

A Fuzzy Inference System for Sleep Staging

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Abstract—In this paper, a fuzzy inference system for sleep staging was developed. Nine input variables including temporal and spectrum analyses of the EEG, EOG, and EMG signals were extracted and normalization was applied to these variables to reduce the effect of individual variability. A fuzzy inference system contains fourteen fuzzy rules was designed to classify the 30-s sleep epochs as five sleep stages. Finally, a smoothing process was applied to the scoring results for fine-tuning. The average accuracy of the proposed method applied to 16 all-night polysomnography (PSG) recordings compared with the manual scorings can reach 87 %. This method can integrate with various PSG systems for sleep monitoring in clinical or homecare applications.

Keywords—Automatic sleep staging; sleep staging, fuzzy inference systems, sleep monitoring, fuzzy rules.

I. INTRODUCTION

Sleep diseases, such as insomnia and obstructive sleep apnea, seriously affect patients' quality of life. The prevalence of insomnia symptoms is approximately 33% in the general population [1]. There are over 4% of adult men and 3% adult women be affected by obstructive sleep apnea [2]. These sleep issues may cause daytime sleepiness, irritability, depression or anxiety. For the diagnosis of sleep issues, all night polysomnographic (PSG) recordings, including electroencephalogram (EEG), electrooculogram (EOG) and electromyogram (EMG), are usually taken from the patients and the recordings are scored by a well-trained expert according to the Rechtschaffen & Kales (R&K) rules presented in 1968 [3].

According to the R&K rules, each epoch (i.e., 30 s of data) is classified into one of the sleep stages, including wakefulness (Wake), non-rapid eye movement (stages 1-4, from light to deep sleep) and rapid eye movement (REM). Recently, stages 3 and 4 were combined and are now known as the slow wave sleep stage (SWS) [4].

Because visual sleep scoring is a time consuming and subjective process, automatic sleep staging methods, including rule-based methods [5-6], numerical classification methods [7-8] and the hybrid system, that take advantage of both approaches [9], were developed. In rule-based methods, signal information and human knowledge are combined to deduce a

reasonable sleep state. In contrast, numerical classification methods do not require a set of rules or any human knowledge. The overall agreement of these methods is in the range of 80% to 85%.

In this paper, a fuzzy inference system for sleep staging was proposed. The central EEG (C3-A2), the difference between two EOG and the chin EMG were analyzed, and nine features were extracted for each 30-s epoch. The features were normalized to reduce the individual variability, so that the system parameters were subject-independent. Finally, a smoothing process was applied to the scoring results for fine-tuning. In future, this method can integrate with various PSG systems for sleep monitoring in homecare applications.

II. METHOD AND MATERIALS

A. Subjects and recordings

All-night polysomnographic sleep recordings were obtained from 20 healthy subjects (12 males and 8 females) ranging from 19 to 23 years in age (mean = 21.2 ± 1.1). The data from four subjects were used to train the system, and data from 16 subjects were used for testing. The recordings included six EEG channels (F3-A2, F4-A1, C3-A2, C4-A1, P3-A2, and P4-A1, according to the international 10-20 standard system), two EOG channels (positioned 1 cm lateral to the left and right outer canthi), and a chin EMG channel (Siesta 802 PSG, Compumedics, Inc.). The sampling rate was 1 KHz with 16-bit resolution. The 20 PSG sleep recordings were visually scored by a sleep specialist using the R&K rules with a 30-s interval (termed the epoch).

B. Feature extraction

The automatic sleep staging system analyzes the data for three channels: the central EEG (C3-A2), the difference of the two EOGs, and the chin EMG. After downsampling the signals to 256 Hz, the EEG and EOG data were filtered with an eighth-order Butterworth band-pass filter with a cutoff frequency of 0.5–30 Hz, and the EMG data were filtered with a 5–100 Hz eighth-order Butterworth band-pass filter. The continuous time signals were segmented with every 30-s epoch.

Before extracting spectral features, the signal was segmented into non-overlapping intervals of 2 seconds for a 512-point fast Fourier transformation (FFT) calculation. The spectrums corresponding to the 15 2-s segments were averaged to represent the spectrum for a 30-s epoch. Table I lists the nine features used in this paper [7-8, 10-11].

