2009 Ninth IEEE International Conference on Bioinformatics and Bioengineering

Automated Sleep Staging using Single EEG Channel for REM Sleep Deprivation

Yu-Hsun Lee
Department of Computer Science
National Chiao Tung University,
Hsinchu, Taiwan
yhli.iie96g@g2.nctu.edu.tw

Yong-Sheng Chen
Department of Computer Science
National Chiao Tung University,
Hsinchu, Taiwan
yschen@cs.nctu.edu.tw

Li-Fen Chen
Department of Brain Science
National Yang-Ming University,
Taipei, Taiwan
lfchen@ym.edu.tw

***Abstract*—In medical literatures, it has been reported that the increased REM (rapid eye movement) density is one of the characters of depressed sleep. Some experiments were conducted to confirm that REM sleep deprivation (REM-SD) for a period of time is therapeutic for endogenous depressed patients. However, because of its high complexity and intensive labor requirement, this therapy has not yet been proved validity by a sufficient amount of depressed patients. Therefore, we propose to develop an automated sleep staging system using only single EEG channel to achieve on-line detection for REM state during sleep. For classifier design, we use a dataset of 25 subjects and the staging accuracy can achieve 80%. Once the REM state is detected by the system, the system will alarm the subject to deprive the REM sleep. The effect of REM sleep deprivation can be examined by hypnogram and the proposed system will be applied for clinical trials of depression therapy.**

Keywords-automated sleep staging; REM; sleep deprivation; depression

I. INTRODUCTION

Sleep is important and essential for human, not only for the function of body restoration but also can enhance our memories. Busy all the time may bring heavy pressure to people and cause the sleep disorder like insomnia, even cause a mental disorder like depression [1]. Since bad sleep quality may cause both bad physical and mental effects, people pay more attention to improving sleep quality. By observing the structure of sleep, physician can evaluate our sleep quality and diagnose sleep disorders.

Recently, sleep centers have been widely established in many hospitals. These centers have professional signal acquisition equipments and the better environments for sleep examinations. In general, several neurophysiological signals are recorded in the polysomnography (PSG) for sleep specialists to visually perform sleep scoring according to the Rechtschaffen and Kales (R&K) rules [2] [3], which is considered as a gold standard for sleep scoring. There are many limitations in R&K rules [4]; nevertheless, it is still a reference method for sleep staging. In R&K rules, sleep scoring is based on EEG, EOG, and EMG. The continuous EEG signals are segmented into epochs for every 30 seconds. According to the frequency, amplitude, and morphology of EEG signals, sleep stage can be classified into 3 classes: wake, rapid eye movement (REM), and non-rapid eye movement (NREM). NREM state can be further split into four states: stage 1, 2, 3, and 4. Although sleep specialists achieve sleep scoring manually based on these principles, it is very subjective and inter-rater variability can be large. Since the R&K rules were proposed in 1968, many computer-assisted staging systems were also proposed expecting to replace the manual scoring. The development history of computer-assisted sleep staging is as long as manual scoring, but so far the automated sleep staging system is not yet widely adopted in clinical use due to the limited accuracy.

In some medical literatures, the relation between sleep and depression was discussed. They suggested that more than 90% of depressed patients may suffer from insomnia and chronic insomnia is probable a trigger to cause depression relatively [1]. The increased REM density is one of the characteristics of depressed sleep. Some experiments were conducted to confirm that REM sleep deprivation is therapeutic for endogenous depression patients [5]. That is, when we alarm the subject at their REM sleeps, the number of occurrence to depression will be abated. To achieve this effect, therapy of REM sleep deprivation (SD) may apply over a long period of time. However, most patients do not prefer a long stay in the hospital. In addition, a sleep specialist must be on duty overnight when the REM state is detected. It is a laborious task. Due to these two difficulties, REM sleep deprivation has not yet been applied widely to the clinical therapy for depression. Only a few depressed patients were involved in this experiment and the therapeutic effect has been confirmed. Thus, by the on-line automated sleep staging system, we can apply REM sleep deprivation for depression patients easily and conveniently.

In this paper, we propose an automated sleep staging system, which uses a single EEG channel for sleep staging and can achieve an objective, effective, and precise judgment. We plan to apply this system for real-time REM detection to assist for REM sleep deprivation to depressed patients in the near future.

