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Automated interictal EEG spike detection using artificial neural networks *

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Summary Feed-forward, error-back-propagation artificial neural networks were applied to recognition of epileptiform patterns in the EEG. The inherent network properties of generalization and variability tolerance were effective in identifying wave forms that differed from the training patterns but still maintained 'epileptiform' spatio-temporal characteristics. The certainty of recognition was measured as a continuous function with a range of 0–1. Two levels of certainty (0.825 and 0.900) were used to indicate recognition of spikes and sharp waves (SSW). An average 94.2% (±7.3) of the SSW were recognized; 20.9% (±22.9) of all recognized SSW were false-positive recognitions. The time required for pattern recognition was well within the time required for digitizing the analogue data. This study provides evidence that neural network technology is, in principle, an effective pattern recognition strategy for identification of epileptiform transients in the EEG. The analysis is sufficiently rapid to be of potential value as a strategy for data reduction of long recordings stored on bulk media.

Key words: Spike detection; Neural network

In fundamental terms the EEG represents a measure of spatial voltage field distributions and the manner in which they change as a function of time. Therefore, strategies designed for computerized 'pattern recognition' of the EEG should ideally identify patterns in terms of 3 dimensions: voltage magnitude and polarity, time and at least 2-dimensional space representing the surface of the scalp.

Neural networks represent an expanding computational technology that is in principle well suited to automated recognition of cerebral electrical activity, and in particular, epileptiform abnormalities with their relatively stereotyped features.

Driven by the work of neurophysiologists, design of artificial neural networks began in the 1940s (Hebb 1949; Lashley 1950). It is only in recent years that different types of neural networks have been designed and shown to have practical applications with improved performance over conventional technologies. Among these applications robust pattern recognition strategies (spatial, temporal and spatio-temporal) have been especially effective.

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Neural networks have the property of being able to generalize consistent features of patterns used to train them. They effectively reconstruct patterns from partial data and remove 'noise' from signals thereby acting as 'filters' to identify patterns. The output of neural networks is graded, providing a continuous measure that can be interpreted as reflecting the degree of certainty that a pattern of interest has been recognized. The properties of generalization, tolerance of pattern variability and graded output mimic the principles electroencephalographers apply to interpretation of EEGs.

The use of computer simulated neural networks as a tool for automated pattern recognition of epileptiform EEG activity is therefore an attractive option. In particular, time dependent data (voltage change as a function of time) may be input to a network maintaining a representation of the spatial relationships of the changing voltages. Also attractive is the fact that it is not necessary to devise a trained network that is appropriate for all cases. A network may be trained to identify only the spatial distributions of those time dependent voltage changes that represent the specific epileptogenic disorder for each patient being examined. The time required for training the network is acceptably short and the number of samples required for training is small.

This study was designed to investigate the utility of one type of neural network as a method for recognition of interictal epileptiform EEG activity (spikes and sharp

waves (SSW)). In order to accomplish this, we were interested in measuring the following parameters:

(1) Specificity/selectivity: the ability of the network to discriminate between relevant and irrelevant patterns (i.e., frequency of false-positive recognitions).

(2) Sensitivity: the ability of the network to identify relevant patterns (i.e., frequency of false-negative errors).

(3) Speed: the relationship of the time required for data acquisition and for data analysis. This relationship is important if computerized analysis is used as a method of data reduction and can best be represented as a ratio (recording time/analysis time).

(4) Utility in a clinical setting: many factors enter into this measure, but the following seem important:

(a) The analysis and recognition strategies should be adaptable to digitized data from any source whether it be on-line, real time data acquisition or from a bulk storage device such as a tape recording.

(b) The features used by the network to recognize patterns should be intuitive to a trained electroencephalographer who ultimately must select the patterns used to train the networks.

(c) Pattern selection should be rapid, simple and relatively few patterns should be required to adequately train the network.

(d) The hardware required for the process should be easily available, industry standard and cost effective.

