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Decision System Integrating Preferences to Support Sleep Staging

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Abstract. Scoring sleep stages can be considered as a classification problem. Once the whole recording segmented into 30-seconds epochs, features, extracted from raw signals, are typically injected into machine learning algorithms in order to build a model able to assign a sleep stage, trying to mimic what experts have done on the training set. Such approaches ignore the advances in sleep medicine, in which guidelines have been published by the AASM, providing definitions and rules that should be followed to score sleep stages. In addition, these approaches are not able to solve conflict situations, in which criteria of different sleep stages are met. This work proposes a novel approach based on AASM guidelines. Rules are formalized integrating, for some of them, preferences allowing to support decision in conflict situations. Applied to a doubtful epoch, our approach has taken the appropriate decision.

Keywords. Sleep stages, clinical practice guidelines, preferences, decision support system, formalization

1. Introduction

The diagnosis of sleep disorders requires the scoring of sleep stages. Sleep stages can be seen as a classification indicating the depth of sleep. Polysomnography is the gold standard diagnostic test for sleep disorders. It consists in recording different physiological signals during a whole night.

To stage sleep, physicians use international standard guidelines defined by the American Academy of Sleep Medicine (AASM) [1]. These guidelines are based on the visual analysis of brain activity - recorded by three electro-encephalograms (EEG) -, eye movements - recorded by two electro-oculograms (EOG) - and muscle tone - recorded by one chin electromyogram (EMG). The whole recording is divided into 30-seconds pages, called epochs. Sleep staging consists in assigning a sleep stage to each epoch. The AASM Manual defines five different sleep stages: W (Wakefulness), N1, N2 (light sleep), N3 (deep sleep) and R (REM, Rapid Eye Movements Sleep).

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Each sleep stage is determined by physiological criteria, deduced from the shape of waves. These criteria include the shape of background signal and the presence of concomitant or lightly delayed patterns on each signal. Nevertheless, it happens that in one given epoch, signals meet the criteria of several, or none of all sleep stages. In this case, a decision needs to be taken using precedence rules defined in AASM Manual. For example, one note of the AASM Manual states: "*If there is a conflict between a stage N2 and stage R scoring rule, the stage R rule takes precedence*".

We propose to formalize such rules by preferences. The notion of preference is crucial in many fields, including medicine. They are used in artificial intelligence to modelize decision problems where a decision should be taken to choose the more appropriate solution among several possible ones. Integrating preferences in medicine is discussed in different works [2,3,4,5]. For example, preferences are used to choose an appropriate treatment [5]. Two approaches have been developed in the literature: 1) a quantitative approach [6,7] where preferences are expressed by means of a utility function, the option with the maximal utility is considered the best one, 2) a qualitative approach [8,9,10] where relative preferences are expressed by ordering the options. However, quantitative approaches are more complex because they require to express preferences with numerical values, which is often difficult in medicine.

Our aim is to propose to formalize AASM precedence rules by qualitative preferences so that a decision can be taken in conflict situations where criteria of several sleep stages are met.

2. Methods

Sleep physicians are used to assign one single sleep stage to a given epoch. Nevertheless, it has been shown that there exist an inter- and intra-scorer variability in this task [11]. This can be explained by the fact that for one given epoch, criteria of different sleep stages may be met. For these situations, AASM has defined precedence rules. We propose to formalize these latter as preferences and include them into a global decision process for automatic sleep staging.

2.1. Formalization of AASM Rules

We propose a preferences-based approach to solve such problems. The precedence rules concern both sleep events, used to stage sleep, and sleep stages.

Let us consider as a first example a precedence rule concerning R and N2 sleep stages. In these 2 sleep stages, EEG activity is composed of low amplitude mixed-frequency waves and muscle tone is low. In R sleep stage, rapid eye movements or transient muscle activity may be observed. In N2 sleep stage, K complexes[2] and/or sleep spindles[3] may be observed on EEG derivations. One note of the AASM Manual states: "*If there is a conflict between a stage N2 and stage R scoring rule, the stage R rule takes precedence*". This note can be formalized as follows:

[2] A well-delineated, negative, sharp wave immediately followed by a positive component standing out from the background EEG, with total duration ≥0.5 seconds, usually maximal in amplitude when recorded using frontal derivations.

