COMBINATION OF AI COMPONENTS FOR BIOSIGNAL PROCESSING – APPLICATION TO SLEEP STAGE RECOGNITION

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Abstract-**We present a novel approach to combining artificial intelligence components for biomedical signal processing. The modular algorithm mimics the step-by-step type procedure of a human expert and includes the two assessment steps most important for sleep stage scoring, pattern recognition in electrophysiological signal channels and rule evaluation for classifying the current sequence of patterns. The application of sleep stage scoring is a complex task in medical informatics. The ARTISANA (artificial intelligence in sleep analysis) algorithm we have developed provides high rates of correspondence with the results produced by human experts. Additional features are the transparent decision-making process and information about the detailed structure of sleep. This has been achieved by utilizing neural networks for pattern recognition and neuro-fuzzy systems for rule evaluation. The AI components chosen to perform these two classification steps were particularly successful due to their individual strengths.**

Keywords - **Neural networks, neuro-fuzzy systems, sleep stage recognition, artificial intelligence, medical informatics**

I. INTRODUCTION

Sleep stage scoring as conceived by Rechtschaffen and Kales (R&K) [1] is complex, ambiguous and difficult to devise and implement an algorithmic solution using classical digital signal processing methods for. Nonetheless, it is the core task necessary for the evaluation of polysomnography [2,3]. In R&K's methodology, a human expert performs two major classification steps as illustrated in Fig. 1: recognition of basic patterns in the 5 signal channels (2 EEG, 2 EOG and EMG) and scoring the current sleep stage based on the sequence of the detected sleep patterns.

The sleep-related patterns which have to be detected in the first step can be distinguished as either periodic (alpha-, theta- and delta- activity) or transient (K-complexes, sleep spindles, vertex sharp waves, rapid / slow eye movements and body movements). A rough idea of the graphical illustration of common wave patterns is presented in [1] but such pattern recognition is primarily based on the expert's experience and knowledge about typical waveforms. The second step consists of an evaluation of the rules defined by R&K. For both assessment steps there is room for personal interpretation leading to an interrater agreement as low as 50-70% in patients with Obstructive Sleep Apnea (OSA) [4].

The ARTISANA algorithm represents the detailed modeling of the described procedure as shown in Fig. 2. Artificial intelligence components were implemented to execute the two classification stages. They were designed to optimize both the quality and transparency of the calculated results. An initial validation of the results emphasized the potential of the system to overcome current shortcomings in automated sleep stage scoring algorithms which have been used less frequently than hoped in upper-grade clinical practice.

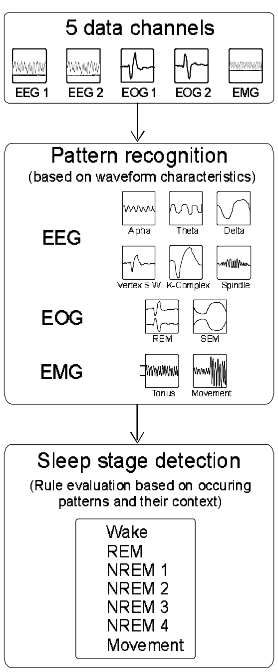

Fig. 1. Visual sleep stage scoring

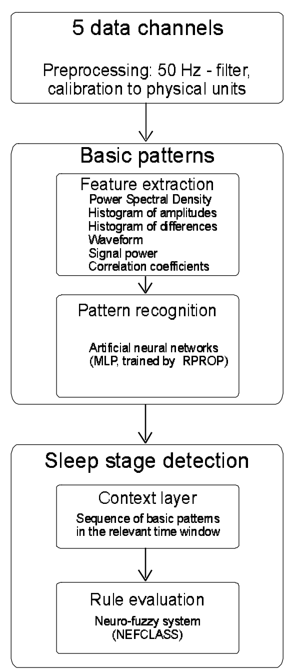

Fig. 2. Processing steps of ARTISANA

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Several applications with similar processing steps for electrophysiological signals exist, e.g. ECG classification which can trigger an alarm in high risk situations.

