A KNOWLEDGE-BASED SYSTEM FOR THE AUTOMATED ON-LINE CLASSIFICATION OF EEG/EOG SIGNALS

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Abstract

This work describes a knowledge-based system for the on-line analysis of electroencephalographic (EEG) data in sleep studies. The system architecture is comprised of a front-end dedicated processor that sends, to a host computer, features extracted in real-time from several data channels. In the host, a knowledge-base hierarchical environment was designed around a layered processing model. The paradigm mimics the visual inspection of sleep records performed by human scorers. A new model for handling uncertainty is also presented.

The system was tested with data from a diverse subject population, and these results are included in the paper.

Key Words

Knowledge-based systems, electroencephalogram, waveform detection, sleep scoring.

1. Introduction

Knowledge-based systems have been designed for a variety of applications, including medical diagnostics, planning, legal reasoning, geological exploration, and chemical structure elucidation and synthesis. These systems all apply heuristic, domain-intensive knowledge of recognized experts in the problem domain. They provide a different approach to the solution of problems that require a significant amount of heuristic knowledge by structuring the available knowledge into a knowledge base and including mechanisms to easily increment the knowledge base. They are also designed to provide the user with a flexible environment, and typically feature transparency to the system knowledge and operations [1-2].

The replacement of a human operator by a system for the automated monitoring and interpretation of biological signals is another application of knowledge-based systems [3-4]. Biological signal monitoring is characterized by the need to monitor multiple data channels and to classify the subject state based on features appearing in time-varying data. These features are often poorly defined: they usually reappear intermittently, and the operator assigns a confidence level to the recognition of individual occurrences. A knowledge-based system for on-line signal monitoring and classification can be expected to differ markedly from one used in applications

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and effectively handle the problem of diverse knowledge present in the problem domain. The layered model, in which each layer is associated with a different processing time-frame, distributes the overall processing efforts; creates an appropriate communication scheme; and improves the system's processing efficiency [11]. A new certainty handling model to capture the human scorer's visual inspection properties is also proposed.

2. An Expert System Model For Classification

The process of classifying sleep stages includes extracting primitive features from the record and describing each epoch in terms of these primitives. The computerized primitive feature extraction process requires intensive signal processing to extract the same information as the human interpreter. This feature discrimination, termed "pattern matching," is a difficult task for computer analysis because the patterns do not exist in a fixed and definable form. Pattern templates must be incrementally incorporated into the system by extracting from the human scorer his heuristic knowledge and then experimentally evaluating the pattern criteria. The scoring process is also more involved than a straightforward epoch description and matching according to waveform occurrence information. The human scorer's classification is a cognitive process based on the gestalt perception of the waveform activities integrated with a heuristic interpretation of the record. It is only vaguely related to precise and analytic measurements of the data.

Some sleep EEG epochs are scored using information contained completely in the epoch, but some epochs must be staged based on context (i.e., information from other epochs) to eliminate ambiguities or to compensate for a lack of information in the epoch. The epoch's sleep stage and associated sleep stage certainty factor are both used to represent the contextual information at the epoch level.

Sleep staging, then, includes waveform recognition using signal processing of data sampled every few milliseconds, classification of the sleep stage based on waveforms occurring within the sixty second epoch, and a refined classification based on contextual information contained in adjacent epochs. Each of the three procedures involved in the classification uses a markedly different time frame and knowledge base.

This paper formulates a three-layer model to process and codify the contextual information present in the signal. Each layer is associated with a different processing time frame (see Figure 1). It uses a layered model with a hierarchical structure that reflects human knowledge about the signals at different time scales (the waveform, the minute, and the context).

The parametric features extracted in the lowest layer are divided into two groups. One group contains the related waveform occurrence information extracted from the EEG signal by the front-end system. This data translates information contained in the signal at the millisecond level. The layer's other group includes those parameters that are not directly related to the signal information, but that are related to the apriori knowledge (if any) about the subject and that subject's signal characteristics. The values for this group are obtained from the user before the processing begins. During data analysis, the system can run without further user intervention.

The intermediate layer processing categorizes each 60 second epoch into one of the six stages based on the features obtained from the bottom layering processing. The classification rules in the intermediate level specify the sleep stages according to signal characteristics, especially the waveforms which appear during the epoch. In this layer, the classification rules are also associated with certainty factors. The assigned certainty level represents the degree of confidence in each classification step and it is presented to the user in Low, Medium, and High degrees.

The top level processing re-evaluates the sleep stages using information from the two lower levels together with contextual information obtained from a five epoch window centered on the current epoch. The length of five epochs for extracting contextual information is a compromise designed to achieve real-time analysis dictated by the complexity of the resulting computer processing. The human scorer's knowledge of local contextual interpretation is also codified into rules. This contextual interpretation is based on a matching of the information in the windows (sleep scoring and certainty factors) with the predefined templates of sleep scoring. The processing for each epoch is done iteratively and exhaustively.

