classification. Although MSE was a good method to quantify the complexity of signals, the sample entropy may not be defined because no template vectors are matched to one another, and the sample entropy may not be accurate with the time series over the larger multiple temporal scales. Therefore, refined composite multiscale entropy (RCMSE) had been proposed to overcome the shortcoming of MSE. RCMSE had proved that RCMSE increases the accuracy of entropy estimation in time series analyses [23]. In this study, MSE and RCMSE were applied to analyze sleep EOG signal from people within healthy and insomnia groups for short-time insomnia detection.

With the gradually increasing understanding that ''prevention is better than a cure,'' consumer sleep trackers are expanding in the home health monitoring market. An increasing number of sleep trackers focus on ease of wear, small size, and comfort. Therefore, most sleep trackers are worn on the wrist [24] or forehead or as eye masks [22], [25] in place of the conventional PSG, which an EEG cap or the placement of electrodes on top of the head. For example, actigraphy was utilized as a valid and convenient method to assess sleep-wake patterns in patients suspected of certain sleep disorders, such as insomnia [24]. Nevertheless, the equipment used for this method must be worn for 24 hours, except for during bathing, and actigraphy requires a two-week continuous measurement for the insomnia screening process in the home environment to understand a user's sleep-wake cycle and actual sleep time. Additionally, single-channel EEG has been very successful in sleep scoring [6], [21], but electrodes must be placed above the hairline on the scalp and expert help is needed to set up the system and collect data. Compared with EEG, EOG offers the advantage of easy placement and can be operated by the user him/herself.

In this study, a short-time insomnia detection system based on a single-channel sleep EOG with RCMSE analysis was proposed. First, a single-channel sleep EOG was filtered with a band pass filter to remove artifacts. Second, the RCMSE values with a scale factor of 1 to 8 were extracted from the all-night sleep EOG in 30-s epochs to compare the differences between the healthy and insomnia groups. Third, the RCMSE values from the first 27.5 min, with scale factor of 1 to 9 were used to compute its mean values as the input of classifier. Finally, the support vector machine (SVM) was used to detect insomnia. In addition, MSE and RCMSE were applied to analyze the sleep EOG signals from subjects belonged the different groups, and the MSE and RCMSE values with different sleep stages were also compared between the healthy and insomnia groups.

II. MATERIALS AND METHODS

A. MATERIALS

In this study, we used PSG data from 16 healthy individuals (sleep efficiency (SE) $\geq$ 85%) and 16 insomnia patients (sleep efficiency (SE) $<$ 85%) recruited from the public by online advertisements and announcements on notice boards at the National Cheng Kung University to collect all-night PSG recording. None of the participants had a prior history of drug or alcohol abuse and no neurological, psychiatric or sleep disorders. The insomnia patients experience insomnia more than three days per week, lasting for at least one month, and suffer from drowsiness, sleepiness, and irritable mood during the daytime, affecting their ability to learn and work. The insomnia patients had SE $<$ 85%, sleep onset time (SOT) $>$ 15 minutes, and/or wake after sleep onset time (WASO) $>$ 30 minutes. Sleep efficiency is the ratio of the total sleep time (TST) to the time spent in bed. If patients sleep efficiency is lower than 85% in clinical diagnosis, they may have a sleep disorder. In our experiments, the range of participants' sleep efficiency was from 56% to 97%. The sleep efficiency of the healthy group was equal to or higher than 85%, and those of the insomnia group were lower than 85%.

These measurements were approved by the internal review board of National Cheng Kung University. Participants had to refrain from any drug/medication and limit caffeine use

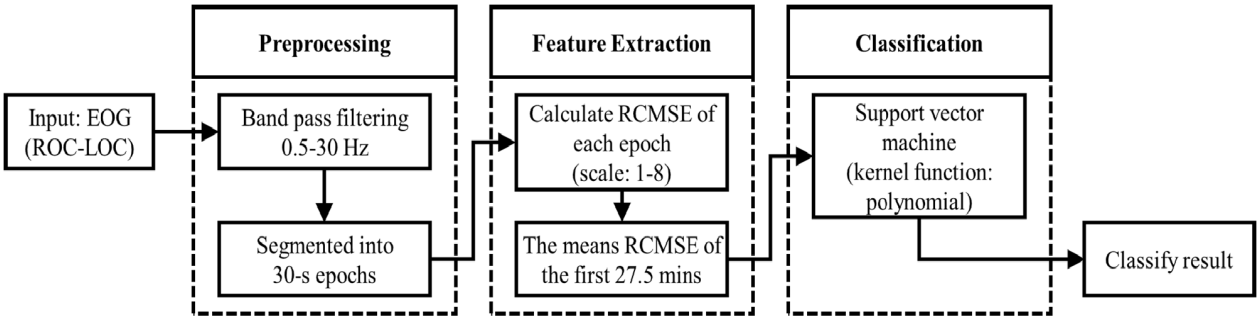


FIGURE 1. Flowchart of the proposed short-time insomnia detection system based on a single-channel sleep EOG with RCMSE analysis.

TABLE 1. Detailed information of the sleep dataset used in this study.

