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NEURAL NETWORK CLASSIFICATION OF CLINICAL NEUROPHYSIOLOGICAL DATA FOR ACUTE CARE MONITORING

JOSEPH SGRO

Alacron, Inc., 71 Spit Brook Rd., Nashua, NH 03060 and The Neurological Institute of New York, 710 West 168 Street, New York, NY 10032

INTRODUCTION

The purpose of neurophysiological monitoring of the "acute care" patient is to allow the accurate recognition of changing or deteriorating neurological function as close to the moment of occurrence as possible, thus permitting immediate intervention.

EEG MONITORING

The electroencephalogram is a sensitive indicator of cerebral ischemia. Slowing of the EEG in man occurs when regional cerebral blood flow drops to 16-22 ml/100g/min., and severe voltage attenuation results if flow is further reduced to 11-19 ml/100g/min. (Trojaborg & Boysen 1973). This observation has lead to the use of EEG monitoring in clinical settings in which cerebral perfusion is at risk. The utility of EEG monitoring during carotid endarterectomy has been demonstrated (Chiappa and Burke, 1979; Myers et al, 1980), and it is routinely used in some major centers to determine the necessity of shunting. During cardiopulmonary bypass for cardiac surgery, the EEG also has been shown to be a sensitive indicator of the effects of hypotension as well as air embolism (Prior, 1979; Stockard et al, 1964). The Practice Committee of the American Academy of Neurology has advised that "EEG monitoring during complex surgical procedures has become an established procedure to safeguard cerebral perfusion" (Pedley and Emerson, 1984).

Recently, a number of EEG monitoring system have been proposed. These are either primarily displays of data reduced EEG, processed by FFTs (Fast Fourier Transforms) or AR (Autoregressive), or heuristic rule based detectors for specific patterns derived from processed or raw EEG.
In our view, the limitations of automated EEG analysis systems heretofore developed are consequences of either the use of data reduction, which obscures morphological characteristics of EEG waveforms critical for their identification, or the reliance on rule based systems which are limited by their design to detect a limited repertoire of EEG patterns and may have excessive false classification rates.

For an EEG monitoring machine to be clinically acceptable for use in ICU or operating room environments, the following four requirement should be satisfied:

1. It must detect artifacts to avoid false interpretation of EEG waveforms.
2. It must be able to identify unambiguously designated patterns and changes in patterns in the EEG.
3. It must have provision for multiple monitoring channels.
4. It must be able to perform these functions in real-time.

EVOKED POTENTIAL MONITORING

Evoked potentials (EPs) are electrophysiologic markers of transmission of sensory signals through afferent neural pathways in the central nervous system following auditory, visual, and somatosensory stimulation. They are widely used in clinical neurology for detection and localization of neural lesions (Chiappa, 1990). Brainstem auditory evoked potentials (BAEPs) and somatosensory evoked potentials (SEPs) are relatively resistant to anesthetic agents and levels of patient arousal, and are therefore ideally suited to monitoring the integrity of the central nervous system of patients in "acute care" settings. The purpose of evoked potential monitoring of the "acute care" patient is to allow the accurate recognition of changing or deteriorating neurological function as close to the moment of occurrence as possible, thus permitting immediate intervention.

BAEPs are widely used to monitor acoustic nerve function during surgery in the cerebellopontine angle (CPA), primarily for resection of acoustic neuromas and other CPA tumors, where the surgery threatens auditory nerve function. They are sensitive to mechanical disruption of the auditory nerve, as well as cochlear and eighth nerve ischemia. Intraoperative BAEP monitoring has been recently demonstrated to be associated with significantly decreased postoperative morbidity (Radtke and Erwin, 1988). BAEPs are also sensitive to disruption of and ischemic insult to structures within the brainstem auditory pathways, and hence are employed during other procedures that risk brainstem injury, including surgery for basilar artery aneurysms, posterior fossa arterio-venous malformations, and intrinsic brainstem tumors (Friedman and Grundy, 1987; Radtke and Erwin, 1988; Abramson et. al. 1985).