Data uncertainty and incompleteness of knowledge are also inherent problems in the classification of biological data [12–13]. Statistical decision theory, as reflected in the use of Bayesian Theorem, cannot provide the appropriate means to handle such uncertainty. This is also true in many other knowledge-based decision-making domains. The application of a pure statistical approach requires either a large amount of valid background (statistical) data or numerous approximations and assumptions, which often cannot be satisfied or validated.

Designers of knowledge-based systems have therefore been exploiting various ways in which uncertainty can be managed without rigorous statistical analysis. The Certainty Factor (CF) model of MYCIN, which aims at
quantitative description and management of uncertainty with predefined combining functions and formulas [14], is a typical example of such approaches. However, such a method cannot explicitly handle the qualitative nature of uncertainty. The quantitative paradigm itself often leads to confusion in handling the logical inference of the domain knowledge. Furthermore, the constraints imposed under the numeric frame cannot be validated in the classification domain. The necessity of non-numerical approaches has been stressed by several researchers [15–16].

The uncertainty handling model of this paper is designed to reflect as accurately as possible the qualitative nature of uncertainty in the classification domain. It is based on the non-probabilistic idea of “weight balancing,” which mimics the human scoring knowledge in the classification domain. Each if-then production rule shows a matching template with the rule conjunction (if part) and abstracted patterns with the rule conclusion (then part). When a rule is stated, the rule conclusion elements are associated with certainty levels and the rule conjunction elements are all assumed to have a medium level of certainty, which is referred to as a balanced state. Net variation is then measured by the algebraic sum of the deviation of the actual certainty levels of conjunction elements from their balanced state (i.e. from the medium level). According to the net variation, the certainty level of rule conclusion elements will be either increased or decreased. Different weights can be associated with the conjunction elements so that the more influential conjunction element can have a greater effect in calculating the net variation (however, this elaboration is not implemented in the present system). If more than one rule is satisfied to derive a same conclusion, the highest certainty level is picked among the rules to associate with the conclusion.

This model differs significantly from other certainty factor models, such as the one typically shown in MYCIN. The idea of “evidence collection” is the basis of the MYCIN CF model. If more than one rule derives (supports) the same conclusion, the combining function incrementally increases the certainty level of the conclusion. The underlying assumptions are that (1) the appearance of more evidences increases the belief level in a hypothesis and that (2) the evidences are independent of each other.

However, in general, none of the assumptions are valid in the domain of visual classification problems. Evidences are more likely to be dependent on each other, and the satisfaction of more than one rule does not necessarily increase the belief level about the hypothesis. The proposed model, on the contrary, does not impose any constraint with such assumptions, and allows for flexibility in constructing a knowledge base.

The next section describes the prototype model implemented in the system.

3. System Descriptions

The system consists of a front-end processor interfaced to a host computer. The front-end processor digitizes four channels of data, detects the waveforms of interest, and transfers the detection information to the host computer with a data rate of 8 bytes/second. The host computer assigns confidence levels to the data and does the classification for sleep staging. It also provides the user interface. The front-end processor is implemented with a TI-9900 16 bit microprocessor system. The classification system is implemented with Common Lisp and an IBM AT type personal computer.

3.1 Front-end Waveforms Detection System

The front-end processor of the system performs measurement and detection of various waveforms in the EEG/EOG data. Recognized waveform information is encoded in a character string (tokens) and is then linked to a host computer for sleep stage scoring.

The system is designed to process all the waveforms on a real-time basis by incorporating several functional blocks, such as a 12 bit A/D conversion unit, a signal conditioning unit, a detection unit, a multi-channel information processing unit, and a data-link unit.

The functional block diagram of the system is shown in Figure 2. Data from three EEG channels and one EOG channel (or two EEG, one EOG, and one EMG, depending on the montage selection) are sampled at 480 Hz per channel and passed through a digital low-pass filter with 120 Hz cutoff frequency (-3dB). It has been shown that a 12 bit A/D converter with 16 bit arithmetic processing is a suitable selection to obtain at least a 40 dB S/N ratio [17]. The signal components under 120 Hz contain enough information for the waveform detection and analysis, including the detection of the muscle artifact and the level discrimination of the EMG.

Figure 2. Functional block diagram of the front-end system.
There are two processing layers in the front-end system. The first layer includes individual waveforms detection through the filter/detector unit. The data obtained at the first layer are used for the second layer processing. The second layer processing is performed at a much wider sampling interval of 0.25 second in order to detect certain waveforms, such as the REM, SEM, and K-complexes, which require the information of the other channels and/or the observation of relatively long periods of adjacent EEG/EOG background patterns. Also, the information of all the detected waveforms and the delta wave measurements are encoded in a character string and sent to a host computer for further analysis.

