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A Hybrid Classification Method using Artificial Neural Network Based Decision Tree for Automatic Sleep Scoring

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***Abstract*—**In this paper we propose a new classification method for automatic sleep scoring using an artificial neural network based decision tree. It attempts to treat sleep scoring progress as a series of two-class problems and solves them with a decision tree made up of a group of neural network classifiers, each of which uses a special feature set and is aimed at only one specific sleep stage in order to maximize the classification effect. A single electroencephalogram (EEG) signal is used for our analysis rather than depending on multiple biological signals, which makes greatly simplifies the data acquisition process. Experimental results demonstrate that the average epoch by epoch agreement between the visual and the proposed method in separating 30s wakefulness+S1, REM, S2 and SWS epochs was 88.83%. This study shows that the proposed method performed well in all the four stages, and can effectively limit error propagation at the same time. It could, therefore, be an efficient method for automatic sleep scoring. Additionally, since it requires only a small volume of data it could be suited to pervasive applications.

***Keywords*—**Sleep, Sleep stage, Automatic sleep scoring, Electroencephalography, Decision tree, Artificial neural network

I. INTRODUCTION

WITH a deepening understanfing of the importance of sleep, sleep analysis has earned widespread interest, especially with the development of bio-information technology. In 1968, the generally accepted standardization for the scoring of sleep of Rechtschaffen and Kales (RKS) was established[1]. According to RKS, sleep is firstly divided into rapid eye movement (REM) and non-rapid eye movement (NREM), which is further divided into four stages consist of stage 1, 2, 3 and 4 (S1/S2/S3/S4). In 2007, The American Academy of Sleep Medicine (AASM) improved this standard by combining sleep stage 3 and 4 into slow-wave-sleep (SWS)[2].In recent years, automatic sleep scoring has become a major issue within the sleep analysis field[3–5]. Thanks to polysomnography, several bio-electrical signals are already in use in the research of automatic sleep scoring. EOG and frontal EEG electrodes were used for delta detection in 1972 by Hilbert and Naitoh[6]. Latterly they have been used for visual sleep stage detection by Dyson et al.[7], Lapinlampi and Himanen[8] and Werth and Borbely[9]. Adnane Mourad and Zhongwei Jiang reported a automatic sleep-wake stages classifier using support vector machine (SVM) to analysis seven features were extracted from the RR series obtained from ECG[10]; Mendez M.O. et al. proposed an algorithm made up by a time-variant auto regressive model used as feature extractor and a hidden Markov model used as classifier, sleep ECG data was used to score sleep as Wake/NREM/REM[11]. Jussi Virkkala, Joel Hasan et al. developed an automatic method for the classification of wakefulness and sleep stages SREM, S1, S2 and SWS based on a two-channel electro-oculography (EOG)[12]. EEG is regarded as an efficient bio-electrical signal used in sleep scoring [13,14]. Over a number of years, many researches have been undertaken to improve the effect and reliability of using EEG in automatic sleep scoring. Tian J.Y. and Liu, J.Q. presented a hybrid system for automated EEG sleep scoring by combining a self-organizing feature map (SOFM) with a fuzzy reasoning-based classifier (FRBC) and utilizing both temporal and spectrum features of the EEG signal[15]; Salih Günes et al proposed a novel data preprocessing method called k-means clustering based feature weighting (KMCFW) and combined it with k-nearest neighbour (k-NN) and decision tree classifiers to classify sleep EEG data according to RKS[16]; Han G.Jo et al designed a fuzzy classifier based on the genetic algorithm (GA) using a single EEG signal that detects differences in spectral features[17].