After feature extraction, normalization of features was employed to reduce the effects of individual variability. For each feature, the mean of maximal 10% data was calculated as the maximum value of the feature, and the mean of minimal 10% data was calculated as the minimum value of the feature for the subject. This process can prevent extremely high or low values from influencing any conclusions. The procedure for normalization is summarized in the following steps:

- Step 1: Calculate the means of the 10% minimal and maximal values for the feature as the min and max values, respectively.
Step 2: Set the min and max values as 0 and 1, and then normalize other values from 0 to 1.
Step 3: If the value is higher than 1, the value is specified as 1. If the value is lower than 0, the value is specified as 0.

TABLE I. The features for sleep scoring

No.	Type	Feature	Source	Label
1	PS	Total power of 0-30 Hz	EEG	0-30 E
2	PS	Total power of 0-30 Hz	EMG	0-30 M
3	PR	0-4 Hz/0-30 Hz	EEG	0-4 E
4	PR	22-30 Hz/0-30 Hz	EEG	22-30 E
5	PR	0-4 Hz/0-30 Hz	EOG	0-4 O
6	SF	Mean frequency of 0-30 Hz	EEG	Mean(fre.) E
7	DR	Alpha ratio	EEG	Alpha E
8	DR	Spindle ratio	EEG	Spindle E
9	EMG energy	Mean amplitude	EMG	Amp M

*PS(=Power spectrum), PR(=Power ratio), SF(=Spectral frequency), DR(=Duration ratio)

C. Fuzzy inference system

In the proposed method, the fuzzy inference system includes 14 fuzzy rules. We use nine features as the input of the fuzzy system to build the fuzzy sets as show in Figure 1.

According to the R&K rules and distributions of the features with respect to various sleep stages, 14 fuzzy rules were constructed. Taking rule 1 as an example, during wake stage, we can observe high frequency activity of EEG such as abundant alpha activity (8-13 Hz) and gamma activity (>20 Hz) in EEG with higher muscle tone. So, The concept of rule 1 is that, when alpha EEG is high (*Alpha E* is G_3) and EMG is high (0-30 *M* is B_2) and low frequency (delta, 0-4 Hz) EEG is

low (0-4 *E* is C_1); then the rule concludes that the stage is wake.

The followings are the summary of the 14 fuzzy rules:

- R_1 : IF *Alpha E* is G_3 AND 0-30 *M* is B_2 AND 0-4 *E* is C_1 THEN out is WAKE
 R_2 : IF *Alpha E* is G_3 AND 0-30 *M* is B_2 AND *Spindle E* is H_3 AND (0-4 *E* is C_2 OR 0-4 *E* is C_3 OR 0-4 *E* is C_4) THEN out is S2
 R_3 : IF *Alpha E* is G_3 AND 0-30 *M* is B_2 AND (*Spindle E* is H_1 OR *Spindle E* is H_2) AND Mean(fre.) *E* is F_2 THEN out is WAKE
 R_4 : IF *Alpha E* is G_3 AND 0-30 *M* is B_2 AND (*Spindle E* is H_1 OR *Spindle E* is H_2) AND Mean(fre.) *E* is F_1 THEN out is S1
 R_5 : IF *Alpha E* is G_3 AND 0-30 *M* is B_1 AND *Amp E* is I_1 AND (*Spindle E* is H_1 OR (*Spindle E* is H_2 AND 0-30 *E* is A_1)) THEN out is REM
 R_6 : IF *Alpha E* is G_3 AND 0-30 *M* is B_1 AND *Amp E* is I_1 AND ((*Spindle E* is H_2 OR *Spindle E* is H_3) AND (0-30 *E* is A_2 OR 0-30 *E* is A_3)) OR (*Spindle E* is H_3 AND 0-30 *E* is A_1)) THEN out is S2
 R_7 : IF *Alpha E* is G_3 AND 0-30 *M* is B_1 AND *Amp E* is I_2 AND (*Spindle E* is H_1 OR *Spindle E* is H_2) THEN out is S1
 R_8 : IF *Alpha E* is G_3 AND 0-30 *M* is B_1 AND *Amp E* is I_2 AND *Spindle E* is H_3 THEN out is S2
 R_9 : IF (*Alpha E* is G_1 OR *Alpha E* is G_2) AND (22-30 *E* is D_1 AND (0-4 *E* is C_3 OR 0-4 *E* is C_4)) AND 0-4 *O* is E_2 THEN out is SWS
 R_{10} : IF (*Alpha E* is G_1 OR *Alpha E* is G_2) AND (22-30 *E* is D_1 AND (0-4 *E* is C_3 OR 0-4 *E* is C_4)) AND 0-4 *O* is E_1 THEN out is S2
 R_{11} : IF (*Alpha E* is G_1 OR *Alpha E* is G_2) AND (22-30 *E* is D_2 OR (22-30 *E* is D_1 AND (0-4 *E* is C_1 OR 0-4 *E* is C_2))) AND *Amp E* is I_1 AND (*Spindle E* is H_1 OR (*Spindle E* is H_2 AND 0-30 *E* is A_1)) THEN out is REM
 R_{12} : IF (*Alpha E* is G_1 OR *Alpha E* is G_2) AND (22-30 *E* is D_2 OR (22-30 *E* is D_1 AND (0-4 *E* is C_1 OR 0-4 *E* is C_2))) AND *Amp E* is I_1 AND ((*Spindle E* is H_2 OR *Spindle E* is H_3) AND (0-30 *E* is A_2 OR 0-30 *E* is A_3)) OR (*Spindle E* is H_3 AND 0-30 *E* is A_1)) THEN out is S2
 R_{13} : IF (*Alpha E* is G_1 OR *Alpha E* is G_2) AND (22-30 *E* is D_2 OR (22-30 *E* is D_1 AND (0-4 *E* is C_1 OR 0-4 *E* is C_2))) AND *Amp E* is I_2 AND (*Spindle E* is H_1 OR *Spindle E* is H_2) THEN out is S1
 R_{14} : IF (*Alpha E* is G_1 OR *Alpha E* is G_2) AND (22-30 *E* is D_2 OR (22-30 *E* is D_1 AND (0-4 *E* is C_1 OR 0-4 *E* is C_2))) AND *Amp E* is I_2 AND *Spindle* is H_3 THEN out is S2

The operations “AND” and “OR” in the fuzzy rules take the minimum and maximum values of the activations, respectively. For each epoch, the inference output is the determined stage that has the maximum activation value among all of the 14 rules.

D. Classification:

The classification process comprises three steps:

1) Movement epochs detection:

The movement (MT) epochs were detected with the following rules: if over 1/3 of the epoch of the absolute EMG amplitude was higher than double of Th1, or if the difference between the two consecutive epochs was higher than Th2, the epoch was defined as MT. Th1 is the mean value of the feature Amp M in Wake epochs of the training data, and Th2 is the mean value of the Amp M difference between every two consecutive epochs of the training data.

2) Fuzzy inference system:

For each epoch, the inference output is the determined stage that has the maximum activation value among all of the 14 rules.

3) Contextual rule smoothing

After classifying the sleep stage, a smoothing process, considering the temporal contextual information, was applied for continuity. Eleven rules [9][12] that refer to the relationship between epochs prior to and posterior to the current epoch were utilized for smoothing.

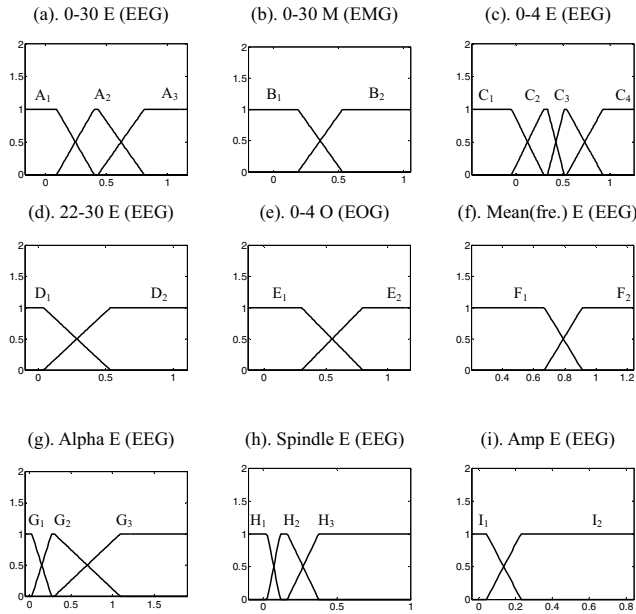


Fig 1. Fuzzy sets in our proposed method

III. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed sleep staging method, 16 all-night PSG recordings from 16 subjects were used for testing. The performance was evaluated in the following aspects: the average performance of the method with smoothing and the sleep staging result of subject's overnight sleep data.