II. MATERIALS AND METHODS

There are two parts in the proposed system. Both in the two parts, the data set of each subject is composed of two whole night sleep recordings. For each subject, the recording of the first night sleep is used as the training data while the second night recording as testing data. The

978-0-7695-3656-9/09 $25.00 © 2009 IEEE
DOI 10.1109/BIBE.2009.68

proposed system uses the training data to construct a subject-specific classification model and then test the accuracy of the model by testing data. The predicted result will be compared to the manual scoring results obtained by sleep specialists.

For the off-line analysis, our data sets were recorded from 25 patients (10 males and 15 females) at Sang-Mei Hospital, Taichung, Taiwan, and each data set consists of two whole night sleep recordings about 6 to 8 hours.

For the on-line analysis, we use the *NuAmps* of Compumedics Neuroscan system as our signal acquisition equipment. NuAmps is a DC amplifier designed to record a wide variety of multichannel neurophysiological signals, such as EEG, EOG, ECG, and EMG. We acquire a data set from a healthy subject, with two night recordings in different days for every subject. EEG signals were acquired from the channel C3 with reference A2. There is a difference in testing procedure between the on-line and the off-line analysis. That is, the testing data is scored epoch-by-epoch which can detect the state in real time. Thus, once the system have been detected the REM state, it may alarm the subject to deprive him/her up REM sleeps.

In the off-line model learning, the aim is to determine the most suitable EEG feature sets for classification, that is, the feature set which can be used to achieve the highest accuracy of classification. The classification result will be compared to the results of manual scoring which is assumed as the ground truth. The outcome of performance evaluation will decide whether to further revise the design of classifier. If the outcome is satisfied, these selected feature sets will be used in the on-line automated staging. The goal is to use the system to detect the REM state in real time during sleep as to apply REM sleep deprivation. If the REM state is detected during sleep, the system will alarm the subject to deprive the REM sleep. We may define a ratio of the amount of the performed SD to that the detected REMs. The ratio can be adjusted according to the therapeutic effect of REM-SD to depressed patient. The overview of the work is shown in Figure 1.

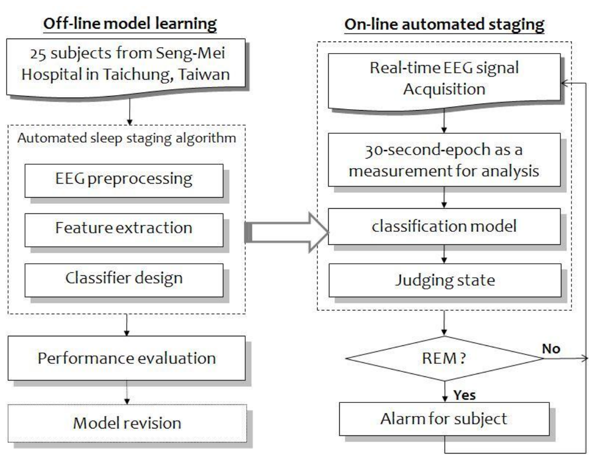

Figure 1. Overview of the work: off-line analysis and on-line analysis

The algorithm of the automated sleep staging comprises three steps [6]: (1) EEG preprocessing, (2) feature extraction, and (3) classification. The most important issues of the algorithm in the automated sleep staging are the EEG features extract and the classifier we choose. For the step of feature extraction, we adopted the spectral analysis [7] as EEG feature sets. In the step of classification, we use the support vector machine (SVM) as our classifier [8], which is popular for binary classification in recent years. Followings are descriptions for each step:

A. Signal preprocessing

First, we segmented continuous EEG signals into segments of 30-seconds epochs. Therefore, an eight hour record contains 960 epochs.

B. Feature extraction

We segmented the frequency band into eight ranges, as shown in Table I. According to these frequency bands, we compute the mean amplitude of each 30-seconds epoch with each frequency band as our feature sets.

TABLE I. THE FREQUENCY RANGE WITH EACH BAND

Frequency band	Range (Hz)
Total band	0.5-45
Lower delta band	0.5-2.5
Upper delta band	2.5-4
Lower theta band	4-6
Upper theta band	6-8
Alpha band	8-12
Lower beta band	12-25
Upper beta band	25-45

C. Classification

The basic idea underlying SVM is to determine a hyperplane which can separate the two classes so that the margin between the training data and decision boundary is maximal. At the beginning of SVM, it needs to train classification model and later used for predicting new given objects. In this work, we used the LIBSVM package developed by Lin, et.al. [9].