	Healthy	Insomnia	Total
Total epoch	15,200	14,326	29,526
Wake (%)	2.84	15.93	9.19
N1 (%)	3.41	4.13	3.76
N2 (%)	47.95	37.86	43.05
N3 (%)	16.22	14.07	15.18
REM (%)	19.22	15.64	17.48
Mov (%)	10.36	12.37	11.34
SE (%)	92.29±3.35	74.85±8.99	84.01±10.96
TST (min)	431.83±31.76	323.50±58.64	380.38±71.34
SOT (min)	11.60±8.17	41.58±37.14	25.84±30.24
WASO (min)	24.55±14.37	68.79±44.77	45.56±39.35

(no caffeine intake for at least 5-6 h prior to sleep laboratory visits). All-night PSGs were recorded in the sleep laboratory at the cognitive institute of National Cheng Kung University. There was no outside interference during data collection, and no medications were used to induce sleep. The PSG recordings (Siesta 802 PSG, Compumedics, Inc.) included two electroencephalogram (EEG) channels (C3-M2 and C4-M1, according to the international 10-20 standard system), one electrooculogram (EOG) channel (positioned 1 cm below and above the left and right outer canthi, ROC-LOC), and a chin electromyogram (EMG) channel. The sampling rate was 256 Hz with a 16-bit resolution. According the AASM rule, all PSG recordings in the experiment were segmented into a number of 30-s intervals called epochs, and each epoch was classified into a specific sleep-stage, including Wake, N1, N2, N3, REM, and body movement. Table 1 shows the number of epochs in different sleep stages and sleep indices of the healthy individuals and insomnia patients.

B. METHODS

Fig. 1 shows the flowchart of the proposed short-time insomnia detection system based on a single-channel sleep EOG with RCMSE analysis, which includes three parts: 1) preprocessing, 2) feature extraction, and 3) classification. The following figure presents each part in greater detail.

1) PREPROCESSING

The sleep EOG signals were filtered with an eighth-order Butterworth band pass filter with a cutoff frequency of 0.5 - 30 Hz according to the suggestion of the AASM rule. Next, we followed the AASM rule on the manual sleep scoring. Therefore, the sleep EOG signals were segmented into several 30-s epochs and then a 30-s epoch was extracted an MSE and RCMSE feature. Therefore, the all-night sleep EOG for one subject could be extracted a number of MSE and RCMSE features.

2) FEATURE EXTRACTION

a: SAMPLE ENTROPY (SampEn)

Let N is the length of the time series, m is the length of sequences to be compared, and r is the tolerance for accepting matches. Defining a time series $\mathbf{x} = \{x_1, x_2, x_3, \ldots, x_N\}$ of length N, and an m-dimensional sequence vector, $\mu^{(m)}(i) = \{x(i), x(i+1), \ldots, x(i+m-1)\}$, a distance measure for two vectors $\mu^{(m)}(i)$ and $\mu^{(m)}(j)$ with length of m points is defined as $d(i,j) = \max\{|x(i+k) - x(j+k)| : 0 \leq k \leq m-1\}$. $\mu^{(m)}(i)$ is similar to $\mu^{(m)}(j)$ when $d(i,j) \leq r$. $C_i^m(r)$ represent the ratio of the number of the $d(i,j) \leq r$ to the total length, which can be calculated by the following (1):

$$C_i^m(r) = \frac{\sum_{j=1, j\neq i}^{N-m-1} \omega_j}{N-m-1}, \tag{1}$$

where $\omega_j = 1$ if $d(i,j) \leq r$, otherwise, $\omega_j = 0$. j is a integer from 1 to N, and $j \neq i$ to exclude self-matches. The probability that the two sequences will match for m points can be calculated by the following (2):

$$C^m(r) = \frac{\sum_{i=1}^{N-m} C_i^m(r)}{N-m}, \tag{2}$$

the probability that the two sequences will match for $m+1$ points is calculated by (3):

$$C^{m+1}(r) = \frac{\sum_{i=1}^{N-m} C_i^{m+1}(r)}{N-m}, \tag{3}$$

for the sample entropy, i and j are integer from 1 to N for the calculation of both m and $(m+1)$-point matching. Finally, the sample entropy is calculated by (4):

$$SpEn(r, m, \boldsymbol{x}) = -ln\left[\frac{C^{m+1}(r)}{C^m(r)}\right], \tag{4}$$

some theoretical and clinical applications have shown that the parameters $m = 1$ or 2 and $r = 0.1$ to 0.25 of the standard

deviation (SD) of the original time series provide good statistical validity for SampEn [26], [27]. The parameters $m = 2$ and $r = 0.15 \times SD$ were used to calculate SampEn values in this study.

b: MULTISCALE ENTROPY (MSE)

Multiscale entropy extends the entropy to multiple temporal scales to analyze the complexity of a time series. MSE can be computed from the different types of entropy which were calculated by multiple coarse-grained time series, such as approximate entropy [28] or SampEn [18]. SampEn was taken as the core for the entropy calculation in this study.

Given a 30-s epoch EOG time series with N samples, $\mathbf{x} = \{x_1, x_2, \ldots, x_N\}$, and a scale factor τ. The time series $\mathbf{x}$ is segmented into non-overlapping windows of length τ. The mean of each window is then computed. Each element of the coarse-grained time series $y_\tau(j)$ is according to (5):

$$y_\tau(j) = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \quad 1 \le j \le \frac{N}{\tau}, \tag{5}$$

after obtaining the coarse-grained time series of the different scale factor, we calculate the sample entropy for each coarse-grained time series. For scale factor τ, we can obtain τ coarse-grained time series which corresponding length is $\frac{N}{\tau}$ and denoted as $\mathbf{y}_\tau = \left\{y_\tau(1), \ldots, y_\tau(i), \ldots, y_\tau\left(\frac{N}{\tau}\right)\right\}$. The MSE at a scale factor of τ is defined as the SampEn of the coarse-grained time series which is computed by (6):

$$MSE = SpEn\left(r, m, \mathbf{y}_\tau\right). \tag{6}$$

c: REFINED COMPOSITE MULTISCALE ENTROPY (RCMSE)

Since each coarse-grained time series is down sampled according to the raw time series, as the scale factor (τ) increases, the length of the coarse-grained time series shortens. However, most of the entropy values are dependent on the length of the time series: therefore, as the length of the coarse-grained time series decreases, the variance of entropy gradually increases. The range of the measurement error of MSE may be very large for large scale factors. For this reason, Wu *et al.* [29] proposed the composite multiscale entropy (CMSE) algorithm to improve the accuracy of the MSE algorithm. In CMSE, τ coarse-grained time series are calculated for a scale factor of τ, and each element of the coarse-grained time series $y_k^{(\tau)}(j)$ is calculated by the following (7):

$$\mathbf{y}_k^{(\tau)}(j) = \frac{1}{\tau} \sum_{i=(j-1)\tau+k}^{j\tau+k-1} x_i, \quad 1 \le j \le \frac{N}{\tau}, 1 \le k \le \tau. \tag{7}$$