Methods

Background

Artificial neural networks may be considered as computer simulations of the nervous system. They consist of neurons or nodes that communicate with each other through connections (synapses). The strength of these connections is represented by weights and the sign of each weight determines whether the connection is 'excitatory' or 'inhibitory.' Each input node assumes an activation value (analogous to frequency of action potentials) which is determined only by the external environment. The activation value of an input node is then multiplied by the weight of a particular connection and that value is transmitted to the next (hidden or output) node. The hidden or output node receiving the information sums all the input values directed to it (net activation), normalizes this value (0–1) with a non-linear activation function and assumes the resultant activation value. The process is repeated for all subsequent nodes in the layer of nodes being processed (Fig. 1). Once activation values have been calculated for all nodes in one layer of nodes the activation values for the next layer are calculated. The activation value(s) of the final output node(s) represent the output of the network.

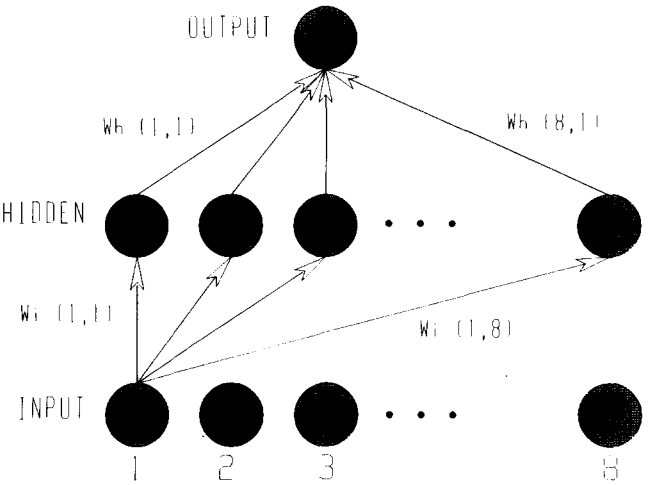

Fig. 1. Graphic representation of network structure. The nodes (neurons) are arranged into layers. The first layer is the INPUT (8 nodes) layer. Each node of the input layer is connected to each node of the HIDDEN (8 nodes) layer. The single node of the OUTPUT layer receives connections from each node of the hidden layer. The influence that one node has through its connections to the next node is determined by the connection weight (e.g., the connection between input node 1 and hidden node 8 has a value represented by Wi(1,8)). The weights may be excitatory (+) or inhibitory (−). Each node of one layer has connections with each node of the next layer.

In order for a network to perform pattern recognition it must be trained. Training is accomplished by first presenting known patterns to the input layer and determining the difference (error) between the expected (target) value(s) and the actual value(s) of the output node(s). The magnitude and sign of the error is used to change the existing weights of all the connections in such a way that the error will be reduced the next time the pattern is presented to the network (i.e., error-back-propagation).

The principles, calculations and mathematical derivations supporting simulated neural networks used in this study are based on well documented theory and application (Rumelhart and McClelland 1988; Maren et al. 1990).

Network architecture

The neural networks used in this study are fully connected, 3 layer (input, hidden, output), feed-forward networks. Each node of the input and hidden layer has connections with all of the nodes of the next layer. There are no connections to preceding layers or to nodes of the same layer. The number of input nodes is determined by the number of EEG channels and each input node corresponds to one recording channel. Therefore, the sequence of the recording channels is maintained by the input nodes representing a spatial dimension in so far as it is characterized by the electrode montage. For example, if an SSW is present only in channels 1 and 2 representing the left temporal

region, this event will be discriminated from an SSW of identical morphology occurring in channels 3 and 4 representing a different part of the cortex. The input nodes therefore reflect the different locations of electrical fields on the scalp. The networks used in this study consist of 8 input nodes, 8 hidden nodes and 1 output node (Fig. 1). Two networks of identical architecture are used to implement pattern recognition of epileptiform complexes.

Training the network

Before a network can be used for pattern recognition it must be trained to recognize patterns of interest. The patterns used for training must be similar in terms of the dimensions of voltage (or voltage gradient), time and spatial distribution.

