Polysomnography Symbolic Fusion for Automatic Sleep Staging

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Abstract— **Sleep staging is a time-consuming work and inter-rater reliability variation exists in sleep-stages scorers. There is a need for automatic sleep staging which can facilitate this process and enhance the reliability. This paper presents a new method based on symbolic fusion to realize automatic sleep staging. By combining multiple signals of polysomnography (PSG) and considering temporal effects, symbolic fusion achieves improved accuracy and more specific inferences for sleep staging. This method was tested on 16 patients PSG and the overall agreement of 65.58% was reached. Proposed symbolic fusion is developed for portable embedded system devices to assist sleep evaluation at home at low complexity and cost.**

Keywords- Automatic Sleep Staging, Symbolic Fusion, polysomnography (PSG).

I. Introduction

Sleep is an indispensable part of our life and contributes to self-repair and self-recover of human body. However, sleep disorders affect more than 10% of the people [1] and this is a significant cause of morbidity and mortality [2]. For clinical diagnosis and treatment of sleep disorders, identification of sleep stages is the fundamental step in sleep studies.

According to the Rechtschaffen and Kales (R&K) manual [3] and the American Academy of Sleep Medicine (AASM) manual [4], sleep stages can be divided into awake, Rapid-Eye-Movement (REM) and Non-Rapid-Eye-Movement (NREM) stages. Currently sleep staging is based on an overnight polysomnography (PSG) study which records multiple bio-signals, such as electroencephalography (EEG), electrocardiography (ECG), electrooculography (EOG), electromyography (EMG), respiratory effort and blood oxygen saturation, and manual sleep staging according to the R&K or AASM manuals. However, manual sleep staging has several limitations: firstly, it is a time consuming and labor intensive task involving interpretation of enormous clinical data; secondly, inter-rater reliability concerns exist due to subjective interpretation and possible human error. In [5], authors reported inter-rater reliability of 80.6% and 82.0% by using R&K and AASM respectively. To overcome these limitations, an automatic sleep staging method is studied and proposed in this paper, which can facilitate sleep staging process and provide objective information.

Machine learning is widely used for sleep staging. Typical approaches of machine learning, such as Decision Tree [6] [7], Artificial Neural Network (ANN) [8] [9] [10], Support Vector Machine (SVM) [11] [12] [13] and Clustering [14] [15] [16], were used in classifying sleep stages. Each approach has its own drawbacks. For decision tree, the accuracy is extremely sensitive to small perturbations, which may not be suitable for individual variability of PSG signals. ANN requires a large set of training data and the performance depends mostly on the quality of the used feature set. SVM has high algorithmic complexity and needs extensive memory. Clustering relies on initial clusters selection, while current selection method for initial clusters may lead to a classification based on some insignificant patterns. Besides the drawbacks of each approach, machine learning does not consider two important factors. Firstly, using machine learning to classify sleep stages is often thought as an independent classification problem, whereas sleep staging is a time dependent classification problem, which can be influenced by the previous sleep stage and can influence the next sleep stage. Secondly, machine learning uses a smaller number of signals to reduce the dimension of the feature set. However, to increase the accuracy and reliability of the sleep staging, there is a need to include more signals in the analysis [17].

In this paper, we propose a symbolic fusion method to realize an automatic sleep staging. Symbolic fusion is an interdisciplinary knowledge-based technique [18]. The symbolic fusion proposed in this paper is based on predefined rules, which were defined under cooperation between engineers and clinicians, according to the AASM manual, instead of only depending on numerical classification methods like machine learning. It can combine most of the PSG signals used in sleep staging and also consider the temporal implications by adding a temporal smooth function in order to generate a composite decision.

The aim of the present study is to develop an automatic sleep staging method based on recorded PSG signals, which can be implemented in embedded systems suitable for assisting doctors to analyze sleep stages. This paper is organized as follows. Subjects and methodology are discussed in Sections 2. Results are presented in Section 3, followed by conclusions in Section 4 with future directions.

II. Subjects and Methodology

1. *Subjects and Data Acquisition*

The PSG signals recordings were done by clinical experts in Hoptial-Tenon (AP-HP) for 16 patients including 4 males and 12 females with ages between 26 and 67 years old (mean = 54.75 years; STD = 12.5 years), most of them with detected sleep apnea events. Recorded PSG data were analyzed by experts and sleep stages were scored. The PSG data was divided into 30-s epoch and classified into Stage W, Stage REM and Stage NREM (Stage N1, Stage N2 and Stage N3). The 16 patients PSG, interpreted by experts, were used as a database in this work. Table 1 shows the details of this database, which has 19468 epochs in total.

Recorded PSG Data					
Number of Patient	Mean Duration of PSG Recording		Total Epochs		
16	14.5 (hours)		278400		
Expert Analysis for Recorded PSG					
Database	Stage W	Stage N1	Stage N2	Stage N3	Stage REM
Epoch Number	4747	1991	6526	3616	2588

Table 1. Database Description

2. *Methodology*

Symbolic fusion was proven efficient to combine information from different sources, such as heterogeneous signals. Overall accuracy of the method is increased because symbolic fusion provides enhanced and complementary perceptions by combining signals from different sources, which have their own limitations and uncertain perceptions.

