ALERTNESS MONITOR USING NEURAL NETWORKS FOR EEG ANALYSIS

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The goal is to detect the instance at which a person has lost the level of alertness necessary to assure safe operation of a vehicle or display vigilance. A neural network is proposed to detect the onset of this signal characteristic. The input to this neural network system is a modified feature vector composed of the associated wavelet representations at different scales. The output of the neural network is a binary decision as to whether the EEG represents an alert state or a drowsy state.

INTRODUCTION

Despite increased automation, many critical aspects of our lives depend on operator control. As we drive more comfortable cars longer distances and run systems with 3 shifts, operator alertness becomes an increasing safety issue. A number of researchers have described the characteristics of alertness exhibited in the EEG signal [1] and have applied neural networks to estimating these alertness levels [2].

The technical challenges in classifying vigilance levels include variations between operators, sensor characteristics, chemical effects such as coffee intake, and reaction to the environmental sounds and lights. The practical challenges to collecting and reacting to EEG data in an operator include the need for non-invasive techniques and comfortable sensors.

For the purposes of this paper, four categories of EEG signals are considered. The alpha wave depicting the early signs of drowsiness is most predominant in the 8-12 Hz spectral range. The theta wave is characterized roughly as 3-7 Hz. The sleep spindles and K complex are prevalent at 12-14 Hz. Delta sleep is defined as 0.5-2 Hz. These categories are used for spectral tuning.

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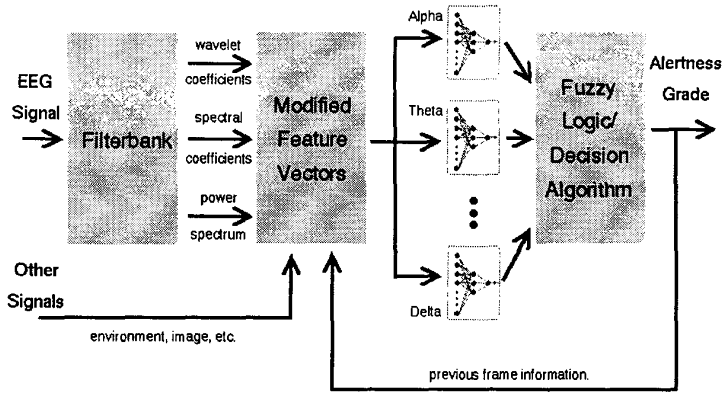

Figure 1: Alertness Monitor Algorithm

Temporal tuning is also required to account for long-term changes between spectral stages. When drowsiness "begins" it can often be shaken off initially. Subsequent events of drowsiness become more difficult to overcome. Eventually the drowsiness appears as a wave of fatigue that cannot be ignored. Similarly, returning to a higher level can follow movement from one alertness level to a lower one. An oscillation about the boundary between levels would be expected before a lower alertness grade can be accurately assigned.

As a result, an alertness label requires a spectral classification and consideration as to how long this spectral classification has been rendered and other factors. There can be some movement between alertness stages before a pattern of sustained onset requires a new classification to be made on the basis of both spectral and temporal evidence.

OVERALL ARCHITECTURE

Figure 1 depicts the overall algorithm for signal processing components of the alertness monitor. The first stage filters the incoming EEG signal capturing regions of interest as wavelet coefficients and power spectrum estimates. A quadrature mirror filterbank first filters into low pass (0-8 Hz) and high pass regions and then into the regions associated with simplified alpha, theta, K complex, and delta characteristics.

The output is a set of wavelet coefficients that are combined with power spectrum estimates to produce a modified feature vector. Wavelet analysis is well suited for the type of signal being considered for this problem. The wavelet transform has been shown to be an effective tool for isolating signal discontinuity [3].

The property exploited in these applications is that the onset of a transient signal will line up across different scales of the wavelet transform. Using the filterbank to represent the signal in the form of the Mallat wavelet transform implementation [4], the successive scale representations are achieved at each stage of the filter bank.