If the SSW patterns used for training have features in common the network will be able to generalize the common characteristics of these patterns and recognize these features during testing. Variability between training patterns is expected and even desirable forcing the network to generalize the training data. If the training patterns are widely divergent however, generalization will not be possible and the network will be unable to converge on a solution.

The datum used as input to the network is the scaled average slope of the voltage (dV_{av}/dt) which is calculated for each channel in the following manner: Prior to selection of training patterns the user identifies the peak of an SSW that will be used as a training pattern. The index point of a window displayed on the screen is then set to the peak of the SSW. The duration of the rising phase and the falling phase is defined by adjusting the left and right limits of the window to the onset of the rising phase and the termination of the falling phase respectively. Once the margins of the window are set, the intervals between each margin and the index point of the window remain unchanged during selection of training patterns and during testing. The intervals before and after the index point (which is located at the peak of the SSW) may be the same or different and are independently selected by the user on the basis of wave form morphology of the SSW.

Each time a training pattern is selected the average voltage slope during each selected interval (pre-peak and post-peak) for each channel is calculated. The average slope is the sum of the voltage changes between each sample within the interval divided by the number of sample intervals representing the total interval. The average slope is then multiplied by a scaling factor which is determined by the AD range (e.g., if an 8-bit A to D converter is used, the AD range = 0–255), the length of the user selected slope interval and the display gain. The measured slopes before the peak for each channel are used as data for one network and the slopes following the peak are used as data for the second network. Once the user has chosen the slope intervals, training patterns are selected simply by identifying the peak of the SSW with the index point of the graphic window.

Selection of training patterns is accomplished by the user viewing a graphic display of the EEG. The index point of a movable window is directed to the peak of a wave form of interest in one channel. The SSW is usually manifest in more than one channel but is of highest voltage in one or two channels. Significant phase shifts between different channels are relatively rare and in any case do not present a problem because the phase shift may be a feature of the spatial distribution of the SSW that is important for training the network. With the peak identified, selection results in the value of the pre-peak and post-peak slopes over the selected interval (for each channel) being saved for use during training. The number of slope values per training pattern corresponds to the number of channels and input nodes. By convention pre-peak slopes are used to train network B (before peak) and network A is trained by post-peak (after peak) slope values.

To summarize, each input node of each network has information regarding the direction and the magnitude of the voltage change as a function of time (rate of change). Since each input node represents an EEG channel and each channel is representative of the location of the recording electrodes on the scalp, the training pattern represents the spatial distribution (as represented by the recording channels) of voltage change as a function of time before or after the peak of the SSW.

The training patterns selected by the user are the patterns that the networks will ultimately be required to identify and may be thought of as 'correct' patterns. These patterns are associated with a target (teaching) value of 1 that is used to train the networks. Patterns used to train the networks must also include 'incorrect' patterns associated with target values of 0. The incorrect patterns are not chosen by the user but rather are calculated using the distribution (mean and standard deviation) of training values for each node in the correct patterns. For example, using all the correct training patterns the mean and standard deviation of the values for the first input node are calculated. In order to calculate incorrect values for the first node, offset and range parameters are determined. The offset is a multiple of the standard deviation of the correct values. The offset is added to or subtracted from the mean of the correct values and locates the mean for incorrect values for the first node. A positive and a negative offset having the same absolute value are used. The range is also a multiple of the standard deviation and will determine the degree to which the incorrect values will vary from the 'incorrect' mean. Four incorrect values for each node of each correct

pattern are calculated (two values greater and two values less than the mean of the correct patterns). The process is repeated for each input node and when completed, the total number of incorrect patterns will be 4 times the number of correct patterns.

Before training begins the networks are 'initialized' setting random values for the weights. The first time the network is tested with a training pattern there will be a large difference between the network output and the target value associated with that training pattern (1 if correct, 0 if incorrect). This difference is the error used to adjust the weights prior to the next test. The adjustment of the weights will in most cases reduce the magnitude of the error that occurs following the next test.