Limitations still, however, exist in this area. Firstly, although every bio-signal feature has its own advantage in discriminating some sleep stages, none of them can show significant difference between all the sleep stages. At the same time, classifiers are not designed to take best advantage of every feature they use most of the time. This causes a number of unsatisfactory experimental results when sleep scoring using automatic classification algorithms. Second, some research only discriminates sleep into Wake, REM and NREM without a more detailed classification[10,11,17], although impressive results have been obtained, these results are still not sufficient when used in further evaluation of sleep quality. Finally, while personalization of sleep evaluation systems is becoming a trend in the application of automatic sleep scoring, using multiple bio-electrical signals increases the cost, causes inconvenience to users and makes it less feasible for the methods to be applied in a pervasive context.In this paper we propose a novel classification method for automatic sleep scoring based on a decision tree and an artificial neural

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network. As performance of artificial neural networks depend mostly on the quality of the feature set used, while the similarities among sleep EEG in different stages make it hard to find a salient feature, our method suggests a possible solution. Also, by describing sleep scoring using a decision tree, all sleep stages are set to different priority level, so that each one of them can be discriminated with a guaranteed accuracy. The proposed method is described in Section 2. In Section 3, the experimental data and results demonstrating the effectiveness of our method are given, and the results are discussed in Section 4. Finally, the conclusions are given in Section 5 with future research directions.

II. METHOD

A. Decision tree

As a rule-based data mining algorithm, decision trees have been successfully used in machine learning and classifier systems. Using decision trees for classification is a reasoning process. The trees consist of nodes, branches, and leaves, with each leaf representing one class, and each node containing some transition rules. By checking whether data matches the rules of the current node or not, data are assigned to nodes of the next layer, and finally to leaves, where the classification is completed.

Decision trees can be used in solving problems in which instances are expressed by attribute-value pairs, and the output of target function is discrete. A high processing throughput is a characteristic of decision trees. Additionally, they can describe the problem in a disjunctive way, and can work with noisy data[16]. This makes decision tree algorithm an excellent choice for automatic sleep scoring, especially considering that RKS itself is a rule-based standard.

On the other hand decision trees exhibit some deficiencies.. In common decision tree algorithms, rules set in decision nodes are usually based on single attribute, which are inefficient in sleep analysis as the similarities in EEG signals in differing stages often make it hard to separate these stages apart by considering only one feature. According to previous research, the predictive ability of a decision tree is in contrast with its size, the smaller the tree is, the better it can perform in classification, but it is hard to construct a tree which is small enough. And finally, a decision tree is not a global optimization method.

B. Artificial neural network

Artificial neural networks (ANNs) are, in essence, attempts to simulate the brain. They are computational tools composed of a large number of highly interconnected elementary neurons. The neurons are made up of synapses, adder, and activation functions. Synapses are the connecting links between neurons. Input signals are transferred by the synapses and multiplied by their specific weight. Then, all the multiplied signals along with the bias are sent to the adder where they are summed up and a value is generated. This value will finally be translated into the output of the neuron by the activation function. Information in the network is stored in each neuron as weights of its connections. Multilayered artificial neural networks, as shown in Fig 1, consist of three types of neuron layers: input, hidden, and output layers, are the most widely used neural networks in sleep analysis. Most of networks are feed-forward, which means the signal flow is from input to output units, strictly in a feed-forward direction.

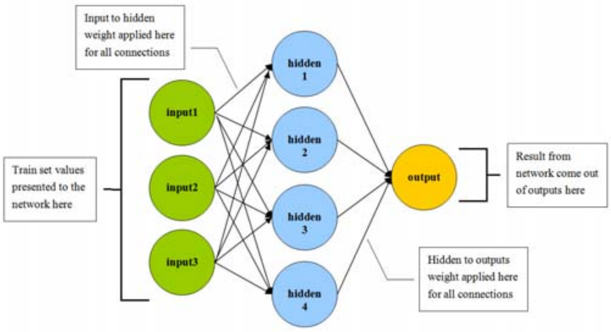

Fig. 1 A demo of multilayered artificial neural network

Claude Robert and Christian Guilpin, argue that many qualities of ANNs make them highly suitable for sleep analysis. ANNs are useful in processing noisy or new data, which is considered to be the main advantage they have over other classifiers in sleep scoring. Fault tolerance is another advantage of ANNs, which is also important for sleep scoring experimentation as the sleep data to be processed can be modified by all kinds of artifacts so that the boundaries between stages are very possibly blurred[18].