SEPs are sensitive to parenchymal damage directly involving the posterior columns, as well as compression, mechanical distraction, and cord ischemia. SEP monitoring during scoliosis surgery has become widely accepted, and has virtually replaced the "wake-up" test. SEP monitoring is also employed to monitor the integrity of the spinal cord during cross clamping of the aorta, and neurosurgical procedures involving the spinal cord and its blood supply (Friedman and Grundy, 1987; Loughnan and Hall, 1989; Emerson and Pedley, 1988). Additionally, cortical components of the SEP can be used to assess integrity of the cerebral cortex during procedures requiring temporary occlusion of cerebral arteries (Buchtal and Belopavlovic, 1988).

In order to achieve widespread use and utility, an automated EP monitoring system should have:

1. The ability to detect artifacts to avoid false interpretation of EP waveforms.

2. The ability to unambiguously identify designated EP waveforms.

3. The ability to measure the amplitudes and latencies of designated EP waveforms.

4. The capability of monitoring multiple EP channels in real time.

The Table below lists the major techniques that have been used for automated EP analysis. To date, none of these is in widespread use. This reflects, in large part, their collective sensitivity to artifacts and noise and their inconsistent ability to correctly track the waveform of interest , its amplitude, or latency.

Methods	Disadvantages	Reference
Discriminant methods	Requires a priori definition of features	Clarson Liang (1989)
Template methods	Requires a priori template definition	Childers et al (1987)
Derivative methods	Extremely noise sensitive	Miskiel and Ozdamar (1987)
Rule based methods	Very sensitive to morphology variations	Boston (1989)

NEURAL NETWORKS

INTRODUCTION

PDP networks, also known as *neural* networks, have recently attracted widespread interest and application in diverse areas of computerized pattern recognition, including handwriting, voice and visual pattern recognition systems (Levinson et. al, 1983; Devijer and Kittler, 1982; Blake and Zimmerman, 1987; Lang and Waibel, 1990; Rajavelu et. al., 1989; Buhmann et. al., 1989). Neural networks are structured as arrays of interconnected units which have the capability of "learning" by examples causing functional modification of interconnections. The units have functional properties modeled after neurons, and interconnections modeled after synapses.

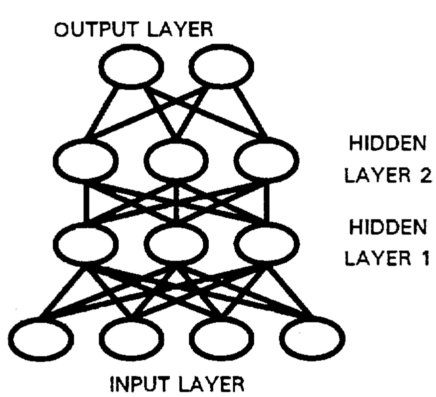
An important feature of neural networks is that it is not necessary to precisely describe the patterns to be recognized. Rather, the network is "trained" by presenting it with examples of patterns to be recognized. While an expert recognition system may be intuitive, or difficult to articulate, the training mechanism only requires examples of classified data (output patterns). In contrast to most other methods, the structure of neural networks allows training to take place in the absence of a specific heuristic method for each feature to be recognized.

The major advantage of neural networks is that they are able generalize, and adapt to distortion or noise without losing their robustness. Neural networks are capable of correctly identifying input patterns that are morphologically similar to but not identical to the patterns on which they were trained. The latter feature makes neural networks ideally suited to EEG and EP analysis which requires correct identification of selected neurally generated signals based upon waveform morphology, and often in the presence of considerable accompanying noise. Neural networks thus have the advantage of allowing an efficient unified system for detection and identification of artifacts, abnormalities, and, EP's waveform latency in the presence of noise. Our results below demonstrate the feasibility of the use of neural networks for EEG/EP analysis.