We divide the sleep stages into three states: Wake, REM and NREM, instead of six states defined above. The sleep stage classification problem can be stated as follows: There are three different classes of stages, denoted by Y, Y = {WAKE, REM, NREM}. Each epoch is computed with their values of mean amplitude which form the feature vector. The training data sets denoted by $(\mathbf{x}_1, \boldsymbol{y}_1), \ldots, (\mathbf{x}_n, \boldsymbol{y}_n)$, which $\boldsymbol{x}_n$ denotes a feature vector of epoch n, $\boldsymbol{y}_n$ denotes a known class label obtained from specialist, and n denotes the number of epoch. By these training data sets, we will obtain a training model for a specific subject. Then, we use this model to predict new sleep recordings.

Two important parameters needed to be specified in SVM. The first one is the kernel function. Usually the radial basis function (RBF) kernel is used [9] . It maps nonlinear separable data into a linear space where they are almost linearly separable. The other issue is the parameter adjustment. We need to select two parameters (C, $\boldsymbol{r}$), where C is the cost in finding maximum margin and $\boldsymbol{r}$ represents gamma for evaluating kernel. In general, it will obtain the better cross validation rate after the process of parameter adjustment.

III. RESULTS

For the off-line analysis, the proposed automated sleep staging algorithm can achieve nearly 80 percents of accuracy. Figure 2 shows the hypnogram of the sleep structure for subject A. The first and second field is the upper night sleep and the third and fourth field is the lower night sleep. The blue line represents the results of manual scoring which we assumed as the ground truth, and the red line is the results of automated scoring by our system. Under the hypnogram is the table which displays scoring agreement between manual scoring and automated scoring for total 823 epochs in the record of subject A. The numbers in bold face represent those correctly classified. The accuracy achieves 88%.

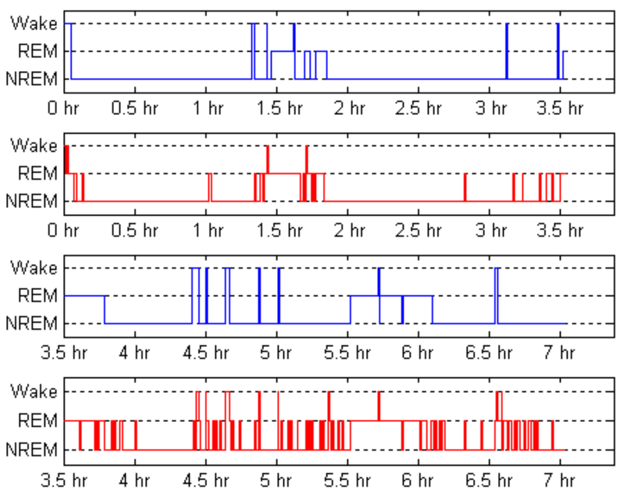

Figure 2. The hypnogram of classification result. Blue line represents the results of manual scoring and we assumed that as the ground truth. Red line represents the result of automated scoring.

TABLE II. SCORING AGREEMENT BETWEEN MANUAL SCORING AND AUTOMATED SCORING

Manual scoring	Automated scoring			
	Wake	REM	NREM	TP/ (TP+FP)
Wake	**10** (34.48%)	3 (10.35%)	16 (55.17%)	34.48%
REM	0 (0%)	**122** (91.04%)	12 (8.96%)	91.04%
NREM	2 (0.3%)	59 (8.94%)	**599** (90.76%)	84.70%

After the calculation of SVM, the original 8-dimension feature space was mapping to a 3-dimension feature space, as shown in Figure 3. We can see the distribution of each feature vectors that three different classes can be well separated.

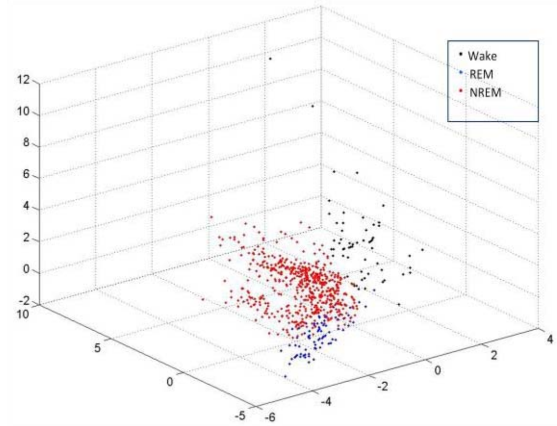

Figure 3. Decision values mapping by RBF. The state of WAKE, REM and NREM is represented by black, blue and red dots respectively. It is shown that three different stages can be well seperated through the SVM classifier.