C. The proposed method: artificial neural network based decision tree

In sleep EEG, although every sleep stage has its own characteristics, boundaries between some stages are still not clear. This could lead to difficulties with AI-based classifiers while performing automatic sleep scoring using EEG data because it causes errors when discriminating similar sleep stages. Furthermore, for some methods, even the accuracy of recognizing those stages which could have been easily discriminated might be dragged down significantly due to the low identification rate of the similar stages. As a result, the total accuracy of sleep scoring is reduced. Our prior research proved this by showing an obvious improvement on classification performances when the range of experiment data was limited in NREM[19].As sleep scoring is, however, a multi-class problem, it can be formulated into a series of two-class problems. By doing this, a multilayered classification can be constructed, in which errors occurred in a posterior layer could not affect the decision of an anterior one. In such a structure, if sleep stages of high recognition rate are set to be separated at the previous layers, it is possible to reduce error propagation in the whole classifier. The accuracy of discriminating every specific sleep stage could therefore be expected to reach the best possible. The overall effect of the algorithm will therefore be improved.In this study, we proposed a novel classification method, an artificial neural network based decision tree, as in Fig2. The main structure of this method was a decision tree. In each layer of the tree, one decision node and one leaf node were placed. Let each leaf node represent a selected sleep stage, and each decision node contains a feature extraction module along with a decision-making module, which is an ANN classifier. All night sleep EEG data should be divided into 30 seconds long fragments, marked as unknown and sent to the root node of the decision tree for analysis. The function of all decision nodes, including the root node, is to decide whether a data fragment belongs to the sleep stage represented by the leaf node of the next layer. Feature extraction modules extract customized feature sets from sleep EEG data for corresponding ANN classifiers. ANN classifiers analyse data fragments originating from the upper decision node, and make a decision. According to these decisions, data fragments are either sent to the leaf node or to the decision node of the next layer. The procedure of classification is not finished until all data fragments are split to a leaf node.

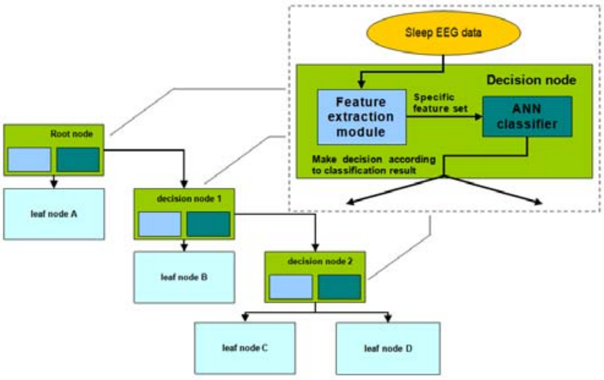

Fig. 2 Structure of the decision tree in the proposed method

Theoretically, this method has four main advantages. Firstly, using a decision tree, the sleep process can be described as a union set of time periods of different sleep stages. It focuses on a certain sleep stage, and marks all time periods that belong to it. Sleep is scored into different stages successively, which is exactly the kind of multilayered classification we require. Secondly, decisions made by this tree are based on judgements of a series of ANN classifiers, not simply by checking some single attributes. Each of these neural networks is given a specific group of features for their analysis. As the result, each decision made by this algorithm can be more reliable than ordinary decision trees. Thirdly, although it is very hard to find a EEG feature that shows significant differences in all the sleep stages, it's rather easier to find some features that can clearly tell the difference between one sleep stage and another. Furthermore, by reducing the classes needed to be discriminated in each decision node, the structures of ANNs used in this method can be simplified as much as possible. These make the classification result of our method more precise, while the training progress become more efficiency. Finally, due to the reducition of the remaining sleep stages as the algorithm progressed, it’s also acceptable if some sleep stages can only be recognized after unkown stages were narrowed down. As a result, the requirement of singal-to-noise ratio of EEG data when using this method is reduced, plus both decision tree and ANN can work well with noisy data, it's quite feasible that this method is appropriate for analysis of sleep EEG data as it often contains strong and complex noise.