IMPLEMENTATION

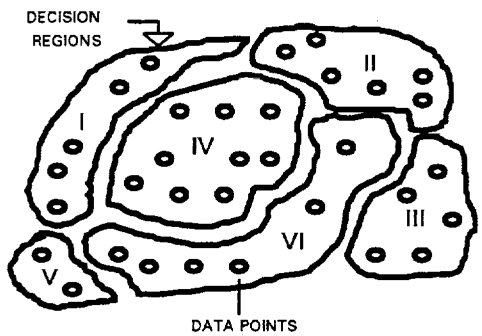
A. NETWORK ARCHITECTURE

We initially implemented a fully interconnected feed forward net with a selectable number of layers and nodes. We used three and four layer networks (i.e. one and two hidden layers) for both EEG and EP analysis. All data processing was performed on AT compatible computer with an Alacron AL860 coprocessor board. The AL860 board uses a 40 MHz Intel i860 RISC processor (80 MFLOPS) and provides 64 MB of memory.



The net initialization is achieved using fixed pseudo-random, unique pseudo-random, seeded pseudo-random or 0 values. The net size, the net structure, the convergence function, the transfer function, and the initialization mode are user selectable at initiation of training. We used nets ranging in size from 512 to 8192 input nodes, hidden layer sizes of between 5 and 500 nodes, and an output layer of less than 20 nodes. The transfer function used was the logistic sigmoid transfer function.

Additionally, we implemented for EP analysis a probabilistic neural network (PNN) as described by Specht (1990) (Figure below), a reduced coulomb energy (RCE) neural network, closely related to PNNs, and a discriminant pattern recognizer (Bow, 1984) .



B. NETWORK TRAINING PARADIGM

Training was achieved using back propagation via modified steepest descent (Rumelhardt, 1987). This entails multiplication of the input values by the interconnection weights, calculation of each layer's output, and propagation of the outputs forward through each successive layer of the network with the calculation of the mean squared error between the output and the desired output. At the end of each training cycle, which consists of a complete presentation of all patterns in the training set, the total calculated error was propagated backwards and the adjustment of the individual weights was made, as outlined in Rumelhardt, 1987. Usually, we obtained an initial pattern match within approximately 50 training cycles using several hundred test patterns, with full convergence taking up to hundred cycles. The network ran entirely in RAM memory on the I860, with an optimized assembly language floating point dot product requiring approximately 10 to 30 minutes per training cycle.

C. NETWORK TESTING PARADIGM

For testing, input data is presented to the network without weight adjustment. The calculated output of the neural network was compared to the expert classification to determine if the classification was successful. Results were then tabulated, and the classification percent correct was calculated.
Separate methods of validation were used for large (>100 epochs) and small (<100 epochs) data sets. For large data sets, the set is split into two subsets - one for training and the other for testing. For small data sets the "holdout" method is employed. A single epoch is held out, and the network is trained on the remaining epochs. The withheld epoch is tested against the trained network. This process is repeated for all epochs in the data set (Specht, 1990; Marchette and Priebe, 1987; Maloney, 1988).

EEG NEURAL NETWORKS

Neural network classification of EEG was investigated using data reduced input via the FFT or an AR model and also raw EEG data.

A. FFT

Input data was decimated to 512 points per channel per 10 second epoch. These data were converted to 512 point power spectra. This is accomplished by applying a standard FFT and taking the squared magnitude of the coefficients. The spectra were then used as input to the neural networks.

B. AR

Input data was initially modeled by a modified covariance ARMA autoregressive moving average model, a Burg model, and a Prony model. The ARMA model was used for classification of EEG because we observed that it consistently produced the most stable and accurate spectra. The ARMA model of EEG consisted of two real coefficients and one hundred complex coefficients. This exceeds the number of coefficients customarily employed to describe EEG spectra (Jansen, 1985). These coefficients were used to compute a 512 point power spectrum. The spectra were the used as inputs to the neural networks.