For scale factor τ, the length of the corresponding coarse-grained time series in CMSE is $\frac{N}{\tau}$, denoted as $\mathbf{y}_k^{(\tau)} = \left\{y_k^{(\tau)}(1), \ldots, y_k^{(\tau)}(2), \ldots, y_k^{(\tau)}\left(\frac{N}{\tau}\right)\right\}$. The coarse-grained time series $\mathbf{y}_k^{(\tau)}$ in RCMSE are calculated by (7). Then, the probabilities $C_{k,\tau}^{m+1}(r)$ and $C_{k,\tau}^{m}(r)$ in (4) are calculated for all τ coarse-grained series and are denoted as $\mathbf{C}_{k,\tau}^{m+1} = \left\{C_{1,\tau}^{m+1}(r), C_{2,\tau}^{m+1}(r), \ldots, C_{k,\tau}^{m+1}(r)\right\}$ and $\mathbf{C}_{k,\tau}^{m+1} = \left\{C_{1,\tau}^{m}(r), C_{2,\tau}^{m}(r), \ldots, C_{k,\tau}^{m}(r)\right\}$. Finally, the RCMSE value is defined as the logarithm of the ratio of the average $\mathbf{C}_{k,\tau}^{m+1}$ to the average $\mathbf{C}_{k,\tau}^{m}$ for a scale factor τ. The RCMSE value is calculated by the following (8):

$$RCMSE = -ln\left[\frac{\frac{1}{\tau}\sum_{K=1}^{\tau} C_{k,\tau}^{m+1}(r)}{\frac{1}{\tau}\sum_{K=1}^{\tau} C_{k,\tau}^{m}(r)}\right]. \tag{8}$$

In the part of the feature extraction, MSE and RCMSE were computed using the coarse-grained time series with scale factor of 1 to 20 which was generated from sleep EOG of each 30-s epoch for each subject. Next, in order to find how long sleep times and which scale factors are adopted to accurately detect insomnia, we used the MSE and RCMSE values from the first 2.5, 5, 7.5,..., 120 minutes to compute their mean values. For example, the mean MSE/RCMSE value of the first 2.5 minutes was calculated from the averaged MSE/RCMSE values of the first five 30-s epoch. Then, we selected the mean values of MSE/RCMSE with scale factor from one to τ as features for insomnia detection. In other word, there are totally 48 different length of the sleep times were used. On the other hand, the averaged MSE/RCMSE values of the different scale factors through the entire night and for different sleep stages were also compared between the healthy and insomnia groups in this study.

Taking to use MSE to detect insomnia for example, sleep time of a subject was eight hours which could be segmented into 960 epochs, namely 960 30-s intervals, and each epoch was computed an MSE with scale factor of 1 to 20. Then, the mean of MSE, which was computed using the MSE of several epochs from the subject, was as an input for classifier. We used $\mathbf{f}_{(i,k)} = \left\{f_{(1,k)}, f_{(2,k)}, \ldots, f_{(i,k)}\right\}$, to present MSE of the k^{th} epoch with scale factor of 1 to i, and the features set $\bar{\mathbf{f}}_{(i,j)} = \left\{\bar{f}_{(1,j)}, \bar{f}_{(2,j)}, \ldots \bar{f}_{(i,j)}\right\}$ to present the average of MSE of the j epochs with scale factor of 1 to i, which is a classifier input. Each element of the average MSE $\bar{f}_{(i,j)}$ is according to the (9):

$$\bar{f}_{(i,j)} = \frac{1}{j} \sum_{k=1}^{j} f_{(i,k)}, \tag{9}$$

where i is presented scale factor, namely the length of the feature set $\bar{\mathbf{f}}_{(i,j)}$, j is presented the 1st to j^{th} epochs, which the ranges of j from 5 to 250 epochs with five epochs interval (i.e., 5, 10, 15, ..., 250 epochs). Finally, the feature set $\bar{\mathbf{f}}_{(i,j)}$ was used as input to the classifier to distinguish insomnia. The procedure for detecting insomnia using RCMSE is also the same as above.

3) CLASSIFICATION

To implement a wearable eye-mask device in the future, we selected three classifiers to experiment which are easy to implement in the microcontroller to distinguish the insomnia, including linear discriminant analysis (LDA), support vector machine (SVM), and ensemble of random subspace discriminant analysis (Ensemble). In addition, the SVM is well known for their good performance in binary classification.

a: LINEAR DISCRIMINANT ANALYSIS

A linear classifier was used to classify the extracted averaged MSE values into the healthy individual and insomnia patient groups. In addition to reduce the computational cost, LDA can demonstrate the distinguishability of the proposed EEG features by using a linear classifier. LDA uses a hyperplane to determine the linear combination of features that best separates two or more classes of objects or events. Usually, within-class, between-class, and mixture scatter matrices are used to formulate the criteria to search the hyperplane so that the distance between the class means is minimized and the interclass variance is maximized.

b: SUPPORT VECTOR MACHINE

Support vector machine was first proposed by Vapnik [30]. SVM methods consider the classification problems as quadratic optimization problems. The SVM attempts to find a separating hyperplane for an input data set, because it can maximize the edge width around the separating hyperplane between two categories and minimize the training error. Therefore, the SVM can also accurately classify future test data sets. Essentially, the SVM is a linear classifier for distinguishing linearly separable data: However, the input data set may not be linearly separable in general. To overcome this problem, kernel tricks such as polynomial, radial basis, and Gaussian kernel, are utilized. Use of the kernel tricks can map the data sets in the original space into high-dimensional space where the data sets become linearly separable. In this study, we employed the polynomial kernel function for insomnia detection, because the polynomial kernel is commonly used with SVMs and is usually used to distinguish EEG of different groups.