The networks are trained until the rms error is reduced to below a criterion value set by the user. This value is usually in the range of 0.01–0.003. The smaller the value the more highly trained and specific the pattern recognition will be. A very high degree of accuracy is not always desirable because of the inherent variability of wave form morphology and distribution that characterizes epileptiform activity.

It is only necessary to 'initialize' the weights of naive networks. Previously trained networks may be retrained with additional training patterns adding the information from the new patterns to the existing feature recognition characteristics developed during earlier training.

At the conclusion of training a set of weights has been calculated for each network's connections that may be used as often as necessary for as many separate recording sessions as necessary. The weights are montage specific. While different patients with identical montages may be tested using the same set of weights, applying the same set of weights to one or more patients with different montages will have unpredictable results.

In practice 4–6 correct training patterns are sufficient to train each network and training usually requires 1 min or less.

Pattern recognition by trained networks

Test patterns are submitted to the appropriate network after calculating the scaled average slope of the voltage before and after the index time. The resultant activation value of the output node is the degree of certainty that a pattern similar to the training patterns has been detected (an SSW has been found). Output node activation values range from 0 to 1. These activation values have no clearly definable stochastic significance. It is appropriate, however, to deal with these values as though they reflect some measure of the likelihood that a pattern similar to the training patterns has been found (a level of certainty) but lacking specifically definable statistical probability. These values become meaningful if an output node activation value of 0.9 is interpreted as recognition of a predefined pattern with high certainty. Any number of recognition thresholds can be defined and the current program uses 2 thresholds (level 1 = 0.9 and level 2 = 0.75–0.85). As the thresholds are lowered the number of false-positive recognitions increases, while raising the threshold increases the chances of missing slopes that vary in some small way from the training patterns but are definitely ones that are being sought (false-negative errors).

The level of certainty that an SSW has been detected is determined by calculation of a cumulative output for both networks. The cumulative output for both networks is the sum of the products of a weighting factor and the output node activation value for each network (e.g., $0.52 \times$ output net B + $0.48 \times$ output net A = cumulative network output). The sum of the weighting factors is always 1 and they are selected by the user or automatically computed on the basis of the sensitivity of network output to a small change of input values. The more sensitive network has the larger weighting factor.

To obtain a measure of network sensitivity the networks are tested with the training patterns used to train them. One training pattern is presented to the network and the output of the network is recorded. The same pattern is presented to the network again but on this occasion the value of the first input node is incremented by a small amount. The difference between the network output on this occasion as compared to the previous network output divided by the incremental change of input represents the sensitivity of the first input node to a small change in input. The increments of input values continue until the sensitivity starts to decrease or a predefined maximum total change in input value has been reached. The calculations are repeated decrementing the first node input. These calculations are repeated for each node of each network. When all nodes of both networks have been tested in this way (using each of the correct patterns) the input nodes responsible for the greatest change in network output for each network are known and usually represent the same EEG channel in each network. This technique to estimate the effects of various inputs on network output is similar to one previously described (Klimasauskas 1991). The ratio of the maximum input node sensitivities of the two networks is used to determine weighting factors to calculate cumulative network output for testing of EEG data (e.g., ratio net B : net A = 2 : 1, weighting factors net B = 0.66, net A = 0.34).

Calculation and testing of data for one window (pre-peak + post-peak voltage slopes) of 8 channel EEG data requires approximately 0.4 msec. This is 20 times faster than the sampling interval at digitizing

rates of 128 Hz and 13 times faster for data digitized at 200 Hz.

Materials and patient data

Eight channels of EEG from 5 patients with epilepsy were recorded on cassette tape using the Oxford Medilog 9200 ambulatory monitoring system. Electrodes were applied to the scalp and their positions designated according to the international 10–20 system. Selected portions of the EEG were digitized with 8 bit resolution at 128 Hz and stored on hard disk. The data were then transferred to an IBM compatible microcomputer with a 33 MHz 80486 processor which was used to analyze the data. The recording times are short because the raw data needed to be transferred between computers using floppy disks with limited storage. The data were not selected to be artifact free, but rather to insure that a sufficient number of SSWs with varied wave form morphology were available for testing.