III. Experiments and Results

Three group of experiments were performed in this study. As in this algorithm errors generated in one layer of the decision tree can only affect the posterior layers, the detailed layer structure of the decision tree become very important. Additionally, with the vary of structure of neural networks, their classification effect change greatly. As a result, in part 3.1 we attempted to find a sequence of sleep stages according to how easily they can be discriminated from each other, and adjust the structure of ANN classifiers that going to be used in the algorithm to improve their classification ability by a prep-experiment. The identification ability of 19 EEG features we planned to use were tested, based on the results, feature sets were selected for every decision node, and the structure and parameters of neural networks used in the algorithm was also determined. Then, in part 3.2 we tested the performance of the proposed method on sleep scoring by the first experiment. Nueral networks were structured and arranged into a decision tree based on the result of prep-experiment. Sleep EEG data were then sent to the decision tree for analysis and the outputs of the algorithm were compared with manual classification results. At last, in part 3.3 we tested whether error propagation can be successfully controlled using this method by the second experiment. Based on the decision tree we had constructed in the first experiment, we added another nueral network at the bottom of the tree to make the classificaition more detailed, we tested the performance of this new decision tree to see how the classification accuracy was affected. 14 all night sleep EEG data, downloaded from MIT-BIH polysomnographic database and filtered with a bandwidth of 0.5~40Hz, were used in the experiments. All features used in the experiments, listed in Table 1,were selected based on our previous researches[19].

TABLE I
FEATURES USED IN THE PREP-EXPERIMENT

FEATURES	abbreviations
C0-Complexity	C0
D2 Correlation Dimension	D2
The Largest Lyapunov Exponent	LLE
Spectral Edge	EDGE
Sample Entropy	SaEn
The first spectral moment	M1
The maximum power	Maxs
The center frequency	F0
Mean of peak-to-peak amplitude	meanPP
Related power (delta, theta, alpha, sigma, beta and K complex rhythms)	Delta,theta,alpha,sigma, beta,KK
Ratio between related powers (alpha and theta, beta and delta, beta and theta, sigma and alpha rhythms)	theta/alpha, delta/beta, theta/beta,alpha/sigma

A. Feature selection and ANN structure experiment

In the prep-experiment, sleep EEG data were clustered into five stages, respectively wakefulness, S1, REM, S2 and SWS. After that, by testing performance of every single feature in recognizing each sleep stage, we tried to find the easiest sleep stage to be discriminated in all four stages, and the feature set to do so as well. Once we found it, data belonged to this stage were removed, then the last step was tried again to find the easiest sleep stage to be discriminated in the rest of three stages, and the respective feature set. The rest was done in the same manner. With this experiment, we attempted to find a sequence of reasoning for our decision tree, which performs as good as possible in limiting error propagation. In the meantime, feature sets of every decision nodes can be determined.We used 3 layer forward feedback back propogation neural networks as classifiers of our algorithm. Three types of transform functions, including tansig, linear and sigmoid function were tested to see which one performed best in classifying sleep EEG data. A variable number of nodes in the input and hidden layer of this neural network weres tested in this experiment, in order to find the network structure that works best in our algorithm.Results of the best-performing features are listed in Table 2. From this table, we can see that Maxs and delta show significant difference between SWS and the other sleep stages; M1 and meanPP perform best when recognizing both REM and SWS; beta and delta/beta are effective when separating S2 from wakefulness+S1; finally, efforts to distinguish wakefulness from S1 are unsatisfactory no matter which feature was used. Given the identification accuracy of every sleep stage shown in the experiment above, it seems to be best to isolate REM first, followed by SWS, and then S2 and finally wakefulness+S1.