We adopted a three-level architecture for symbolic fusion: data fusion, feature fusion and decision fusion, as proposed in [24]. Figure 1 shows the flow of symbolic method and parameters used in each level. Details of the method will be discussed in this section.

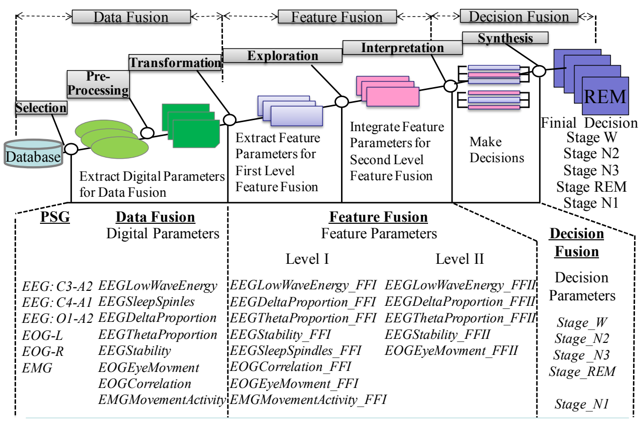

Figure 1. Symbolic Fusion Flow and Parameters Distribution

2.1 Data Fusion

Data fusion is used to extract digital parameters from PSG recording by using appropriate signal processing methods corresponding to the AASM manual [4]. At data fusion level, we maximize useful information and minimize the noise in PSG recordings. Eight digital parameters were extracted from recorded PSG by different signal processing methods. The first 5 parameters were extracted from three different EEG channels: C3-A2, C4-A1, O1-A2; the middle 2 parameters were extracted from 2 EOG channels: EOG-L, EOG-R; the last parameter was extracted from EMG. Below is the brief description of the parameters.

1. **EEGLowWaveEnergy**: EEGLowWaveEnergy indicates the energy of the slow wave of frequency between 0 Hz to 2 Hz in EEG signal.
2. **EEGSleepSpindles:** The Sleep Spindle is a train of distinct waves with frequency 11-16 Hz and duration more than 0.5 seconds. It is a significant indicator of stage N2. EEGSleepSpinles is calculated by using Short Time Fourier Transform (STFT).
3. **EEGDeltaProportion:** EEGDeltaProportion signifies the power ratio between Delta frequency band (frequency smaller than 2 Hz) and the total power of each 30-s epoch.
4. **EEGThetaProportion:** EEGThetaProportion signifies the power ratio between Theta frequency band (frequency between 4 Hz and 7 Hz) and the total power of each 30-s epoch.
5. **EEGStability:** EEGStability signifies the power ratio between the fast wave (frequency more than 18 Hz) and the total power. The fast wave is one characteristics of Stage W.
6. **EOGEyeMovment**: The EOGEyeMovement represents the number of times eye moves during sleep. The algorithm we used to calculate this parameter is based on [19]. This parameter is a significant indicator to distinguish between REM and NREM stage.
7. **EOGCorrelation**: EOGCorrelation is the correlation between the left and right eye movements. It indicates whether the movement of the two eyes are interdependent or not.
8. **EMGMovementActivity**: This represents the mean absolute value of the EMG signal. This parameter is used to indicate the activity level of EMG, which can be used as an indicator of the muscle tone movement in sleep staging.

2.2 Feature Fusion

Features fusion is used to transfer digital parameter into feature parameters. By using appropriate fusion methods, we realized reduction, matching and normalization of feature sets.

In feature fusion, the first 6 parameters (*EEGLowWaveEnergy to EOGEyeMovment*) need 2-level feature fusion except EEGSleepSpindles. EEGSleepSpindles, EOGCorrelation and EMGMovementActivity only need 1-level feature fusion. For 2-level feature fusion, the first step is to fuse digital parameters to feature parameters. Second step is to integrate either 3 different EEG signals or 2 different EOG signals. However, EEGSleepSpindles is the total number of sleep spindles of 3 EEG signals; EOGCorrelation is correlation of EOG-L and EOG-R signal; Since EMG signal is only one channel, thus EMGMovementActivity need only 1-level feature fusion.

2.3 Decision Fusion

Decision fusion is used to make decisions according to the AASM manual to generate a composite decision for sleep staging. Inference methods used in decision fusion have been discussed with doctors.

Using AASM as a guideline, we integrated feature parameters to generate a composite decision. Figure 2 is the design flow of classifying REM stage by using symbolic fusion as an example.