Since the single processor (TI-9900) system must be capable of processing multi-tasks for real-time detection of the various waveforms, an appropriate time-multiplexing scheme is designed for the parallel processing architecture of the waveform detection system.

Relatively broad-band linear phase FIR filters are used for the signal conditioning filters in the system, because narrow-band filters may distort the waveforms of interest. The broad-band characteristics and the marginal requirement in pass-band amplitude response and cut-off characteristics of the filter make it feasible to come up with a simplified filter implementation which does not require any multiplications or floating point arithmetic calculations [17].

The format of token data is shown in Figure 3. The data for all detected waveforms and delta measurements are encoded into a character string using a signature and bit mapping scheme. Token-encoding routine reads the flag of each waveform detector at every 0.25 second interval and uses two bytes for the encoding of all flag information. If a delta wave is detected, then an additional two bytes are assigned for the amplitude and period information of the delta wave respectively.

```
- - - - T α β τ θ
```

Token Information

```
- - D - f REM SEM K
```

Delta Information

```
- - DF -
```

```
- - D -
```

Amplitude

```
- -
```

Period

Figure 3. Format of token data.

Waveform Detection Methodologies

The heuristic signal processing approach employed in this research emphasizes the correct recognition of all the waveforms of interest to the clinicians. The waveforms which are used by the human scorer’s visual analysis include alpha, beta, delta, sigma, theta, muscle artifact, REM (rapid eye movement), SEM (slow eye movement), and K-complexes. The recognition is performed by using various grapho-elements and background patterns of the multichannel EEGs and EOG, similar to the ones the human scorer uses for the visual perception of the waveforms. The waveforms are extensively defined in terms of these grapho-elements and background patterns for computer analysis. The waveform definition criteria include the individual full-cycle wave period window between zero-crossings and peaks, amplitude thresholds, pattern specifications, waveform average period window, half-wave period, wave leading edge slope, background pattern screening, and time-coherence of wave shapes in the multiple channel data. Table 1 shows the summarized list of waveform definitions.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Pattern</th>
<th>Frequency Window [Hz]</th>
<th>Amplitude Threshold [µV]</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha</td>
<td>8/6/3</td>
<td>7.5 - 12.0</td>
<td>7.0</td>
<td>-</td>
</tr>
<tr>
<td>Beta</td>
<td>6/6/4</td>
<td>16.0 - 22.0</td>
<td>3.0</td>
<td>-</td>
</tr>
<tr>
<td>Delta</td>
<td>6/6/3</td>
<td>2.0 - 7.5</td>
<td>15.0</td>
<td>-</td>
</tr>
<tr>
<td>Sigma</td>
<td>6/6/4</td>
<td>12.0 - 16.0</td>
<td>5.0</td>
<td>-</td>
</tr>
<tr>
<td>REM</td>
<td>-</td>
<td>0.5 - 5.5</td>
<td>30.0</td>
<td>Leading slope background pattern screening</td>
</tr>
<tr>
<td>K-Complexes</td>
<td>-</td>
<td>0.5 - 2.0</td>
<td>70.0</td>
<td>Time synchrony background pattern screening</td>
</tr>
<tr>
<td>Delta</td>
<td>Half-Wave</td>
<td>0.5 - 2.0</td>
<td>16.7</td>
<td>-</td>
</tr>
<tr>
<td>SEM</td>
<td>-</td>
<td>0.2 - 0.5</td>
<td>15.0</td>
<td>Leading slope background pattern screening</td>
</tr>
<tr>
<td>Muscle Artifact</td>
<td>6/6/3</td>
<td>above 32.0</td>
<td>5.0</td>
<td>-</td>
</tr>
<tr>
<td>EMG</td>
<td>6/6/3</td>
<td>above 32.0</td>
<td>-</td>
<td>Level discrimination</td>
</tr>
</tbody>
</table>

Table 1. Summarized list of waveform definitions.

Spindles Detection

The appearance of spindle bursts, such as the alpha spindle, beta spindle, theta spindle, and sigma spindle, is a well-observed phenomenon in human sleep EEGs. These waveforms are conveniently grouped as spindles, and their detection schemes are basically similar, although the detailed nature of the waveforms is slightly different for each.

A spindle is a short, sequential burst of waves that forms a waveform, giving a distinct appearance from the background. The spindles are roughly defined by the measure of the periodicity of the individual waves and by the specification of the grouping (bursting) nature of the waveform. These can be further broken down into the following criteria:

(i) Individual wave period window: zero-crossings, peaks
(ii) Individual wave amplitude threshold
(iii) Average period window for the whole sequence of waves in a spindle
(iv) Pattern specification for the waveform

A typical functional block diagram of the spindle detector is shown in Figure 4.
Table 3. Summarized specifications of spindle waveforms.