In order to obtain the optimal cross validation rate of training model in SVM, there are two parameters needed to decide: the cost C and the gamma $\boldsymbol{r}$. For searching the optimal (C, $\boldsymbol{r}$), we use the grid search for seeking in the range of [-15, 15] x [-15, 15]. Searching in this range is enough for obtaining a better cross validation rate of training model. The process of grid search was shown in Figure 4.

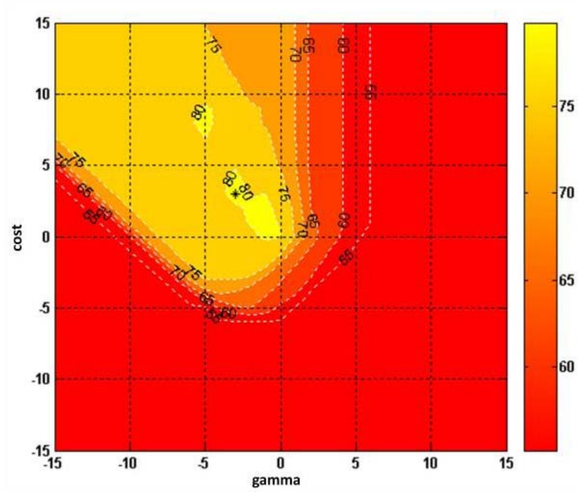

Figure 4. SVM parameter adjustments. The best cross validation rate locates at (3,-3), which represents cost = 3 and gamma = -3.

IV. DISCUSSION AND CONCLUSIONS

Our goal is to alarm the subject upon detected the REM state for the REM sleep deprivation. Therefore, the important issue of our work is the accuracy of staging, especially for REM state. As the hypnogram shown in

Figure 2, most results of classification were coherent with manual scoring. There are two types of system errors: false alarm and miss detection. If the real state is not REM but the system misclassifies it as REM and send the false alarm to wake up the subject, the system may disturb the sleep of the subject. Thus, this situation of misclassification is considered undesirable and needs to be minimized. On the other hand, miss detection occurs when the real state is REM but the system misclassifies it as NREM or WAKE. In this situation, it is usually tolerable because it is not necessary to deprive all of the REM states.

In this paper, we use the normal subject for testing REM sleep deprivation. In the future, we plan to apply this on-line automated sleep staging system for REM sleep deprivation on depressed patients and longitudinally track its therapy in a long-term period.

Acknowledgment

We would like to thank Sang-Mei Hospital in Taichung, Taiwan. They provided good quality of EEG recordings for our off-line analysis.

References

[1] D. Riemann, M. Berger, and U. Voderholzer, *Sleep and depression - results from psychobiological studies: an overview.* Biological Psychology, 2001. **57**(1-3): p. 67-103.

[2] A. Rechtschaffen, A.Kales, *A Manual of standardized terminology, techniques and scoring system for sleep stages of human subjects.* 1968

[3] Penzel, T. and R. Conradt, *Computer based sleep recording and analysis.* Sleep Medicine Reviews, 2000. **4**(2): p. 131-148.

[4] S. L. Himanen and J. Hasan, *Limitations of Rechtschaffen and Kales.* Sleep Medicine Reviews, 2000. **4**(2): p. 149-167.

[5] H. Giedke and F. Schwarzler, *Therapeutic use of sleep deprivation in depression.* Sleep Medicine Reviews, 2002. **6**(5): p. 361-377.

[6] P. Van Hese, W.P., J.DE Koninck, R. Van de Walle, and I.Lemahieu. *Automatic detection of sleep stages using the EEG.* Proceedings of the 23rd Annual EMBS International Conference. 2001. Istanbul, Turkey.

[7] E. Estrada, H. Nazeran, P. Nava, K. Behbehani, J. Burk and E Lucas. *EEG feature extraction for classification of sleep stages.* Proceedings of the 26th Annual International Conference of the IEEE EMBS. 2004. San Francisco, CA, USA.

[8] S. Gudmundsson, T. P. Runarsson, S. Sigurdsson. *Automatic Sleep Staging using Support Vector Machines with Posterior Probability Estimates.* Proceedings of the 2005 International Conference on Computational Intelligence for Modelling, Control and Automation, and International Conference Intelligent Agents, Web Technologies and Internet Commerce IEEE computer society.

[9] Chih-Wei Hsu, Chih-Chung Chang, and Chih Jen Lin (2008) *A Practical Guide to Support Vector Classication*. National Taiwan University