II. Methodology

A. Pattern Recognition

Examples of EEG, EOG and EMG sleep-related patterns are illustrated in Fig. 1. Alpha, theta and delta activity are periodic signals and can be identified by their amplitude and frequency ranges [1]. The waveforms differ between patients and due to crosstalk, noise or combined mixed-frequency activity. The detection of these periodic EEG signals is based on parameters which are extracted from their course in 1 s intervals.

K complexes, sleep spindles and vertex sharp waves are transient patterns with isolated incidences and can be roughly described by their typical shapes. Thus, their detection in the ARTISANA algorithm is based on a combination of calculated, shape describing parameters and direct waveforms. An approach with solely direct recognition did not provide sufficient results. Regarding eye movements, additional parameters were defined, identifying the antiparallel course of the two EOG channels.

The classification task itself is performed by artificial neural networks of the Multi-Layer-Perceptron (MLP) type [5]. Resilient Propagation (RPROP) was applied as a training procedure. The activation of a specific output neuron provides information about the corresponding membership grade of the currently assessed interval which belongs to the associated pattern class.

Neural networks adapt themselves to typical structures in their input vectors during a supervised learning procedure. The expert's recognition experience is transferred to the automatic system with the accessible prior knowledge (frequency ranges, amplitude ranges and wave patterns) implemented into the input vector and the structure of the network.

B. The Context Layer

The sleep stage of a current interval not only depends on the sequence of patterns within the interval itself, but also on a certain time window. Thus, a context layer provides all pertinent information about preceding and succeeding patterns to the final decision stage, which is necessary to evaluate the rules of R&K. An example of contextual information is the time (in s) since the last rapid eye movement or K complex.

C. Rule Evaluation

The rule evaluation stage consists of a hybrid neuro-fuzzy system which mimics the definitions of R&K in predefined IF-THEN rules. During the supervised learning phase, the fuzzy membership functions in the premise parts of the rules are adapted. The NEFCLASS algorithm [6], consisting of triangular membership functions and a selective rule-based adaptation process, is used.

Finally, a defuzzification stage identifies the sleep stage for each 30 s epochs using maximum search and summation of the seven membership grades of the 1 s intervals for the corresponding sleep stages.

D. Initial Validation

The learning procedure for the adaptive systems in pattern recognition and rule evaluation was based on the training and validation sets of 4 polysomnographic records of healthy subjects each. In order to proof the validity of the concept employed, an evaluation of the adapted system was performed using the data on 8 OSA patients.

The data was recorded and manually assessed at the University Hospital of Marburg, Germany. The sampling frequency was 200 Hz. Channels C3A2 and C4A1 for EEG, E1A1 and E2A2 for EOG were used, as well as the EMG chin lead. For each data set, a sequence of 9 990 s was assessed by the automatic system.

III. Results

An example of an automatically assessed hypnogram in comparison to a manually assessed hypnogram is shown in Fig. 3. In this diagram, the agreement rate was 84.6 % of the 30 s epochs. The average value was 70.7 % for OSA patients and 79.8 % for healthy subjects. Detailed results of the matching of single sleep stages are given in Tab. 1. Quality of pattern recognition was also high. The pattern class that was detected, as well as most active fuzzy classification rules can be visualized for the human expert in the form of intermediate results that duplicate the system's decision. An example can be seen in Fig. 4.

IV. Discussion

The first validating results of the ARTISANA concept underline the potential of self-learning systems for biomedical signal processing. Nonetheless mismatches in manual and automatic sleep stage identification, especially in regards to the Wake- and Non-Wake stages, are typical for OSA patients [4] and can predominantly be explained by frequent arousals. The sleep is fragmented in intervals of Wake and light sleep stages or even REM sleep with a duration of only a few seconds. Thus, the identification of a dominant sleep stage for 30 s is often very complex.