<table>
<thead>
<tr>
<th>Spindles</th>
<th>Wave period window (Hz)</th>
<th>Average period window (Hz)</th>
<th>Amplitude threshold (V)</th>
<th>Pattern criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha</td>
<td>7.0 - 13.3</td>
<td>7.5 - 12.0</td>
<td>8.0 - 12.0</td>
<td>7.0, 6/6/3</td>
</tr>
<tr>
<td>Beta</td>
<td>15.0 - 34.0</td>
<td>15.0 - 30.0</td>
<td>16.0 - 30.0</td>
<td>2.0, 6/6/3</td>
</tr>
<tr>
<td>Sigma</td>
<td>11.0 - 17.1</td>
<td>11.0 - 17.1</td>
<td>11.43 - 16.9</td>
<td>3.0, 6/6/3</td>
</tr>
<tr>
<td>Theta</td>
<td>2.5 - 7.0</td>
<td>-</td>
<td>2.5 - 5.0</td>
<td>10.0, 6/4/3</td>
</tr>
</tbody>
</table>

Rapid Eye Movement Detection

The main idea behind the REM wave detection is to get a robust REM wave detection by using both the descriptive REM wave criteria and the EEG channels' background screening with the appropriately chosen time windows. The descriptive REM wave criteria include a slope threshold (350 μV/sec) on the leading edge of the wave, a period window (0.2 - 2.0 sec/half-wave), and a peak amplitude threshold (30 μV). The leading edge slope is defined by the line connecting the leading zero-crossing point and the wave peak point of the signal. Two quiescent testing time windows are applied (one each) to the central (C3-A2) and to the frontal (F1-F7) channel EEGs. The central channel time window is applied to the preceding and succeeding two seconds from the terminating edge zero-crossing point of the REM wave. The frontal channel time window is applied to the preceding and succeeding one second from the terminating edge zero-crossing point of the REM wave. The REM wave definition is therefore the following:

(i) Period: 0.2 - 2.0 sec/half-wave
(ii) Amplitude: 30 μV
(iii) Slope: 350 μV/sec
(iv) Quiescent Test
   Frontal channel: +1 sec window, peak amplitude ratio > 0.5 (between the biggest waves in the window)
   Central channel: +2 sec window, no delta wave

A two-layered screening scheme implements the real-time REM detection algorithm. Each REM wave is detected at the bottom layer through the filter/detector unit with the descriptive waveform criteria, and the EEG channels' background screening is performed at the upper layer with the 0.25 second sampling interval. The functional block diagram of the REM detection is shown in Figure 6.

Slow Eye Movement Detection

The slow eye movements (SEM) cause the EOG channel's slow, rolling fluctuations from the baseline. The SEM is physiologically related to the floating of the eyes, especially during the transition period between being awake and being asleep caused by drowsiness. The SEM detection scheme includes a half-wave period window, an amplitude threshold, the central EEG channel's background screening, and a wave leading slope threshold. The algorithm structure for the SEM detection is basically similar to that of REM detector, except for the absence of the peak comparison criteria with the other EEG channels.

K-complexes Detection

The main usage of the K-complexes detector in the present system is twofold: to gain better confidence in scoring sleep stage two by complementing the spindle detector information, and to accurately demarcate sleep stages two and three. The K-complexes detector uses an algorithm structure similar to that of the REM wave detector, since the detection of the K-complexes also requires cross-channel information such as the synchronization of peaks, the opposite phasic relationship between EEGs and EOG, and a quiescent criterion.

Presently, the synchronization of EEGs and EOG is detected with a time window, i.e., 0.75 second, across the EEG and EOG channels (specifically F1-F7, C3-A2, and EOG). The amplitude threshold (50 μV) and the relatively loose period threshold (0.3 - 1.5 sec/half-wave) are used as the K-complexes criteria. The current definition of K-complexes in the algorithm requires no delta-like slow and large-amplitude wave within the interval of preceding and succeeding two seconds from the K-complexes, since the present K-complexes detection algorithm is less reliable in sleep stages three and four. Therefore, the K-complexes information in these sleep stages is not utilized in the sleep scoring process.

The more descriptive K-complexes detection criteria, such as the opposite phasic relationship between the cross EEG channels and the EOG channel, upward going characteristic, and slope criterion, should be utilized for a better K-complexes detection.

Delta Wave Detection and Measurement

The delta detector is implemented with a period window (0.25 - 1.0 sec/half-wave) and a relatively low amplitude
A spindle detector consists of a linear phase FIR filter followed by a full-cycle period discriminator, an amplitude detector, a positive-peak interval discriminator, and a pattern recognizer.