A. Performance of accuracy

TABLE II shows the confusion matrices of the five-stage epoch classification by the proposed sleep staging method. The rows and column are the results staged by expert and our fuzzy inference system, respectively. The testing dataset for performance estimation was comprised of 13,626 30-second epochs. As shown in Table 1, the overall sensitivity was 87.05% for the proposed fuzzy inference system.

B. Performance evaluation of consecutive staging

Figure 2 shows the hypnograms of one subject, including the manual scoring by the expert, the automatic staging without smoothing, and the automatic staging with smoothing.

It was observed that the hypnogram of our proposed method followed the changes in sleep stages of the subject. After smoothing, the resultant hypnogram is closer to the hypnogram scored by the expert.

TABLE II. Confusion table for comparison between computer scoring with smoothing and visual scoring for all 16 subjects.

		Computer						
		Wake	S1	S2	SWS	REM	Total	SE(%)
Expert	Wake	323	30	12	0	3	368	87.77
	S1	60	194	79	2	118	452	42.92
	S2	111	205	6591	258	241	7406	89
	SWS	5	17	239	2216	19	2496	88.78
	REM	38	172	118	38	2538	2904	87.4
	Overall						13626	87.05

* SE = sensitivity

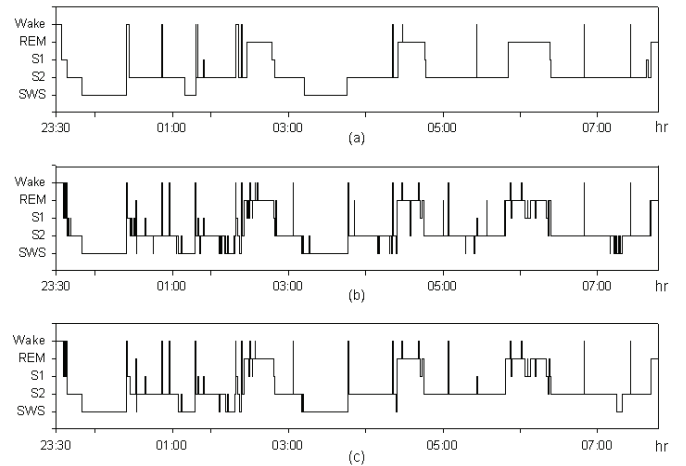


Fig 2. The sleep hypnogram of a subject: (a) the original manually score, (b) the automatic staging without smoothing, and (c) the automatic staging with smoothing.

IV. DISCUSSION

In this paper, an automated sleep staging system based on the fuzzy inference system was proposed. Temporal and spectral features of the EEG, EOG, and EMG signals were extracted and normalization was applied to these features to reduce the effect of individual variability. Experimental results show that the overall accuracy of the proposed fuzzy inference

system can reach 87.05%. Except for S1, the sensitivities of each stage are higher than 87%. The performance is superior to the previous studies [5-9, 12].

In the observation of the PSG signal for each stage, we found that there are many types of signals present in one stage, particularly during S1. So the developed multi-rule staging method that considers various kinds of situations according to the features of frequency and time domain is better than only referring to the R&K rules.

In previous studies, the sensitivity of expert and automatic sleep staging has high accuracy, but the sensitivity of S1 was about only 20% [8, 14]. Some previous studies try to improve the sensitivity of S1 to about 35% [7] [12], but the overall accuracy is about only 80%. S1 is easily mistakenly categorized as one of the other stages, except for SWS, and the number of S1 epochs is significantly lower than that of other stages. So, it is difficult to train a model with a high sensitivity for S1.

The proposed sleep staging method has high sensitivity and the resultant hypnogram is closer to the results scored by the expert. In future, we expect this method can integrate with various PSG systems for sleep monitoring in homecare applications.

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