C. RAW EEG DATA.

A limitation of the use of raw EEG for neural network input is that the data is scale and translation dependent, but EEG interpretation is largely translation and scale independent. Our initial solution to this problem was to train the neural network on rotated and scaled versions of each training epoch. This approach, however, would have resulted in a prohibitive increase in the required number of training epochs. For example, in investigations described below, we used typically 150 training epochs. Each epoch would be transformed into 2560 translated and scaled versions, resulting in a total of 384,000 training epochs [256 translations and 10 amplitude scale levels]. Training the neural network with this number of epochs would not have been practical.

We investigated structural modifications to the neural network to make it immune to translation and amplitude variations in the training set. We implemented a modification of the method of Goggin et al (1991) which preprocesses the epoch into a form that is not effected by translation and amplitude variations. Each epoch contains typically 16 channels, each of which is a time series of 512 data points. Each channel is transformed into a translation and scale invariant form as shown in equation 1, below:

$$Y_i = \frac{\sum_{k=0}^{N-1} X_k \cdot X_{MOD(k+i,N)}}{\sum_{k=0}^{N-1} (X_k)^2}$$

The transformed data is then processed by the back propagation neural network. Neural network employing polynomial transformed data have been named "higher order neural networks" (HONN).

EP NEURAL NETWORKS

In all cases, input to the recognition software consisted of raw 1024 point per channel (both replications). We implemented a fully interconnected feed forward net with a selectable number of nodes (Figure above). The neural network had four layers (i.e. two hidden layers).

The desired outputs were presented to the network as ones and zeros to indicate normal, abnormal, or uninterpretable. Latency and amplitude data were encoded as eight bit binary values. An output of the network was assigned to each bit of the binary value. BAEP and SEP latencies where encoded after multiplying by 10, or 0.1 msec per unit. Amplitude data was encoded as eight bit binary values, 0.1 microvolts per unit.

The interconnection weights of the net were initialized to small random values using a random number generator. We used nets ranging in size from 1024 to 8192 input nodes, and an output layer of less than 100 nodes. First and second hidden layers contained 512 and 256 nodes respectively. The transfer function used was the logistic sigmoid transfer function.

Network training was achieved using back propagation via modified steepest descent as described above. Usually, we obtained an initial pattern match within approximately 50 training cycles using several hundred test patterns, with full convergence taking typically one hundred cycles. The network ran entirely in RAM memory on the I860, with an optimized assembly language floating point dot product requiring approximately 10 to 30 minutes per training cycle, or about 4 to 12 hours for full convergence.

For testing, input data is presented to the network without weight adjustment. The calculated output of the neural network was compared to the expert classification to determine if the classification was successful. Results were then tabulated, and the classification percent correct was calculated. For each data sets the "holdout" method described above was employed.

In addition to back propagation, we also implemented and evaluated RCE and PNN networks.

NEURAL NETWORK RESULTS

EEG CLASSIFICATION RESULTS

All results presented below were obtained using a four layer network (i.e. two hidden layers). We observed that when a sufficient number of nodes were present in the network, training required less than 100 passes over all the epochs in the training set In all cases the net converged and 100% correct identification of the training set was obtained prior to testing.

In all cases, EEG pattern classification using raw EEG was superior to that using FFT or AR input. Furthermore, the HONN outperformed the standard neural network, producing excellent results in all cases. Typical results obtained using the small data set paradigm are illustrated in Table 2, below. In the table, EF refers to eye flutter, IRS to intermittent rhythmic generalized slowing, SH to focal sharp waves, CPD to continuous polymorphic delta, M to muscle artifact and NL to normal. The network size designation in the Table is as follows: number of nodes in the input layer X number of hidden nodes in first hidden layer X number of hidden nodes in the second hidden layer X number of nodes in the output layer.