c: ENSEMBLE OF RANDOM SUBSPACE DISCRIMINANT ANALYSIS

Ensemble methods can be used to improve the performance of a classifier. In these methods, instead of a single classifier, a group of classifiers is trained, and the final result is obtained using these classifiers. Ensemble methods are utilized to solve various problems, as well as to obtain higher accuracy. In this study, we used the ensemble of subspace discriminant analysis method. The random subspace method is a relatively recent method of combining models. Learning machines are trained on randomly chosen subspaces of the original input space (i.e., the training set is sampled in the feature space). The outputs of the models are then combined, usually by a simple majority vote.

C. PERFORMANCE EVALUATION

1) VALIDATION PROCESSING

In methods, we illustrate the feature set $\bar{\mathbf{f}}_{(i,j)}$ is used as input to the classifier to distinguish insomnia, and $\bar{\mathbf{f}}_{(i,j)}$ is the mean of MSE or RCMSE with the subject. It is independent of subjects and is also independent of the subjects' epochs which was used to compute $\bar{\mathbf{f}}_{(i,j)}$ in training and testing set. Namely, the epochs from the same subject does not simultaneously exist in both the training and testing sets in each validation. This method is more rigorous, because the epochs from the same subject does not exist in the training and testing set at the same time. To verify the robustness of our proposed method, the half subjects of the healthy and insomnia groups were randomly divided into training and the other half subject was used for testing set. The number of scale factor and different length of time are 20 and 48. Then, we fixed the number of scale factor and the length of time and repeated 100 times the validation processing with randomly training and testing set. In other word, there are totally 100 trained model in each scale factor and the different length of time. Next, we got 100 confusion matrices from 100 randomly testing sets by 100 different trained models. We summed the 100 confusion matrices as a confusion matrix to present the final result of the number of scale factor and the length time. Finally, we got 960 summed confusion matrices, and the corresponding accuracy, sensitivity, specificity, F_1 score, and kappa coefficient to present the different scale factor with different length of time.

2) METRICS

We used different metrics from confusion matrix to evaluate the performance of the proposed method, including the overall accuracy (overallAcc), sensitivity (Se), specificity (Sp), and F1 score (F1). These metrics are defined as follows:

$$overallAcc = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

$$Se = \frac{TP}{TP + FN} \tag{11}$$

$$Sp = \frac{TN}{TN + FP} \tag{12}$$

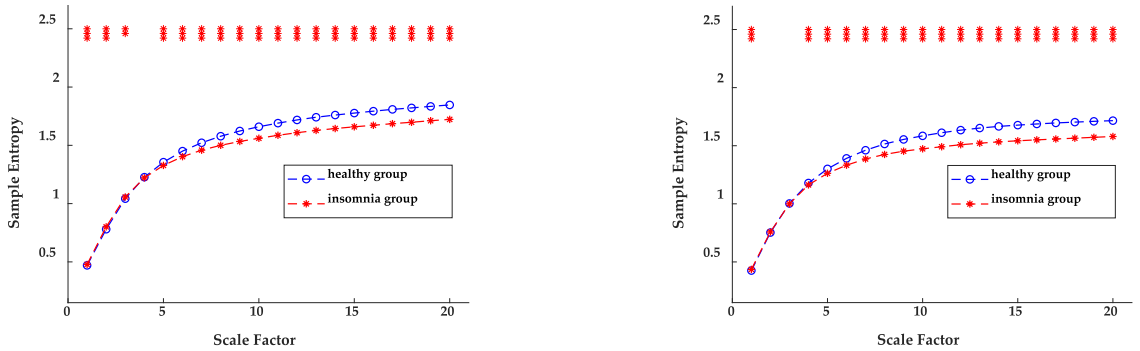
$$F_1 = 2 \times \frac{Precision \times Se}{Precision + Se} \tag{13}$$

where, TP is true positive, TN is true negative, FP is false positive and FN is false negative, which indicate correctly classified, correctly rejected, incorrectly classified (type I error), and incorrectly rejected (type II error) cases, respectively. $Precision$ is the ratio of the true positive to the predicted condition positive. F_1 is the harmonic mean of precision and recall. In addition, we have also calculated Cohen's kappa coefficient (κ) [31] to assess the agreement between the expert and our proposed method. Cohen's kappa coefficient is a statistical measure of inter-rater agreement among two or more raters.

III. RESULTS

A. RELATIONSHIP BETWEEN THE AVERAGED MSE AND RCMSE VALUES FOR EACH SCALE FACTOR WITH DIFFERENT GROUPS

We calculated the all-night averaged MSE and RCMSE values of the scale factor 1 to 20 from healthy and insomnia groups. Fig. 2 (a) and (b) show the all-night averaged MSE



(a) MSE curve (b) RCMSE curve

FIGURE 2. Average MSE and RCMSE curves of the all-night EOG data derived from two groups: healthy and insomnia. SampEn was evaluated from 1-20 scale factors. The symbols represent the mean values of SampEn for each group. (***$p < 0.001$, **$p < 0.01$, *$p < 0.05$).