Appropriate signal pre-conditioning is necessary to remove the effects of high frequency noise and of large-amplitude, slow waves. In particular, if a spindle is superimposed on a large-amplitude, slow wave, it is impossible to detect the spindle at the next detector unit by the zero-crossing and peak detection scheme. A relatively broad-band linear phase filter is used for this signal pre-conditioning purpose. Figure 5 provides an example of the effect of the conditioning filter designed for the detection of the sigma spindle waveform. The filters for each spindle are summarized together with the filters for the other waveforms in Table 2.

![Functional block diagram of the spindle detectors.](image)

![Figure 5. Effects of signal conditioning filter.](image)

Table 2. Signal conditioning filters.

<table>
<thead>
<tr>
<th>WAVES</th>
<th>SAMPLING FREQUENCY (Hz)</th>
<th>PASS BAND</th>
<th>FILTER TRANSFER FUNCTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALPHA</td>
<td>240</td>
<td>0 - 18</td>
<td>H(z) = (z^-2 + 1)(z^-2 + z^-1 + 1)(z^-1 + 1)</td>
</tr>
<tr>
<td></td>
<td>120</td>
<td>0 - 16</td>
<td>H(z) = (z^-2 + 0.5z^-1 + 1)(z^-1 + 1)</td>
</tr>
<tr>
<td>BETA</td>
<td>240</td>
<td>9 - 40</td>
<td>H(z) = (z^-4 - 1)(z^-2 + 1.5z^-1 + 1)(z^-1 + 1)</td>
</tr>
<tr>
<td>DELTA</td>
<td>80</td>
<td>no filter</td>
<td>H(z) = (z^-1 + 1)</td>
</tr>
<tr>
<td>SIGMA</td>
<td>240</td>
<td>12 - 40</td>
<td>H(z) = (z^-2 + 1)(z^-2 + 0.5z^-1 + 1)(z^-1 + 1)(z^-1 + 1)</td>
</tr>
<tr>
<td>THETA</td>
<td>120</td>
<td>0 - 9</td>
<td>H(z) = (z^-2 + 1)(z^-2 + z^-1)(z^-1 + 1)</td>
</tr>
<tr>
<td>MUSCLE</td>
<td>240</td>
<td>60 - 120</td>
<td>H(z) = (z^-1 + 1)</td>
</tr>
<tr>
<td>ENG</td>
<td>240</td>
<td>60 - 120</td>
<td>H(z) = (z^-1 + 1)</td>
</tr>
<tr>
<td>SLOWS</td>
<td>120</td>
<td>0 - 9</td>
<td>H(z) = (z^-2 + 1)(z^-2 + z^-1 + 1)(z^-1 + 1)</td>
</tr>
<tr>
<td>REM</td>
<td>120</td>
<td>no filter</td>
<td>H(z) = (z^-1 + 1)</td>
</tr>
<tr>
<td>SCN</td>
<td>120</td>
<td>no filter</td>
<td>H(z) = (z^-1 + 1)</td>
</tr>
</tbody>
</table>

The signal passed through the conditioning filter is processed at the next detection unit with various criteria. The frequency of an individual wave is first defined as the inverse of the full-cycle period, which is measured by counting the interval between two adjacent positive-peaks and/or two positive-going zero-crossing points (see Figure 5). A certain amplitude threshold is applied to detect the valid peaks of the wave.

The positive-peak interval criterion is used with the zero-crossing period specification for a reliable spindle detection, since the positive-peak interval alone cannot impose any restriction on the wave's vertical variation in terms of the vertical asymmetry from the baseline. Also, the two-period-window scheme gives more flexibility in specifying the spindle wave periodicity. The scheme allows for a looser specification for each period window, allowing more variations in terms of each period specification. But, on the other hand, the scheme reflects a tighter specification in terms of the global spindle shape specification by using the two period windows.

The human scorer is not very sensitive to the individual wave period and amplitude variances in detecting the spindles. On the contrary, he relies more on the well-shaped global appearance of the whole waveform. The pattern criterion and the average period window are used to specify the global spindle waveform grouping (bursting) nature. The average period window is applied to the total period of several adjacent waves sequence in the waveform. The average period window increases the measurement accuracy by a factor equal to the number of waves averaged, as shown by the following:

\[ df = f_o / (N \cdot f_s) \]

- \( df \): the error in frequency
- \( f_o \): the period of the two points
- \( f_s \): the sampling frequency
- \( N \): the number of waves averaged

A tighter average period window is applied for the specification of the spindle waveform; on the other hand, however, the period windows for individual waves can be loosened to reflect individual wave variances in the spindle. The three numbers in the pattern criteria specify the total number of waves kept in a window; the minimum required number of consecutive in-band waves in the waveform at onset; and the minimum number of the in-band waves to sustain the detection. The summarized specifications for the spindle waveforms are shown in Table 3. The same detection scheme is applied for all the spindle detectors with appropriate changes in the parameter values according to the criteria of each spindle waveform.
threshold of 16.7 μY. The amplitude and period values of each delta wave are sent to the host computer through a serial port for post delta processing. The post delta processing is necessary for an accurate delta summary because the variations of the EEG amplitude level provide poor delta wave detections if the same amplitude threshold is used for all subjects. Individual delta wave amplitudes and periods are also necessary for more quantitative delta studies.