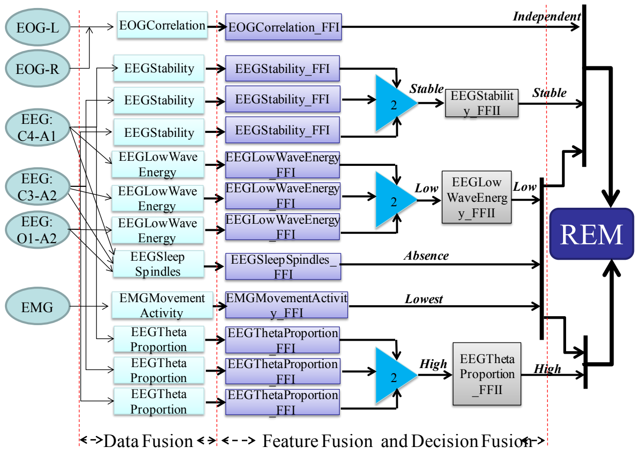

Figure 2. Design Flow for Stage REM Classification Using Symbolic Fusion

III. Results

Figure 3 shows comparison between the symbolic fusion method and the visual analysis by sleep-stages scorer using one patient as an example. X-axis represents the epoch number of this patient and Y-axis shows the different sleep stages. From the figure we can see a high agreement between our method and a visual analysis. Meanwhile, symbolic fusion failed to classify Stage N1. This is because Stage N1 is considered as a transition between wake and sleep. It occurs upon falling asleep and during brief arousal periods within sleep and usually accounts for 2-5% of total sleep time [20]. Since Stage N1 accounts only for a small part of the total sleep time, we mainly focus on classifying other sleep stages. Identification of Stage N1 will be considered in our future work.

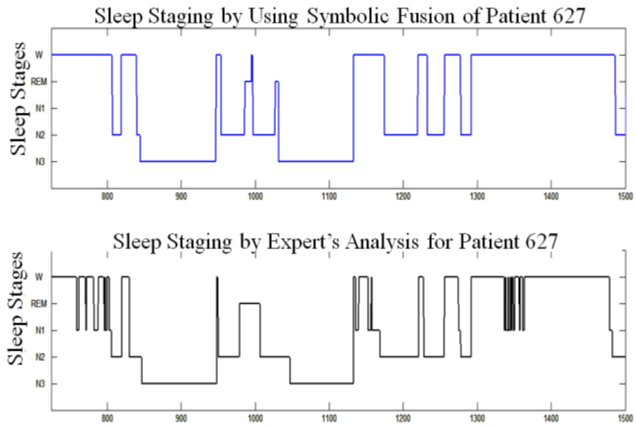

Figure 3. Symbolic Fusion Result for Patient 627 in Sleep Staging

In this study, we adopted the Agreement Rate (AR) to assess the performance of symbolic fusion. Table 2 shows the AR in each sleep stage and the comparison with other method. Up to 65.58% AR is achieved based on our database which is better in comparison to several machine learning methods, as reported in [22] [23]. In [22], authors reported 61% AR by using Linear Discriminant Analysis. 55.88% AR was reported in [23], by using K-Nearest Neighbor method. In comparison to a recent report in literature [21], which used Fuzzy Inference, our method showed 4.8% and 14.27% better AR in Stage W and Stage N3, respectively. However, it has relatively 11.6% low AR in classifying Stage N2 because K-Complex is not considered during classification. K-Complex is a well-delineated negative sharp wave immediately followed by a positive component standing out from the background EEG, with total duration ≥ 0.5 sec [4] which is also a significant indicator to classify Stage N2. In our future work, K-Complex will be added into symbolic fusion as a parameter to classify Stage N2.

Sleep Stages	Agreement Rate Using Symbolic Fusion	Agreement Rate Using Fuzzy Inference [21]
Stage W	89.80%	85%
Stage N1	0.05%	18%
Stage N2	62.40%	74%
Stage N3	77.27%	63%
Stage REM	63.45%	67%

Table 2. Agreement Rate Using Symbolic Fusion.

IV. Conclusion and Perspective

In this study, we proposed a new symbolic fusion method to realize sleep staging. In comparison to sleep staging methods using signal channel PSG data, symbolic fusion provides enhanced and complementary decision combining multiple channels which increases overall accuracy. Meanwhile, symbolic fusion proved to be an effective method in comparison to machine learning for sleep staging because it takes temporal implications into account. Using symbolic fusion, we reached an overall agreement rate of 65.58% and approximately 90% for classifying Stage W. Our current work focus mainly on classifying Stage W, Stage N2, Stage N3 and Stage REM. Classification of Stage N1 will be done in our future work and more parameters will be added into our method to improve overall agreement rate.

In February 2015 a new project is started. It is under the collaboration among the Laboratoire d'Informatique de Paris 6 (LIP6), Informatique Médicale et Ingénierie des connaissances pour la e-Santé(LIMICS) and AP-HP Hôpital Universitaire Pitié-Salpêtrière. This project is funded by the Institut Universitaire d'Ingénierie pour la Santé (IUIS). The aim of this new project is firstly the improvement of the symbolic techniques to take into account the uniqueness of the individual, secondly the algorithms integration into an embedded system and thirdly a new database set acquisition.

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