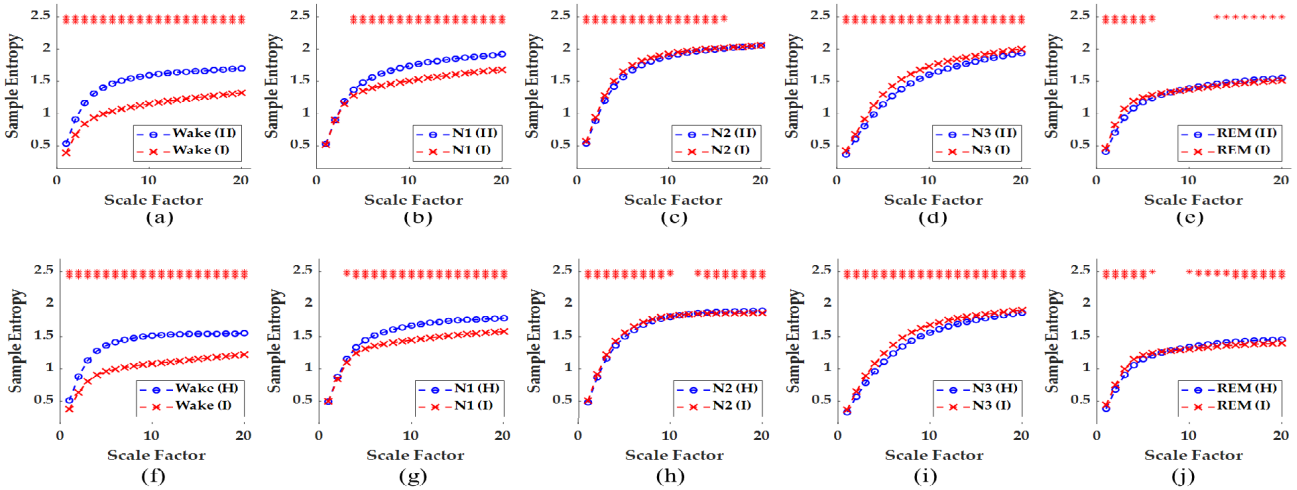


FIGURE 3. MSE (Figs. (a)-(e)) and RCMSE (Figs. (f)-(j)) curves and the repeated-measure one-way ANOVA results of the healthy and insomnia groups in five different stages. (H, healthy; I, insomnia; ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$).

and RCMSE curves of the healthy and insomnia groups, respectively. We find that the averaged MSE and RCMSE values of the insomnia groups are lower than those of the healthy groups when the scale factor is larger than 4. Moreover, the averaged MSE and RCMSE values between the healthy and insomnia groups are very close when the scale factor is less than 4. This finding proved that the MSE and RCMSE analysis can be used to detect insomnia. In addition, One-way repeated-measure analysis of variance (ANOVA) was applied to the data as shown in Fig. 2 for statistical analysis. The results show that the SampEn values are significantly different ($p < 0.05$) between the healthy and insomnia groups for almost all scale factors. This finding proves that the MSE and RCMSE results from sleep EOG data can be used to detect insomnia.

MSE and RCMSE value of each scale factor and the independent sample t-test results of the healthy and insomnia groups in five sleep stages were also compared. Fig. 3 (a)-(e) and Fig. 3 (f)-(j) shows the MSE and RCMSE results of the comparison in the Wake, N1, N2, N3, and REM, respectively. A few interesting characteristics can be noted from Fig. 3.

1) The tendency of the MSE and RCMSE curves of the healthy groups are similar to those of insomnia groups in each sleep stage.
2) In the Wake and N1 stages, the averaged SampEn values of MSE and RCMSE of the healthy groups are clearly higher than those of the insomnia groups.
3) The N2 and REM stages between the healthy and insomnia groups almost overlap for each scale factor.
4) When the scale factor is larger than 5, the SampEn values of the REM stage are less than those of Non-REM stages. In each sleep stage, almost all of the MSE and RCMSE values between the healthy and insomnia groups exhibit significant differences for each scale factor.

B. EVALUATION OF THE SHORT-TIME INSOMNIA DETECTION

1) CLASSIFICATION RESULTS FOR EACH SCALE FACTOR

We utilized the average of the MSE and RCMSE values with different sleep times as the SVM input, to determine how much sleep needed to detect insomnia. Fig. 4 shows