TABLE II
AVERAGE PERFORMANCE OF FEATURES IN IDENTIFYING EACH SLEEP STAGE

Feature	Sleep Stage	
	SWS	Others
M1	95.00%	99.46%
Maxs	100%	96.74%
meanPP	100%	99.46%
delta	100%	93.48%
Feature	Sleep Stage	
	REM	Others
M1	100%	99.32%
meanPP	100%	98.65%
Feature	Sleep Stage	
	S2	wakefulness+S1
beta	79.86%	63.98%
delta/beta	76.98%	66.67%
Feature	Sleep Stage	
	wakefulness	S1
F0	52.78%	65.47%
theta	30.56%	76.98%
theta/beta	30.56%	74.10%

Also, through the prep-experiment, we set 8 nodes in the hidden layer of the neural network, with tansig function as the transform function of input and hidden layer and linear function as the transform function of output layer respectively. Neural networks used in the two experiments were initialized with this network structure.

B. Algorithm performance experiment

In the first experiment, we tested the performance of the proposed system in automatic sleep scoring. Based on the result of the prep-experiment, feature sets to be used in ANNs at each layer of the decision tree were determined, as well as the sequence of sleep stages to be analyzed. All sleep data fragments were grouped randomly into training group and testing group. The first step of this experiment is to train all the ANNs used in the tree. Given that the result of using an artificial neural network could be different every time it's been trained, each ANN was trained several times and the best performing one was chosen for the following data analysis. The second step was to verify the effectiveness of the algorithm. We used the trained algorithm to classify the sleep EEG data fragments that belonged to the testing group and compare the result with the manual calssification result, the agreement ratio was recorded, as is shown in Table 3. The result of this experiment shows that this method performed superbly in discriminating REM and SWS, none of the data fragments belonged to these two stages were identified mistakenly. The result of identifying S2 reached 80.56%, which was also satisfactory. Also, the accuracy of discriminating wakefulness and S1 reached 79.35%, which was improved compared to the result obtained from the prep-experiment.

TABLE III
EPOCH BY EPOCH AGREEMENT RESULT OF THE FIRST EXPERIMENT

Tests	Sleep Stage				
	wakefulness+S1	REM	S2	SWS	Total
Test 1	74.10%	100%	80.56%	100%	88.66%
Test 2	79.35%	100%	80.56%	100%	89.98%
Test 3	79.14%	100%	72.22%	100%	87.84%

C. Error propagation experiment

The second experiment was undertaken to find if the proposed system is effective in reducing error propagation. It was much the same as the first experiment, except sleep EEG data were clustered into five stages, which means wakefulness and S1 will be separated from each other. For this reason, the leaf node representing wakefulness+S1 was replaced by an additional decision node, and sleep data that were considered as wakefulness or S1 were analyzed again by this node and separated into two additional leaf nodes. Again the epoch by epoch agreement between the trained algorithm and the manual calssification result was recorded, as listed in Table 4. The result shows that the performance in recognizing wakefulness state was very poor. In addition, the classification accuracy of S1 was affected. They were reduced quite a bit, and became unstable. In spite of this, the rest stages were not influenced.

TABLE IV
EPOCH BY EPOCH AGREEMENT RESULT OF THE SECOND EXPERIMENT

Tests	Sleep Stage					
	wakefulness	REM	S1	S2	SWS	Total
Test 1	29.8%	100%	59.8%	80.6%	100%	74.0%
Test 2	27.7%	100%	70.7%	72.2%	100%	74.1%
Test 3	28.5%	100%	69.1%	72.2%	100%	74.0%

IV. Discussion

The results of the prep-experiment shows that in this method, as each ANN was set to focus on only one specific sleep stage, the interference caused by weak features in training and classifying proceed of ANNs were effectively reduced. Thus it could be expected that as few errors as possible were generated by these classifiers. In addition, by combining ANN classifiers with the decision tree, high accuracies of ANNs on identifying every single stage were well inherited by this algorithm. As shown by the results of the first experiment, the performance of discriminating each sleep stage inherited the good performances shown in the prep-experiment fairly well, which indicated that the combining of the two classification algorithm did bring some improvements and led to a satisfying result when undertaking a detailed automatic sleep scoring with all night sleep EEG data.