Preprocessing of the digitized data (i.e., prior to network testing) consisted of digital filtering at 2 Hz (high pass filter, −6 dB). Values for the average pre-peak and post-peak slopes using a moving window were calculated for each channel to obtain the values ultimately presented to the networks. If the average slope of the voltage during one half the predefined interval exceeded a user defined percentage (range: 50–100%) of the average slope over the entire interval, the input from that channel to the network was set to zero. The smaller the percentage the greater the artifact rejection. This had the effect of acting as a low pass filter and reduced the frequency of false-positive recognition of muscle artifact.

The amount of data manipulation prior to testing by the network was kept at a minimum in order to assess the ability of the networks to discriminate patterns without heuristically determined constraints. Artifact identification/rejection represents a difficult but separate problem that requires some understanding of the inherent artifact rejection properties of the networks as a point of departure.

Estimation of network capabilities

In order to obtain a measure of the utility of neural networks applied to EEG pattern recognition, an estimate of the selectivity and the sensitivity of the procedure was sought.

Selectivity was calculated in terms of the number of false-positive recognitions. False-positive recognitions were defined as recognition (at any predefined threshold certainty) of wave forms that were unequivocally NOT epileptiform in character (defined by visual inspection). The total number of false-positive recognitions at each recognition threshold was then translated to the number of recognitions as a function of total

TABLE I

Summary of results of neural network analysis of EEGs from 5 patients. Two of the patients (2, 4) had independent epileptiform abnormalities and were treated as 2 separate cases for purposes of testing the networks.

Patient	Network output	1	2	2a	3	4	4a	5	M	S.D.
No. of total network recognitions		74	56	20	23	376	232	44		
No. of true SSW		82	52	18	15	349	218	18		
True SSW/h		387	318	110	65	899	561	152		
Record time (min)		12.7	9.8	9.8	13.8	23.3	23.3	7.1		
No. of false pos	≥ 0.825	2	5	2	11	27	23	26		
	≥ 0.900	0	1	0	4	2	6	9		
No. of false pos/h	≥ 0.825	10	31	12	48	70	59	219		
	≥ 0.900	0	6	0	17	5	16	76		
No. of false neg	< 0.825	9	1	0	3	12	9	0		
No. of false neg/h		43	6	0	13	31	23	0		
% false pos	≥ 0.825	3.6	8.9	10.0	49.8	7.2	9.9	59.1	20.9	±22.6
	≥ 0.900	0	1.8	0	17.4	0.5	2.6	20.5	3.7	±6.8
% false pos blks		< 0.01	3.0	1.2	2.5	5.2	4.1	7.3	3.3	±2.5
% true SSW found	≥ 0.825	89.0	98.1	100	80.0	96.6	95.9	100	94.2	±7.3

No. of total network recognitions: total number of spikes and sharp waves (SSW) recognized by network. No. of true SSW: the number of SSW identified by visual inspection of EEG. True SSW/h: SSW frequency of occurrence normalized to 1 h of recording. Record time (min): actual duration of recording analyzed by networks. No. of false pos: number of wave forms that were unequivocally NOT epileptiform when the cumulative network output (level of certainty) equaled or exceeded the network output values indicated (0.900, 0.825). No. of false pos/h: number of false-positive recognitions normalized to 1 h. No. of false neg: number of unequivocal SSW identified by visual inspection of EEG but unrecognized with adequate certainty (< 0.825) by the networks. No. of false neg/h: number of unrecognized SSW normalized to 1 h. % false pos: (no. of false pos ÷ total network recognitions) × 100. % false pos blks: (3.5 sec epochs containing only false-positive recognitions ÷ total number of 3.5 sec epochs) × 100. % true SSW found: (no. of true SSW identified by networks/no. of true SSW) × 100 recognized with certainty ≥ 0.825. M, S.D.: mean and standard deviation.

network recognitions (percent) and as a function of the total recording time (average false-positive/h). The purpose of this latter measure was to provide a measure normalized to time since the duration of the samples tested varied widely.