The absolute value of the detail signals will give insight as to the onset of a signal change in this application. At any one resolution there may be noise that appears as a discontinuity associated with that particular scale. If there is a true discontinuity in the signal as is apparent for the change from an alert state to a drowsy state, this discontinuity will be present in successive scales.

The modified feature vector [5] takes into account wavelet coefficients over successive scales, power spectrum estimates from the current and previous frames, and signals from the environment (such as light patterns for nighttime driving). Labeled outputs for training vectors are used to train a bank of neural networks tuned to alertness levels.

The proposed decision algorithm would take into account spectral and temporal tuning. The overall alertness label would use previous classifications as part of the decision. For example, the first instance of alpha waves usually does not lead to sleep. However, repeated alpha and theta transitions would indicate a classification of lower alertness. Different applications (console operator versus truck driver, for example) would have different categories.

NEURAL NETWORK DEVELOPMENT

A neural network implementation of the detector can be trained to learn the desired alertness mappings from labeled examples of EEG signals and the resulting networks can be applied to a wide range of people in that same environment. Using a bank of simple feedforward networks, the structure is simple allowing efficient pipeline architecture suitable for real-time operation.

The architecture selected is a bank of binary-output Multilayer Perceptrons. The individual neural networks are designed implementing a design algorithm developed to calculate the number of hidden nodes required and compute starting weights [5].

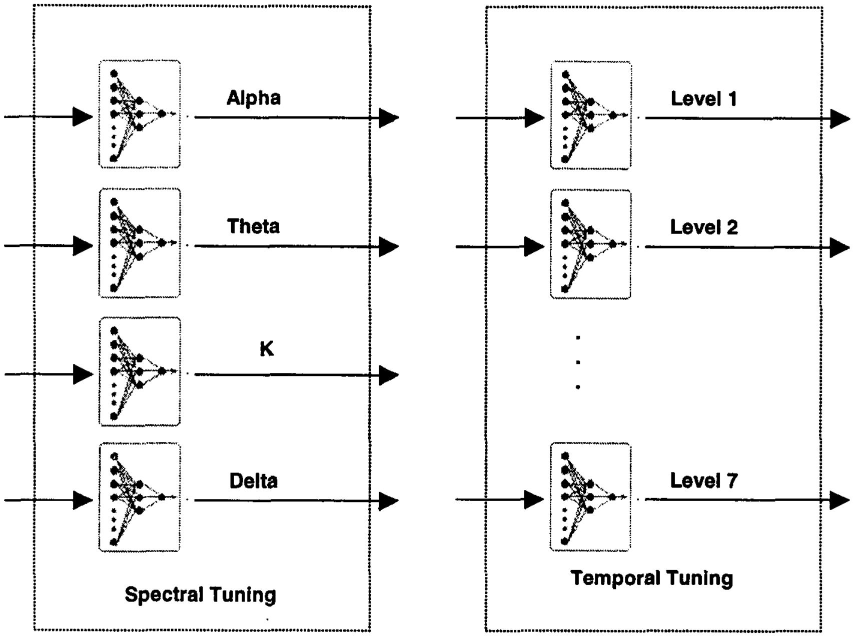

Figure 2: Neural Network Filterbanks

Figure 2 shows the architecture designed and tested with synthetic data. The first stage is spectral tuning of the incoming EEG signal to classify into one of the four categories. The second stage is temporal tuning to use current and previous results to classify into one of seven alertness levels.

The spectral tuning networks were trained with synthetic data with random noise of 10 dB. The data frames are 5 seconds with signal duration ranging between 1 and 5 seconds. A training set was designed for each of the spectral tuning networks. Each training set was comprised of 100 frames of noise only and 100 frames of signal plus noise in varying duration and frequency within the category. For example, the alpha network training set data ranges in time between 1 and 5 seconds and in frequency between 8 and 12 Hz.