The delta amplitude is quantized into 16 levels from 16.7 μY to 100 μY with the 5.2 μY resolution and the period is also quantized into 16 levels from 0.25 to 1.0 second with the 47 msec resolution.

**Muscle Artifact and EMG Analysis**

Muscle artifact is associated with the movement of the body. The signal consists of high frequency components, usually above 30 Hz. The detector consists of a highpass filter, a zero-crossing detector, an amplitude threshold (10 μY), a full-cycle period discriminator (34.3 - 120 Hz), an average period window, a 60 Hz notch filter, and a pattern specification (6/6/3). The muscle artifact detector has the same structure as that of the spindle detector, except for the addition of a 60 Hz notch filter. The 60 Hz notch filter is operated in conjunction with the average period window. The purpose of this filter is to reduce the effect of the 60 Hz environmental noise when detecting muscle artifact.

The EMG signal amplitude is described using three levels, i.e., below 10 μY, between 10 μY and 20 μY, and above 20 μY. The EMG discriminator structure is the same as the muscle artifact detector but three different amplitude thresholds are applied for the EMG level discrimination.

**3.2 Knowledge-based Classification System**

The host classification system performs the sleep scoring using the entire night's data, which is received from the front-end processor. A functional block diagram of the knowledge-based classification system is shown in Figure 7.

The database consists of static and dynamic databases. The static database contains the token data and the dynamic database contains three data planes, which are updated during the system's sleep staging of the record.

The knowledge base consists of three different layers of knowledge, each associated with one data plane in the dynamic database. The knowledge base contains parametric feature extraction knowledge at the bottom level, template matching and classification knowledge at the intermediate level, and contextual interpretation knowledge at the top level. A different rule-interpreter is used in each layer. A scheduler globally arranges the rule interpreters and controls the sequencing of the signal processing in all three layers. The system development included the design of an expert system shell with a knowledge-base editor and menu-driven, user-friendly interface for the knowledge base editor.

**Layered Structure of Knowledge Base and Database**

Table 4 outlines the layered structure of the knowledge base and database. The structure of the database corresponds to the layered organization of the knowledge base. The dynamic database contains all the input data and intermediate solution states produced by the corresponding layer knowledge.

The parametric level knowledge includes procedures to extract parametric data from the input data, features, and the input token data sent by the front-end system. They provide the initial data for the second layer processing. The parameters implemented in the present system are depicted in Table 5. These data are composed of the token data summarized each epoch and tagged with a certainty level (High, Medium and Low) which reflects the reliability of the waveform detectors implemented in the front-end system. The detector reliability factors are stored in the system knowledge base and can be modified through the knowledge-base editor.

Table 4. Layered structure of knowledge base and database.

Any number of query parameters can be defined in the knowledge base. The query parameters, such
Table 5. Parametric and user query data.

As Subject-alpha, Under-medication, etc., reflect apriori knowledge of subject dependent characteristics. The operator can elect to include this information in the system's scoring rules, and they can be assigned a default value. Before the system starts an epoch-by-epoch classification of the entire night's data, it displays the default value for every query parameter and asks the user if the value needs to be modified.

The intermediate level knowledge contains the rules that will derive the "wave activity descriptors" of an epoch and which represent (symbolically) the epoch's waveform activities. There are two types of wave activity descriptors. One is derived directly through the fuzzification of the waveform summary data obtained from the first layer. The fuzzification operation applies a set of numerical thresholds to the waveform activity data and creates a symbolic description of the waveform activities (e.g. alpha-activity high with a high certainty). This operation simulates the information and data abstraction process of the human scorer. The sleep scoring manuals are a major source of information for establishing the fuzzification criteria, but they do not contain the numeric thresholds utilized. All threshold values were derived empirically and are presented in Table 6.

Table 6. Fuzzification of parameters.

The second type of wave activity descriptor is based on a combination of activities that are used to define meaningful subject status (e.g. the awake descriptor is related to subject's awake status and is derived from the information on the alpha, beta and artifact wave activity descriptors).

Finally, in this layer, the epoch is tentatively classified as one of the six stages by a set of production rules involving the wave activity descriptors and the knowledge of sleep condensation primarily in the sleep scoring manuals. A rule consists of a rule identification code, a premise, an action, an author, a date, and a justification. Rules are stored internally in Lisp. Presently, the system includes 112 domain rules.