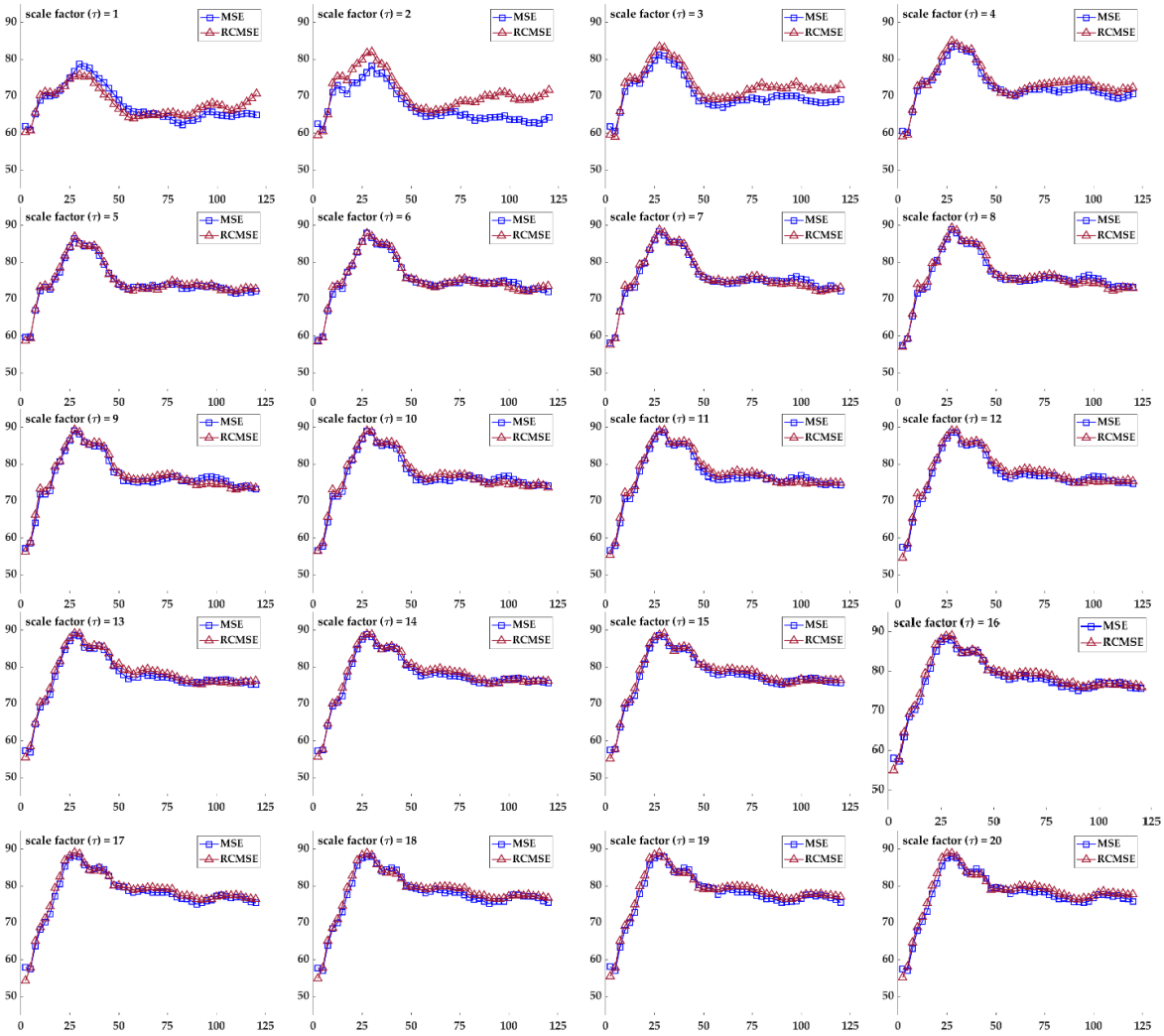


FIGURE 4. Averaged overall accuracy curves of the fixed scale factor for different sleep times. The x-axis represents the first 2.5, 5, 7.5, ..., and 120 minutes of sleep, and the y-axis represents the average overall accuracy.

the averaged overall accuracy curves of each fixed scale factor with different sleep times. Using the averaged MSE or RCMSE values of the first 25 to 35 minutes of sleep to detect insomnia exhibit a good result for each scale factor, and the average overall accuracy is approximately 85% or more, but using the average MSE or RCMSE values of the first 47.5 minutes or more during sleep produces a bad result: the averaged overall accuracy drops below 80%. Fig. 5 (a) and (b) show a heat map of the averaged overall accuracy from using different lengths of sleep to compute the MSE and RCMSE means for each scale factor, respectively. Each cell which used average MSE and RCMSE of the different sleep times and scale factors is the average accuracy of the 100 validation results. This map more clearly displays the above condition. Therefore, we determined that the most suitable length of sleep time to detect insomnia is the first 25 to 35 minutes of sleep.

Table 2 shows the best averaged overall accuracy (mean $\pm$ standard deviation) values of the different classification strategies. The best classification strategy is to combine the average of the RCMSE (scale factor of 8) of the first 27.5 minutes of sleep with the SVM. The best averaged overall accuracy is obtained by using the average MSE or RCMSE of the first 27.5 minutes of sleep in different classification strategies, except the strategy which combined RCMSE with LDA. Comparing SVM with LDA, although the computational complexity of LDA is lower than that of the SVM, the classification agreement is poor, so the standard deviation of the overall accuracy is higher. Ensemble includes multiple LDA classifiers, and therefore, the mean and standard deviation of the accuracy are better than the single LDA classifier, but the classification agreement is slightly poorer than for the SVM. In this study, we that find the best classification strategy is the combined average of the RCMSE values (scale factor of 8) of the first 27.5 minutes of sleep and that its best averaged overall accuracy is 89.31 $\pm$ 6.04%.

2) INSOMNIA DETECTION PERFORMANCE

Table 3 (A) and (B) show the best performance of the strategy of the SVM combined with the MSE or RCMSE features,

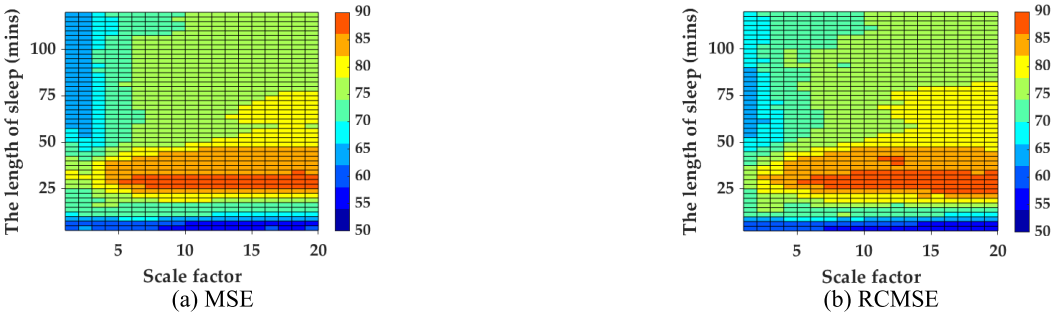


FIGURE 5. Heat map of the average overall accuracy resulting from using different lengths of sleep to compute the MSE and RCMSE means for each scale factor.

TABLE 2. Best average overall accuracy for each scale factor with different sleep times (bold letters indicate the best results).

	MSE			RCMSE		
Classifier	overallAcc (%)	The length of time for computing mean (mins)	Scale factor	overallAcc (%)	The length of time for computing mean (mins)	Scale factor
LDA	87.06±8.62	27.5	3	86.50±8.22	35.0	3
SVM	89.06±6.43	27.5	9	**89.31±6.04**	**27.5**	**8**
Ensemble	88.19±7.27	27.5	4	88.69±7.88	27.5	4

TABLE 3. (A) Confusion matrix and performance rate of the strategy that combines the average MSE (scale factor of 9) of the first 27.5 minutes of sleep with SVM. (B) Confusion matrix and performance rate of the strategy that combines the average RCMSE (scale factor of 8) of the first 27.5 minutes of sleep with SVM.