Sensitivity was calculated in terms of the number of times an unequivocal SSW remained unrecognized at either user defined recognition threshold (false-negative error). The percent false-negative errors as a function of unequivocal SSWs (defined by visual inspection) and average false-negative errors/h were calculated.

The decision to use measures dependent on a high degree of interpreter certainty (e.g., unequivocal epileptiform complexes) was aimed at reducing the effect of potential inter-interpreter variability and bias. This strategy, however, is only partially effective. Identifying unequivocal epileptiform complexes should be relatively straightforward and non-controversial. On the other hand, identifying unequivocally non-epileptiform events is more problematic. This could cause interpreter dependent variability in determining the number of false-positive recognitions by the network. This

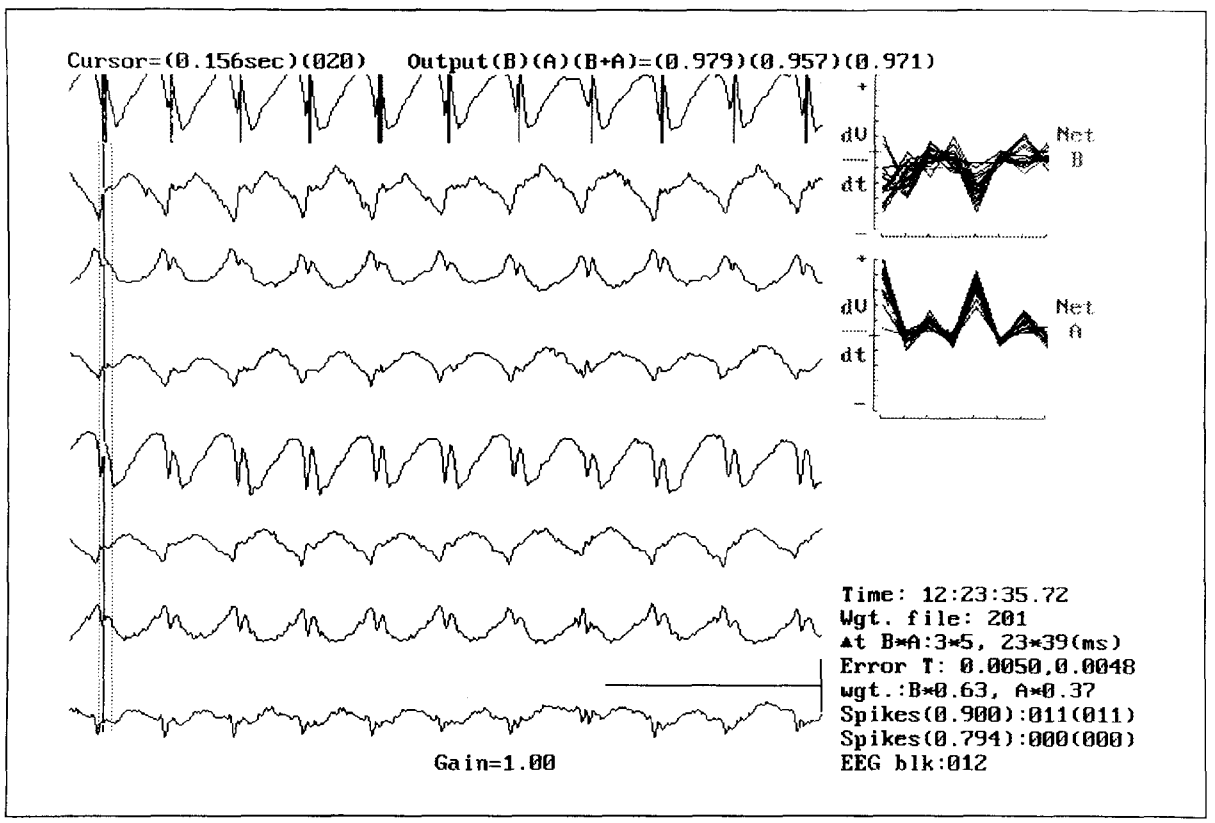

Fig. 2. Case 1. Video display of one epoch of 8 channels of EEG with the results of testing by 2 neural networks. The first channel is over-plotted by vertical lines indicating those times where the cumulative network level of certainty was above a criterion value representing a probable SSW peak. Note that each of the vertical marks are placed over the spike component of a spike and wave complex. A cursor is situated to the left of the figure and is positioned at the first time location associated with recognition by the networks. The cursor is actually a window, with the center-line representing the index point for determining the pre- and post-peak voltage slopes. The dotted lines on either side of the cursor represent the pre- and post-peak intervals. The graphs in the upper right corner display the computed voltage slopes for all recognized time points and are over-plotted as a function of the channels in which they occurred. The abscissae of each of the graphs represent EEG recording channels (range: 1–8), the ordinates are scaled average voltage slopes (dV_{av}/dt) (range: -0.5 to $+0.5$). The pre-peak slopes are drawn in the graph marked 'Net B' (before peak) and the post-peak slopes are marked 'Net A' (after peak). Text top of figure: 'Cursor =' indicates the position of the cursor measured in elapsed time from beginning of the epoch (0.156 sec) and in number of samples (020). The 'Output' of network (B) then (A) and the cumulative network certainty (B + A) are (0.979), (0.957) and (0.971) respectively for the time slice indicated by the cursor. Text bottom right corner: The actual time of the beginning of the epoch is indicated (12:23:25.72). Next, 'Wgt. file:' is the name of the file in which the weights for the trained network were stored. '▲t' indicates the slope intervals used by networks B and A. The intervals are displayed in number of samples and in milliseconds. In this example the pre-peak interval is shorter than the post-peak interval. 