The top level knowledge source includes context manipulation rules for the re-examination of an epoch's stage classification and search sequence scheduling rules. The contextual interpretation matches the data in the sliding window with a set of templates in the form of if-then production rules. Figure 8 contains an example of a sliding window together with a contextual smoothing rule. The contextual interpretation rules continuously update the scoring of the minutes present in the sliding window, often more than once for each epoch. The matching is done sequentially, with the set of templates from the first epoch to the last one. When the sliding window data matches a template, the window is updated by the corresponding rule and the matching starts again from the first template. The process ends when there are no more rules that match the window's data. The sliding window advances one epoch and then receives information about the next epoch from the second layer.

Figure 8. Sliding window example.

The attribution of a sleep stage to an epoch provides for a heuristic search of the intermediate level knowledge during the top level processing. For example, if the previous record segments show several consecutive epochs of stage two, the most likely stage or the next epoch is also stage two and the search for other goals (i.e. other sleep stages) are arranged in the order of their likelihood of occurring immediately after several consecutive epochs of stage two, e.g., stage three, one, five, zero, and four.
When a scheduling rule matches the window, the new search path information is stored in the contextual data plane. This rescheduling makes the search more efficient, reducing the processing time without any significant implementation overhead.

**Control Mechanism**

The bottom level knowledge source is implemented in the form of fixed signal processing criteria within the front-end system plus procedures in the host computer.

The inferencing method for the intermediate level template matching is a goal-driven backward chaining scheme. The limited number of goal hypotheses, i.e., sleep stages, makes the application of a goal-driven backward chaining scheme very efficient.

The rule interpreter scheme for the highest level knowledge is in the form of a data-driven (forward chaining) template matching scheme, since the large number of patterns in a window makes the application of a goal-driven backward chaining scheme difficult [16].

The scheduler performs the global control for the execution of the diverse layers of knowledge. It also works as a data dispatcher for the dynamic database. Figure 9 illustrates the scheduler. The scheduler triggers the rule interpreters in a strict bottom-up fashion providing a hierarchy for the reasoning procedure. At the beginning of each epoch’s processing, the scheduler triggers a procedure to the waveform occurrence information stored in the dynamic database. The window is also updated by sliding one epoch. Next, the scheduler triggers the rule interpreter of the immediate level template matching knowledge. The rule interpreter performs reasoning in a backward chaining scheme to derive a conclusion based on the rules and information in the dynamic database. All the derived conclusions and intermediate results are stored in the dynamic database. The derived final conclusion is stored in the sliding window for the next epoch’s processing. The scheduler triggers the contextual smoothing rules and search sequence scheduling rules. Finally, the scheduler triggers a procedure to attach the conclusion of the final report.

The data processing nature of the problem requires special consideration of the explanation mechanism design. The explanation mechanism can be accessed any time: during system execution and also after the system has finished processing. The system stores all the rule identification codes of the executed rules in each epoch in the order of the fired sequence. When an explanation is requested for a certain epoch, the system displays all the parameters associated with the fired rules in the epoch. The user, then, can trace the line of reasoning by selecting the parameters from the menu screen. The system displays an explanation of how it has derived the parameter by displaying translated phrases with a list of the rule. Figure 10 shows an example of this type of explanation.

### Reasoning with Uncertainty

The prototype uncertainty handling model implemented in this research employs a symbolic presentation of certainty, i.e., High (H), Medium (M), and Low (L). A rule associates one of the three certainty levels to each conclusion under the assumption that every condition element in the rule premise is true with a medium level of certainty. When a rule fires, the net variation of certainty level in the rule premise causes the certainty level of every conclusion element to be either increased or decreased by one level. The certainty level is modified only when the combined level of certainties in the rule premise deviates beyond an assigned level from the balanced weight.

The symbolic representation of certainty, combined with the weight balancing, is designed to simulate the human expert’s confidence in a particular decision. The EEG data includes wide variations and many ambiguities, and the classification process is heavily dependent on an understanding of the contextual flow of the signal. The coarse description of certainty provides the information necessary for classification process. Moreover, the certainty level information does not participate directly in the rule execution mechanism. It is manipu-
lated separately and provides augmented information for each epoch, which is then used in the top level's context layer processing. This approach effectively incorporates the certainty handling model into the layered processing model.

Each variable of the certainty level has a corresponding weight value associated with it (see Figure 11).

<table>
<thead>
<tr>
<th>CERTAINTY VARIABLE</th>
<th>WEIGHT VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>HIGH</td>
<td>+1</td>
</tr>
<tr>
<td>MEDIUM</td>
<td>0</td>
</tr>
<tr>
<td>LOW</td>
<td>-1</td>
</tr>
</tbody>
</table>

Figure 11. Certainty variables definition and combining scheme.