[3] A train of distinct waves with frequency 11-16 Hz (most commonly 12-14 Hz) with a duration ≥0.5 seconds, usually maximal in amplitude in the central derivations.

$$O_i^{N2} \wedge O_i^{R} \Rightarrow O_i^{R} \succ O_i^{N2} \quad \text{(I4)}$$

This formalized rule means that if, in given slot *i*, criteria of N2 and R sleep stages are both observed then R criteria are preferred to N2 criteria to assign the right stage.

Let us consider, as a second example, a rule concerning K complexes and slow wave activity[4] in a given slot *i*. A note in AASM states that "*K complexes would be considered slow waves if they meet the definition of slow wave activity*". This rule can be formalized by either prefering slow wave activity to K complex, or either by only considering slow waves and discarding the K complex. We chose to keep the preference rule and formalize it as follows:

$$O_i^{Kcomplex} \wedge O_i^{slowwaveactivity} \Rightarrow O_i^{slowwaveactivity} \succ O_i^{Kcomplex} \quad \text{(H, Note 2)}$$

2.2. *Global process for staging automatically an epoch*

We propose the following steps to score automatically an epoch:

1. Observations of sleep events are extracted on the whole recording using *ad hoc* algorithms validated by a physician.
2. Each 30-seconds epoch is divided into 6 slots of 5-seconds segments.
3. Observations are represented in a table where rows contain observations and columns contain 5-seconds slots.
4. AASM rules based on observations of events – including preference ones – are applied on each slot on the basis of observations.
5. Majority sleep stage is searched over the whole epoch.
6. If necessary, AASM preference rules on sleep stages are applied.

3. Results

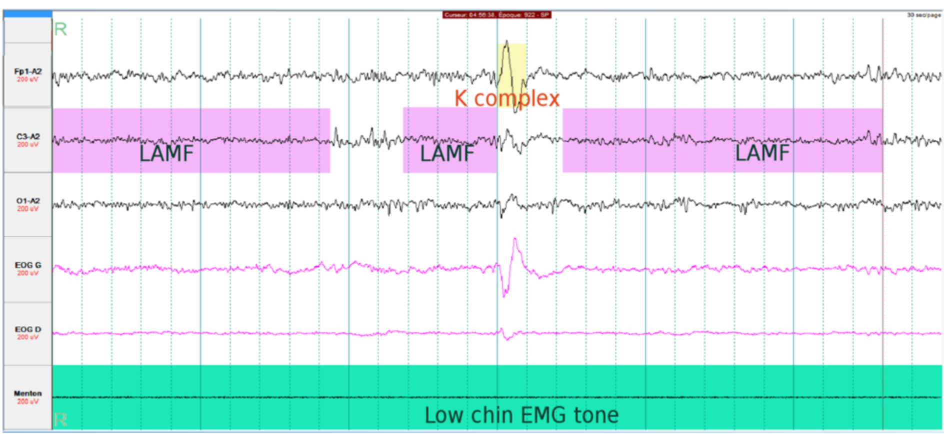

Figure 1. Example of epoch with a doubt on the sleep stage

We will illustrate our method on the example of epoch given in Figure 1. The previous epoch, and the following one, clearly meets criteria of R, with Rapid eye movements and low muscle tone. Nevertheless, the slot *i* is more doubtful since there is no more

[4] Waves of frequency 0.5 Hz-2 Hz and peak-to-peak amplitude >75 µV,

eye movement, but a K complex occurs in the middle, which seems to meet criteria of N2 sleep stage.

Step 1: Observations are extracted. They are represented by colour rectangles on the Figure. *LAMF* is Low-amplitude, mixed-frequency (LAMF) EEG activity. In the rest of the paper *LCT* stands for "Low Chin EMG tone" and *REM* for "Rapid Eye Movements".