(a)

		Expert		Metrics				
		Insomnia	Healthy	Se (%)	Sp (%)	overallAcc (%)	kappa	F_1 (%)
Our method	Insomnia	767	142	95.88	82.25	89.06	0.78	89.76
	Healthy	33	658	82.25	95.88			

(b)

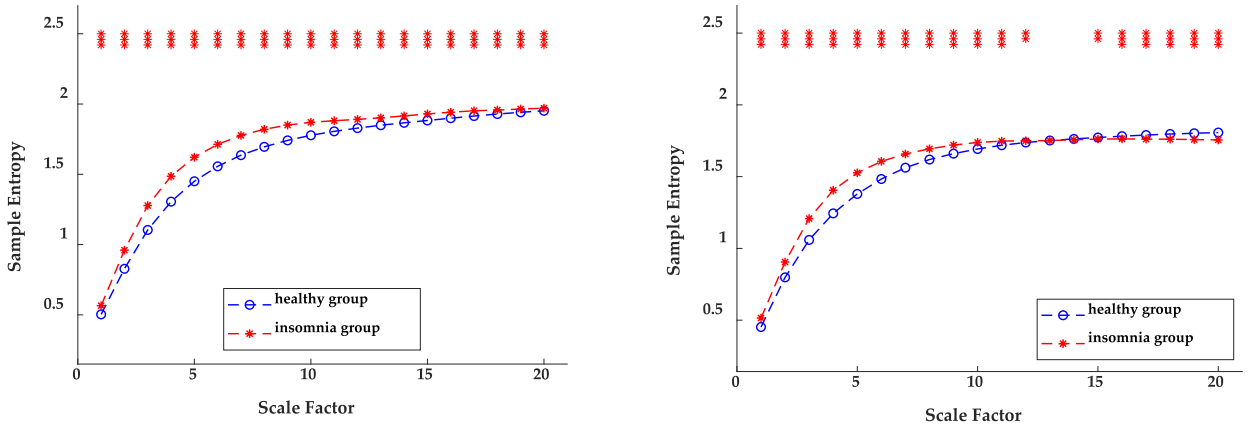
		Expert		Metrics				
		Insomnia	Healthy	Se (%)	Sp (%)	overallAcc (%)	kappa	F_1 (%)
Our method	Insomnia	773	144	96.63	82.00	89.31	0.79	90.04
	Healthy	27	656	82.00	96.63			

respectively, in terms of the confusion matrix, sensitivity, specificity, and accuracy rates when comparing expert and our proposed method. The confusion matrix contains 100 test results from the random testing index. When using the average MSE (scale factor of 9) of the first 27.5 minutes of sleep the as SVM input, the average overall accuracy is 89.06% and the kappa value is 0.78. Moreover, when using the average RCMSE (scale factor of 8) of the first 27.5 minutes of sleep as the SVM input, the average overall accuracy is 89.31% and the kappa value is 0.79. These result shows that RCMSE is superior to MSE.

IV. DISCUSSION AND CONCLUSIONS

In this study, we used the average RCMSE of the first 27.5 minutes of sleep with a scale factor of 8 as a classifier input to achieve a short-time insomnia detection system. The first 27.5 minutes of sleep mostly constitute the Wake and N1 stages. The healthy group required approximately 15-20 minutes to enter the N1 stage, while the insomnia groups required more time to enter the N1 stage. In addition, the MSE and RCMSE values of the sleep EOG signal clearly distinguish the two groups in the Wake and N1 stages, as shown in Figure 3, and therefore, we can utilize this feature to implement short-time insomnia detection. In our experiment, the averages of the overall accuracy, sensitivity, specificity, kappa, and F1 score over 100 tests are 89.31%, 96.63%, 82.00%, 0.79, and 90.04%, respectively. Compared with currently clinical measurement methods, the proposed method only needed to measure the first few minutes (27.5 min) of sleep.

In Fig. 2, it observed that the MSE and RCMSE values of the insomnia group are smaller than those of the healthy group. This may be because the sleep stages of healthy people undergo significant changes with respect to Non-REM and REM, with no excessive sleep stage transition, but the insomnia groups often experience arousal after sleep onset, which causes eye movement and a lack of significant changes with respect to Non-REM and REM. These results indicate that



(a) MSE curve (b) RCMSE curve

FIGURE 6. Averaged RCMSE curves of the all-night EEG data derived from the healthy and insomnia groups. SampEn was evaluated for scale factors of 1-20. The symbols represent the mean values of SampEn for each group. (***$p < 0.001$, **$p < 0.01$, *$p < 0.05$).

TABLE 4. Best average overall accuracy for each scale factor with different sleep times (bold letters indicate the best results).

	MSE			RCMSE		
	overallAcc (%)	The length of time for computing mean (mins)	Scale factor	overallAcc (%)	The length of time for computing mean (mins)	Scale factor
EEG	88.81±6.78	105	20	89.19±6.92	110	20
EOG	89.06±6.43	27.5	9	**89.31±6.04**	27.5	8

the sample entropy values obtained using RCMSE were more consistent than those obtained using MSE.