Upon rule execution, the certainty level of the rule conclusion elements is modified according to the combined certainty level of all the premise elements. The combined weight (CWT) value of a rule premise is defined as follows:

\[
CWT = \frac{\sum W_i}{N}
\]

where
CWT: the normalized combined weight
\(W_i\): the weight value of the i-th condition in the rule premise
N: total number of conditions in the rule premise

The combining scheme is also illustrated in Figure 11.

If more than one rule is executed, the rule which gives the highest certainty level is selected. This scheme is reasonable because of the implied mutual exclusiveness of the templates. The following example illustrates the operation of the certainty factor scheme.

IF:
1) The sigma spindle activity is high, and
2) The delta wave activity is low, and
3) The wave wave activity is low
THEN:
The sleep stage of the epoch is STAGE 2 with HIGH level of certainty.

The above rule implies that the sleep stage of an epoch would be scored as STAGE 2 with a high level of certainty provided that all of the conditions of the IF part of the rule are satisfied with a medium level of certainty. The certainty level for a given epoch will be modified according to the actual certainty level of each condition in the rule premise. For instance, if the epoch contains one sigma spindle, five seconds of alpha, and one second of delta, then the associated certainty levels for each condition in the rule premise are defined as LOW, MEDIUM, and HIGH, respectively. So the weight combining scheme gives

\[
CWT = \frac{(W_1 + W_2 + W_3)}{3} = \frac{(-1 + 1)}{3} = -1/3
\]

Thus, the certainty level of the rule action part is modified by decreasing the level by one, i.e., from High to Medium.

4. Results and Discussion

The complete system was developed and tested with data from a wide range of subjects by incrementally incorporating relevant rules into the system's knowledge base. Most of the classification rules are based on the published sleep staging criteria. The system has the flexibility to allow modification and incorporation of more rules in the system through the knowledge-base editor. There exists room for further performance improvement by elaborating on the system's knowledge base with a variety of additional contextual information.

The system was tested with a set of 16 records from subjects ranging in age from 5 to 70 years. Validation is an involved process, so the processing of much more data is advisable, but by using this subject population, general trends in the system performance can be shown.

EEG/EOG data for an entire night were recorded on a 1-inch Sangamo FM tape recorder Model 3500 at 15/16 inch/sec. The data were replayed at the same speed for processing. Three EEG channels, i.e., F1-F7, C3-A2, and O3-OzPz, and one LE-A2 EOG channel were used in the analysis. System performance is measured in terms of a man-machine agreement for the record scoring. In most EEG laboratories, a 90% agreement rate with standard calibration records is required for the qualification of an individual as a scorer, although the published figures for the inter-laboratory agreement are much lower [19].

This study compared the system scoring with human scoring done at the Sleep Research Laboratory of the Baylor College of Medicine, Houston, Texas. Table 7 shows the overall man-machine average agreement for the records. The matrix columns represent the machine score and the matrix rows display the human score. The perfect man-machine agreement is a diagonal matrix. The average agreement considering 5 sleep and awake stages in the 16 records is 83.6% and 87.3% if stages 3 and 4 are combined into one stage in the scoring. So, if the sleep 3 and 4 scoring are combined into a single state, the system performance is very close to that of human experts. The man/machine agreement is greater than that reported for inter-laboratory human scoring agreement.

This table also indicates that the computer performance is robust in scoring sleep stage 2 and 5, which
Machine Score (false negative)

<table>
<thead>
<tr>
<th>Stage</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>436</td>
<td>36</td>
<td>4</td>
<td>0</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>1</td>
<td>52</td>
<td>117</td>
<td>67</td>
<td>0</td>
<td>0</td>
<td>52</td>
</tr>
<tr>
<td>2</td>
<td>44</td>
<td>37</td>
<td>3425</td>
<td>130</td>
<td>3</td>
<td>169</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>1</td>
<td>85</td>
<td>212</td>
<td>21</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>1</td>
<td>19</td>
<td>260</td>
<td>484</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>79</td>
<td>45</td>
<td>113</td>
<td>7</td>
<td>0</td>
<td>1441</td>
</tr>
<tr>
<td>total</td>
<td>611</td>
<td>237</td>
<td>3713</td>
<td>609</td>
<td>509</td>
<td>1878</td>
</tr>
<tr>
<td>agr(%)</td>
<td>71.4</td>
<td>49.4</td>
<td>92.2</td>
<td>34.6</td>
<td>95.1</td>
<td>87.4</td>
</tr>
<tr>
<td>total</td>
<td>7557</td>
<td>83.6</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* 4 no stages 3 and 4 discrimination.*

Table 7. Man-machine agreement table.

where the knowledge-based system is implemented. This combination of signal processing and knowledge-based techniques creates a very powerful environment and effectively merges algorithmic and symbolic processing. The approach and the techniques developed in this study can be further applied to other signal processing applications involving the monitoring and interpretation of signals.

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References