The temporal tuning networks were trained with synthetic data patterns of discrete input values mapping the outputs of the spectral tuning networks to the alertness level assignments ranging from 1 (very alert) to 7 (sleep). In designing the desired output values, level changes required a consistent classification of at least 30 seconds with strong emphasis on stage classifications of 4 minutes or longer. The input vector included 5 minutes (60 data frames) of binary output classifications from the 4 spectral tuning networks for a total of 240 input values.

A principal component analysis was conducted on each of the training sets to implement the neural network design algorithm. The structure computed for each of the spectral tuning networks was 64 input nodes, 4 hidden nodes, and a single output node for the binary classification desired. The structure computed for each of the temporal tuning networks was 240 input nodes, 5 hidden nodes, and a single output node for the binary classification for each alertness level.

Starting weights for each of the networks was also computed with the algorithm and the networks were then trained with their training datasets. Each completed network achieved 0 misses and 0 false alarms (100% correct) when tested with their training data.

NEURAL NETWORK RESULTS

The test dataset for the spectral networks was generated with a different random noise seed and 500 examples of signals in noise and 500 examples of noise only where the noise level was 10 dB as in the training set. The spectral tuning neural networks achieved 0 misses and 0 false alarms (100% correct).

In attempting to simulate the noise environment that might actually be experienced, the test dataset was supplemented with additional levels of noise. For example, EEG noise due to chemical effects such as caffeine intake would increase or decrease the noise over a period of time frames. Chemical noise would vary over long time intervals, but would most likely be similar between two successive time frames. The testing was repeated for 21 dB of noise and 30 dB of noise. The results were no false alarms and 10 misses for the data with 21 dB of noise (99.0% correct). For the data with 30 dB of noise, there were no false alarms and 8 misses (99.2% correct).

A third trial was conducted with 5,000 examples of varying noise from 6 dB to 21 dB. Half of the examples had signal plus noise and half were noise only. The result was 99.1% correct, with all the errors being misses.

Noise from biological effects, such as a sneeze or cough, has not been simulated. This type of noise would be expected to introduce a sharp artifact in the EEG signal that would be considered an outlier when minutes of data were taken into consideration.

The temporal neural networks were not tested with data other than the training set because the assignment values to alertness levels were arbitrary. Validation was planned with experts in EEG analysis and alertness, but the project was suspended before that occurred. The errors that did occur in preliminary evaluation, however, were mostly related to addressing input combinations that would be unlikely, such as large changes in alertness levels between frames.

PRODUCT CONSIDERATIONS

When the correlation between EEG patterns and alertness levels were first being discovered, EEG measurements required carefully placed sensors with messy materials to reduce the noise. When a Boston-based data collection effort required Bonanza bus drivers to wear EEG sensors as head gear, more than a few passengers gave a second look climbing onto the bus. Sensor improvements have eliminated many of the mechanical obstacles with the introduction of soft sensors and dry attachments.

The sensor must provide a good correlation with the synthetic results and be non-intrusive. An alertness monitor must be small, light, and comfortable to wear to be effective. The model we propose is similar to a hearing aid with wireless transmission of the data to a remote processor.

Application areas include a variety of operator positions where alertness is critical. Console operators could include sonar and radar operators, plant controllers and air traffic controllers. Transportation applications could include automobile and truck drivers, and airline and ship pilots.

In addition to alertness monitoring, such a design could be applied to medical monitoring. Such a device could provide early warning to epileptics or narcoleptics.

CONCLUSIONS

Neural networks have been shown to be a viable component in an alertness monitor. Neural networks have been used to solve difficult problems when the statistics associated with the mapping of the input signal characteristics to the desired output are not completely known and/or are nonlinear. The neural network can be trained to learn this desired mapping from examples and apply this relationship to data that has not yet been seen. This generalization is key to applying the theoretical principles of labeling alertness levels to a variety of individuals under many environmental conditions.

The simulations conducted on the neural network component of the overall alertness monitor architecture show this to be a feasible approach to the signal processing of EEG signals for vigilance classification. More work is required to properly determine the temporal characteristics and develop a decision algorithm capable of adapting to different operator settings.

References

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