Step 2: The current epoch is divided into six 5-seconds slots ($Slot1_i$, …, $Slot6_i$). On the figure they are separated by vertical solid lines.

Step 3: Observations are represented in table 1. $Slot6_{i-1}$ represents le last slot of precedent epoch.

Table 1. Observations extracted automatically from epoch of Figure 1. The observation of an event on a slot is marked by the symbol X.

Observations	$Slot6_{i-1}$	$Slot1_i$	$Slot2_i$	$Slot3_i$	$Slot4_i$	$Slot5_i$	$Slot6_i$
LAMF	X	X	X	X	X	X	X
K complex					X		
Sleep spindle							
REM	X						
LCT	X	X	X	X	X	X	X
Arousal							

Step 4: In epoch of Figure 1, on the basis of observations, we apply following rules. Each of them is formalized from a corresponding one in the AASM Manual, whose reference is given into brackets.

$$\neg O_{i-1}^{N2} \wedge \left(O_i^{Kcomplex} \vee O_i^{sleepspindle}\right) \wedge \neg O_i^{N3} \Rightarrow O_i^{N2} \quad \text{(G2)}$$

$$\left(O_{j\in[i-5;i-1]}^{sleepspindle} \vee O_{j\in[i-5;i-1]}^{Kcomplex}\right) \wedge \neg O_{j\in[i-5;i-1]}^{arousal} \wedge O_i^{LAMF} \wedge \neg O_i^{sleepspindle} \wedge \neg O_i^{Kcomplex} \Rightarrow O_i^{N2} \quad \text{(G4)}$$

$$O_i^{LAMF} \wedge \neg O_i^{Kcomplew} \wedge \neg O_i^{sleepspindle} \wedge O_i^{LCT} \wedge O_i^{REM} \Rightarrow O_i^{R} \quad \text{(I2)}$$

$$O_{i-1}^{R} \wedge \neg O_i^{REM} \wedge O_i^{LAMF} \wedge \neg O_i^{Kcomplex} \wedge \neg O_i^{sleepspindle} \wedge O_i^{LCT} \wedge \neg O_i^{arousal} \Rightarrow O_i^{R} \quad \text{(I5)}$$

For example, G2 rule can be interpreted as follows: if in the precedent slot, N2 is not observed and in the current slot, N3 is not observed, but either a K complex and/or a sleep spindle is observed then we deduce that N2 is observed on current slot.

Table 2. Results of step 4 applied to observations of table 1.

Observations	$Slot6_{i-1}$	$Slot1_i$	$Slot2_i$	$Slot3_i$	$Slot4_i$	$Slot5_i$	$Slot6_i$
Applied Rule	I2	I5	I5	I5	G2	G4	G4
Sleep stage observed	R	R	R	R	N2	N2	N2

Step 5: We can now compute the ratio of R and N2 sleep stage during epoch *i*. R is observed on 3/6 slots, then it is observed in 50% of the epoch. N2 is observed on 3/6 slots, then it is observed in 50% of the epoch. R and N2 sleep stages are both observed in current epoch. There is a conflict.

Step 6: To solve the conflict, we apply rule I4, formalized previously, and conclude that, criteria of N2 and R sleep stages being both observed, R criteria are preferred to N2 criteria to assign the appropriate sleep stage. We can now stage current epoch as R.

4. Discussion and conclusion

We proposed a novel approach to support sleep stages recognition, using formalized rules integrating preferences. The approach differs from existing ones which consider sleep staging as a classification problem [12,13,14], solved by using usual classification algorithms (e.g. decision tree, bayesian network, artificial neural network, …).

Our method requires a proper formalization of rules defined by AASM by differentiating rules that concern sleep events and rules that concern sleep stages. Both should also be then clustered in two groups; some integrate preferences, others don't.

Integrating preferences appears to be efficient in conflict situations, where criteria of several sleep stages are met. In such situations, physicians often hesitate and may appreciate the help of a decision support system implementing our method.

As future work, we would like to formalize all AASM rules and apply this method on real data coming from a whole-night polysomnography.

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