TABLE I
CLASSIFICATION OF MANUALLY ASSESSED 30 S EPOCHS BY THE AUTOMATIC SYSTEM IN OSA PATIENTS

manual	automatic					
	Wake	REM	NREM 1	NREM 2	NREM 3	NREM 4
Wake	829	5	65	49	1	0
REM	9	115	3	18	0	0
NREM 1	104	11	139	186	1	0
NREM 2	37	35	153	649	10	0
NREM 3	8	0	0	47	51	1
NREM 4	0	0	0	7	30	101

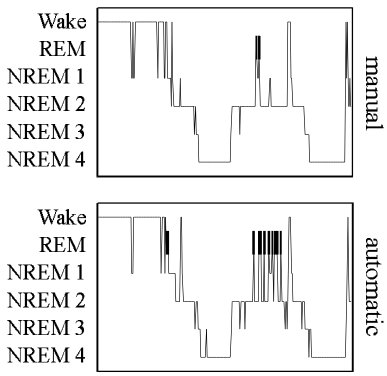

Fig. 3. Manually and automatically assessed sleep classification of an OSA patient

One can not definitely decide which classification is 'correct' or 'incorrect', a fact which is easily attested to when regarding the variations between different human scorers. There is room for variation and error in both manual and automatic results.

The modular structure of the ARTISANA algorithm and the utilization of AI components mimic the procedure a human expert would go through to achieve the same results. Intermediate results can be visualized to illustrate the microstructure of sleep. One of the major advantages of our approach is the ability to preserve this data. It is lost when using a single-step 'blackbox' algorithm. A specific extraction of decisive parameters and the detection of the complete set of sleep-related patterns, as well as the consideration of all the relevant time windows represent the maximum implementation of prior knowledge about the classification process to improve the performance of knowledge-based systems.

Artificial neural networks and neuro-fuzzy systems substantially differ in terms of transparency and calculation complexity. Neuro-fuzzy systems consist of logic rules similar to an expert system; they can be predefined and duplicated by a human expert to guarantee fundamental behavior which is based upon well-accepted medical assessment definitions.

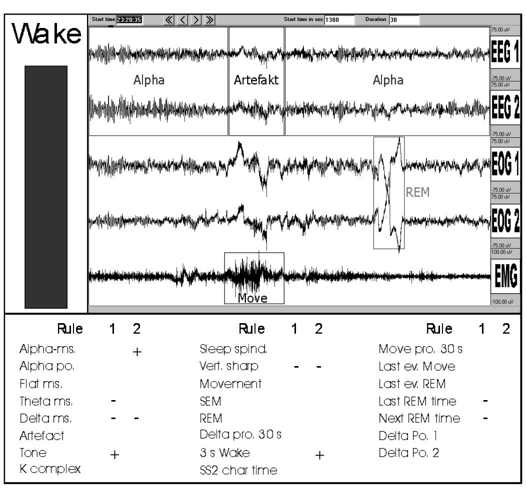

Fig. 4. Example of an automatic evaluation of a 30 s interval. Sleep stage Wake was detected due to the recognized patterns with high certainty. The two most active fuzzy rules are printed at the bottom (+: large, -: small)

In sleep stage recognition, they mimic the manual methodology of R&K. The major advantage of a neuro-fuzzy system compared to an expert system is the self-learning capacity which enables the neuro-fuzzy network to adapt itself to optimized input parameter ranges.

Neural networks comprise a more complex mathematical combination of input parameters using different layers of interacting neurons. With several powerful learning algorithms they can adapt themselves to typical structures in the input space. Implementation of prior knowledge is reduced to selecting input vectors and the topology of the network. The application of neural networks was selected for the recognition of sleep-related patterns because of their lack of detailed identification rules.

The optimization of input vectors is difficult for both types of AI systems, because classical statistics approaches which try to identify independent explanation factors do not reflect connectionist reasoning. This will be a focus of further improvement of the ARTISANA algorithm. We will also try to define improved neuro-fuzzy learning rules, since several existing systems including NEFCLASS showed weaknesses in regards to convergence. A final training and evaluation procedure with a large number of manually classified samples will provide robustness and detailed validation for the optimized system.

V. Conclusion

As a combination of AI components, ARTISANA showed a high potential for performing the complex biosignal processing task of sleep stage recognition. Neural networks and neuro-fuzzy systems were utilized regarding their specific advantages in the area of pattern recognition and rule evaluation. A high rate of agreement with human scorers and the provision of intermediate results, which help to understand the system's scoring decisions, as well as the sleep microstructure should improve the acceptance of automated systems in clinical practice.

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