	EEG Test	Patterns				
	EF vs. NL	RS vs. EF	RS vs. EF	SH vs. CPD	SP vs. NL	SP vs. M
Network Size	512x20x 10x2	512x20x 10x2	1024x20x 10x2	2048x20x 10x2	8192x50 x10x2	8192x50 x10x2
Channels	1	1	2	4	16	16
Data Types	Percent	Correct	Classification			
FFT	57	50	55	52	60	62
AR	52	45	50	48	52	55
Raw EEG	82.5	75	85	75	80	75
HONN AR	75	70	65	60	75	76
HONN FFT	80	65	78	75	78	79
HONN Raw	95	90	95	90	95	95

The above results indicate that superior classification is obtained using raw EEG input when compared to either AR or FFT spectra. We speculate that the inferior performance of AR and FFT based methods is attributable to information loss inherent in these spectral representation of the EEG waveforms. Our results further indicate that use of multiple channels (IRS vs. EF comparisons) improves performance. The best performance, achieving level of EEG pattern recognition accuracy suitable for clinical applications, was obtained using the high order neural network (HONN) methods.

Performance of the our initial, non-translational invariant, network (STD) and the high order neural network (HONN) using raw EEG data was further evaluated using the large data set paradigm to test classification of states of arousal, abnormalities, and artifact identification. For state, 150 sixteen channel test epochs were used. The size of the network was 8192 x 200 x 50 x 3. Results are shown below .

State	% Correct Classification	
	STD	HONN
Wake	82	93
Stage I Sleep	86	97
Stage II Sleep	66	95

Again, using the large data set paradigm, 150 test epochs were classified as normal or demonstrating any of the following "abnormalities": continuous slowing (any type), intermittent slowing (any type), slow alpha, or uninterpretable. The network size was 8192 x 200 x 50 x 5. Results are shown in Table 4, below.

Category	% Correct Classification	
	STD	HONN
Normal	82	98
Intrm slowing	70	93
Cont slowing	70	97
Slow alpha	77	92
Uninterpretable	50	98

Finally, for detection of the presence and classification of types of artifacts, 150 sixteen channel test epochs were used. The size of the network was 8192 x 200 x 50 x 6. Results are shown below .

Artifact	% Correct Classification	
	STD	HONN
None	70	97
Eye Flutter	90	97
Eye Blinks	80	95
Horiz Eye Mnts	66	98
Muscle	73	98
Movements	68	98

The above results confirm the suitability of the HONN network for accurate identification of a wide variety of EEG waveform patterns.

EVOKED POTENTIAL CLASSIFICATION RESULTS

I. LATENCY MEASUREMENT RESULTS

The Table below depicts the latency measurement errors for wave I, III and V of the BAEP, as made by three different neural networks and a discriminant method. All neural network methods performed well, with errors close to human measurement error on BEAPs recordings, which is approximately 0.1 - 0.2 MS or 1-2% of the standard 10 msec sweep. The discriminant methods was not as successful. The most accurate classification was achieved by the back propagation method.

BAEP Latency Error Std Dev

Milliseconds	BP	RCE	PNN	Discr	# Cases
I	0.20	0.22	0.24	1.00	172
III	0.30	0.33	0.40	1.20	168
V	0.30	0.33	0.30	1.50	178

The Table below presents the classification results for median nerve SEP data. The latency measurement accuracy achieved by all neural network methods was excellent. The back propagation performed best. The latency measurement error of the BP network was similar to human measurement errors, which is approximately 0.5 MS, or 1% of the standard 50 msec sweep. Again the discriminant method performed poorly.

SEP Latency Error Std Dev

Milliseconds	BP	RCE	PNN	Discr	# Cases
N9	0.30	0.33	0.45	1.10	221
P14	0.70	0.77	1.05	2.10	218
N20	0.30	0.33	0.45	4.20	213

Similarly, the Table below illustrates classifications for VEPs. Classification accuracy was excellent for all neural network techniques, the best performance being achieved by the back propagation method. The 1 msec error for BP is 0.5% of the standard 200 msec sweep. The discriminant method performed poorly.

VEP Latency Error Std Dev

Milliseconds	BP	RCE	PNN	Discr	# Cases
P100	1.00	1.10	1.50	5.10	270

II. AMPLITUDE MEASUREMENT RESULTS

The Table below presents our amplitude measurement results using BAEP data. Accurate amplitude measurement were made by all neural network methods tested. The best performance was achieved by the back propagation network and the discriminant method performed poorly.