Also, the results of prep-experiment indicated that wakefulness and S1 were hard to separate by any of the features we used. When we tried to achieve it in the second experiment, the results were uniformly poor. We found, however, that besides wakefulness and S1, the rest of sleep stages can still be discriminated with similar accuracies of the first experiment. This proved that if the order of discrimination is set properly, the method proposed is capable of preventing errors generated by the posterior layers affecting anterior layers, and limit the influence brought by weak features in a minimized area.

The idea of combining different sleep scoring methods to exploit advantages of all of them has been proposed before. The earlier hybrid sleep scoring system simply tried to combine multiple biological signal processors with a reasoning module. E.g. in 1971, an hybrid EEG sleep scoring system SAHC, combined by a series of EEG pattern detectors and a rule based decision tree as logic mechanism, was proposed by Jack R. Smith and Ismet Karacan. SAHC used 3 channels of EEG and 2 channels of EOG for its analysis, and the percent agreement of all sleep stages(stage 1 and stage REM combined) between this system and human scoring was 83.52%[20]. Recent work tends to focus on combining classification algorithms. Irena Koprinska, Gert Pfurtscheller and Doris Flotzinger reported a system called TBNN in 1996, which used a decision-tree generator to provide knowledge that defines the architecture of a back propagation neural network, including feature selection and initialization of the weights. 15 features extracted from EEG, EOG, EMG and ECG were used in this system, the average accuracy of this system was 78% when applied to automated off-line analysis of the all-night sleep in infants aged 6 months[3]. Hae-Jeong Park et al.proposed an automated method for sleep stage scoring using hybrid rule- and case-based reasoning in 2000. Their system first performs rule-based sleep stage scoring, and then supplements the scoring with case-based reasoning. With features extracted from EEG, EOG and EMG, this system got an average agreement rate in normal recordings of 87.5%, which was enhanced by 5.6% by case-based scoring[21].

It is necessary to point out that all the above work used multiple biological signals for analysis to ensure the high accuracy and reliability of the systems, which made the analysis expensive and inconvenient. By contrast, our method uses only 8 parameters extracted from a single EEG signal, with the average epoch by epoch agreement kept at 88.83%. This means the method we propose could provide an efficient and reliable automatic sleep scoring while reducing the analysis cost. Additionally, it could make sleep analysis more easily applied in a pervasive computing context.

Although these experiments obtained encouraging results, limitations still exist in our study. Firstly, wakefulness and S1 can still not be separated using current features, as was discussed. Secondly, as our data is limited, the distribution of data belong to different stages used in the experiments was nonuniform, which may have some affect on our experiment. Finally, the accuracy in our experimental results concerned Type I errors only, which means these accuracies indicated how many data fragments were not identified as a wrong sleep stage. Type II errors were not explicitly shown in the results.

V. Conclusion

This study demonstrated a novel method for automatic sleep scoring using an artificial neural networks based decision tree. By describing sleep scoring problem with this tree-like structure, the calssification process was divided into multiple layers, errors generated in any layer can only affect the posterior layers, thus the error propagation could be controlled easily by arranging decision nodes properly. Because each ANN has a specific feature set for their analysis, and they only separate data on one sleep stage from the others, they are hardly affected by weak features and their performances are greatly improved. Also, decisions made by ANN classifiers in the decision tree made the classification result more reliable, and the total accuracy of this system can be ensured. To make this method low cost and convenient for pervasive applications, we used 8 features extracted from single EEG data for our analysis. The experimental results demonstrates that the proposed method is effective in performing automatic sleep scoring. In further research, we intend to make attempts to discriminate wakefulness with a higher degree of accuracy using new features extracted from EEG signals.

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