We also compared the MSE and RCMSE values of the EOG with the EEG. Fig. 6 (a) and (b) show the EEG all-night averaged MSE and RCMSE curves of the healthy and insomnia groups, respectively. We also find that the averaged MSE and RCMSE values of the insomnia groups are higher than those of the healthy groups the scale factors less than 12. Moreover, the average RCMSE values between the healthy and insomnia groups are close when the scale factor is 1; the difference of the averaged MSE and RCMSE values between the healthy and insomnia groups when the scale factor ranged from 2 to 8 are more obvious than for other scale factors. In addition, the EEG signal (C3-A2), instead of EOG, was applied in our proposed method with the same classifier (SVM) and validation processing in this study. The comparisons of the results between EEG and EOG was listed in Table 4. The best accuracy and kappa value from the MSE of EEG is 88.81% and 0.77, respectively. The best accuracy and kappa value from the RCMSE of EEG is 89.19% and 0.78, respectively. Compare to the result of the EOG, the performances of EOG based method are better than EEG based method. Moreover, the best result of EOG used the length of time and the number of the features (scale factors) are less than the best result of EEG.

Moreover, the main advantages of our proposed method are three innovations: (1) Our proposed method only need the first 27.5 minutes of data during sleep (i.e., 1^{st}–55^{th} epochs). The previous researches [13]–[16] were usually used sleep signals from the specific sleep stages to compute features for detection insomnia.

Therefore, they needed all-night sleep signal recording and sleep scoring by clinical staff or automatic sleep scoring system. Subjects may need to wait more than one night to know the diagnosis. In our proposed method, RCMSE features used to detect insomnia were computed by the first 27.5 minutes sleep EOG. In other words, RCMSE features in our proposed method is dependent on sleep time. Therefore, our proposed method can screen insomnia in a short time and eliminate the need for clinical staffs to monitor the quality of the sleep signal all night. (2) The proposed method doesn't need manual scoring in the preprocessing. Unlike the previous studies [13]–[16], their methods need manual scoring in the preprocessing (need to know the information of all-night sleep stage or some specific sleep stages). Because our proposed method to detect insomnia was only dependent on sleep time, instead of the specific sleep stages, it can save clinical staff time to manually score sleep stages. In the other hand, the patients do not have to wait clinical staff for a sleep report. (3) The use of a single-channel sleep EOG. When using EEG [13]–[16], the electrodes must be placed above the hairline on the scalp and expert help is needed to set up the system and collect data. Compared with EOG, EOG offers the advantage of easy placement and can be operated by the user him/herself.

Additionally, it let our proposed method easy to implement in a wearable eye-mask device in the future that allows users to easily measure at home environment. Therefore, our

TABLE 5. Comparison between our proposed method and other insomnia detection methods.

Reference	Subject	Sleep stage used	Used Signals	Validation	Classification strategy	OverallAcc (%)	Se (%)	Sp (%)	kappa
[14]	20 H & 20 I	Wake, N1, and N2 (prior to first N3 epoch)	EEG× 1	Leave-one-out	Logistic regression	81.00	87.00	75.00	--
[15]	41H & 42 I	all-night non-Wake	EEG× 2	5-fold	DNN	92.00	89.00	--	0.84
[16]	16 H & 19 I	all-night N3	EEG× 1	50%-50% (training-testing)	PCA	91.60	90.20	--	0.81
[17]	10 H & 10 I	all-night non-Wake	EEG× 1	50%-50%	SVM	83.00	85.00	80.00	--
proposed method	16 H & 16 I	first 27.5 minutes during sleep	EOG	50%-50% (random 100 times)	SVM	89.31	96.63	82.00	0.79

H, healthy; I, insomnia; DNN, deep neural network; PCA, principal components analysis

proposed method can obviate the need for sleep scoring to achieve short-time insomnia detection. As a result, a large amount of medical costs can be saved. In terms of medical personnel, no medical personnel are required to monitor the PSG signals throughout the night. In terms of subjects, each subject can assess insomnia at home, and the ''first-night effect'' is also reduced.

Table 5 shows a comparison between our proposed method and other insomnia detection methods with respect to the overall accuracy, sensitivity, specificity, and kappa value. Except for reference [15], all of the other methods use a single-channel EEG for insomnia detection. These methods all utilize hand-engineered features [14]–[17], including statistical, spectral, and nonlinear features. These methods for insomnia detection have been proposed by the above references and exhibit good performance. Reference [14] used hypnograms, which were generated from automatic sleep scoring, to find all epochs between the first Wake stage until the last N2 stage. The method then used the epochs prior to the first N3 stage to detect insomnia. Comparing our proposed method with reference [14], the lengths of sleep times for using insomnia detection are almost the same. References [15]–[17] used expert hypnograms to select non-Wake stages as the feature of insomnia. Good result can be obtained compared with our proposed method, but our proposed method does not need manual scoring by experts or automatic sleep scoring. The novelty of our proposed method is that RCMSE from sleep single EOG channel were first applied in detection insomnia. It does not need all-night PSG recording and sleep scoring and only takes a short time (less than 30 mins) to classify the subject with insomnia or not. Therefore, it also can reduce the human resources of medical care. Besides, only RCMSE with scale factor of 1-9 and a simple classifier are utilized, it let our proposed method easy to implement in a wearable eye-mask device in the future that allows users to easily measure at home environment.

In future work, we can integrate the proposed system with an EOG eye mask or portable PSG system for sleep quality assessment or insomnia screening in the home environment, as home-based measurements are less affected by the first night effect than hospital. In addition, the all-night PSG recording, and sleep scoring does not need in this system, because of the short time insomnia screening. At the same time, a large amount of medical resources is reduced. The number of subjects was currently 32 persons in the experiment which contained 16 healthy individuals and 16 primary insomnia patients. The limitations of this study are the subjects belong to healthy individual or with primary insomnia. The subject groups with other sleep disorder, such as apnea, restless legs syndrome, should be considered in the future. We will increase the number of subjects to improve the system generality, and made our method be applied to the groups of different genders and age in future work. In addition, MSE analysis of the EEG can distinguish different groups, such as epilepsy, Parkinson's, and insomnia. EOG may contain some EEG information, and MSE analysis of EOG may be able to distinguish between these different groups. We hope that a large amount of data can be used to find the correlations between the MSE analyses of the EEG and EOG in the specific groups so that EOG can become a simple examination tool.

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