BAEP Amplitude Error Std Dev

micro	BP	RCE	PNN	Discr	# Cases
V	0.08	0.48	0.62	1.01	101

Similarly, the Table below presents our amplitude measurement results for SEP data.

SEP Amplitude Error

micro	BP	RCE	PNN	Discr	# Cases
N9	0.32	0.38	0.47	0.71	105
P14	0.15	0.72	0.75	1.17	105
N20	0.23	0.51	0.50	0.71	105

Our amplitude measurement results are presented in the Table. Again, the back propagation method provides the most accurate amplitude measurement.

VEP Amplitude Error Std Dev

micro	BP	RCE	PNN	Discr	# Cases
P100	1.20	1.23	1.32	2.34	270

III. CLASSIFICATION RESULTS

The Tables below present the accuracy by which the three neural network and the discriminate method classified EP recording of the three modalities and "Normal", "Abnormal" or "Uninterpretable". The best performance was achieved by the back propagation method, which classified 94% of EP studies in agreement with the "expert" reader. Additionally, ninety percent of records that were uninterpretable due to noise contamination were correctly identified.

BAEP

% Correct	BP	RCE	PNN	Discr	# Cases
Result					
Normal	95%	91%	82%	56%	96
Abnormal	92%	87%	80%	54%	91
Uninterpr	90%	80%	80%	60%	10
Overall	93%	89%	81%	55%	197

SEP

% Correct	BP	RCE	PNN	Discr	# Cases
Result					
Normal	97%	89%	84%	64%	155
Abnormal	93%	86%	82%	61%	30
Uninterpr	90%	83%	77%	60%	44
Overall	95%	87%	82%	63%	229

VEP

% Correct	BP	RCE	PNN	Discr	# Cases
Result					
Normal	97%	93%	91%	63%	166
Abnormal	91%	89%	87%	60%	45
Uninterpr	91%	87%	85%	59%	95
Overall	94%	91%	89%	61%	306

IV. *MULTICHANNEL RESULTS*

The above results were obtained by presenting the neural networks with multiple channels (3 for BAEPs, 4 for SEP, and 6 for VEP). The effect of multiple channels on the performance of neural network classification was examined by omitting channels which did not specifically contain a designated waveform of interest, but provided information which is used in human waveform recognition. Specifically, Ac-Cz and Ai-Ac channels for BAEPs, and SC5-Fpz for SEPs. In all cases, inclusion of these "extra" channels improved classification and measurement results slightly. In some cases, major improvements were linked to the use of extra channels. For examples, use of three channel resulted in a 24% improvement in wave III amplitude measurement.

BAEPs

%	Number of channels		
Correct	1	2	3
Result			
Norm	94%	95%	95%
Abnormal	90%	91%	92%
Uninterp	90%	90%	90%

BAEP Latency Error

	Number of channels		
msec	1	2	3
Wave			
I	0.23	0.21	0.20
III	0.53	0.42	0.40
V	0.32	0.33	0.30

BAEP Amplitude Error

	Number of channels		
u-Volts	1	2	3
Wave			
I	0.32	0.30	0.30
III	0.42	0.33	0.32
V	0.34	0.27	0.26

SEP Classification accuracy

%	Number of channels	
Correct	3	4
Result		
Norm	97%	97%
Abnormal	93%	93%
Uninterp	87%	90%

SEP Latency Error

	Number of channels	
msec	3	4
Wave		
N9	0.31	0.30
P14	0.89	0.75
N20	0.32	0.30

CONCLUSIONS

Our results confirm that:

1. Neural networks are able to accurately identifying EEG patterns and evoked potential wave components, and measuring evoked potential waveform latencies and amplitudes.

2. Neural networks are able to accurately detect EP and EEG recordings that have been contaminated by noise.

3. The best performance was attained consistently with the back propagation network for EP and the HONN for EEGs.

4. Neural network performed consistently better than other methods evaluated.

5. Neural network EEG and EP analyses are readily performed on multichannel data.

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