'ERROR T:' are the error levels to which each of the networks (B then A) were originally trained. 'wgt.:' shows the weighting factors used to multiply the output of each network. Each product was summed to obtain the cumulative level of certainty (e.g., $(0.979 \times 0.63) + (0.957 \times 0.37) = 0.971$). 'Spikes' represents the number of SSWs found by the networks at each level of certainty indicated. The first number in parentheses represents the threshold level of certainty. The next number is the cumulative number of SSWs recognized in all epochs previously analyzed including the current epoch. The final number in parentheses is the number of SSWs found in the current epoch. 'EEG blk:' is the sequential epoch number counted from the beginning of the EEG. Text bottom: 'Gain =' is a scaling factor applied to the raw digital data. CHANNELS: (F4-C4)(C4-T4)(T4-P4)(P4-02)(F3-C3)(C3-T3)(T3-P3)(P4-01). Calibration: 1 sec, 200 μV.

parameter, however, is in principle less critical (a difference of 2–3% has little practical significance) than the likelihood of failing to recognize unequivocal epileptiform complexes considering the goals of this study. Only one author (AJG) interpreted the EEGs, presumably introducing bias but also increasing the consistency of the variance from any potential democratic consensus which, in any case, carries no assurance of accuracy in absolute terms.

Results

All of the 5 patients studied were recorded using bipolar montages (Table I). Two of the patients had independent epileptogenic foci (cases 2 and 4), 2 patients had a single unilateral focus (cases 3 and 5) and 1 patient (case 1) had a generalized abnormality characterized by 3/sec spike and wave complexes. Therefore, 7 sets of trained networks were tested and the 2 patients with independent foci were treated as 2 separate cases for purposes of analysis.

The data and results of testing by the networks was displayed in 3.5 sec epochs (Fig. 2). The recognized SSWs were marked and a 'spike count' maintained.

The networks were always able to generalize the important features of the training patterns and recognize epileptiform wave forms that were incomplete or varied from those of the patterns used to train the networks. In the example shown in Fig. 3 a spike (manifest in the top 3 EEG channels) has been recognized by the network with a high degree of certainty (Fig. 3A: cumulative network output = 0.965 at vertical line). The voltage slopes (pre-peak: net B, post-peak: net A) at the recognized time slices are graphically displayed as a function of channel number (Fig. 3B). The recognized voltage slope distributions may be compared with the voltage slope distributions of the

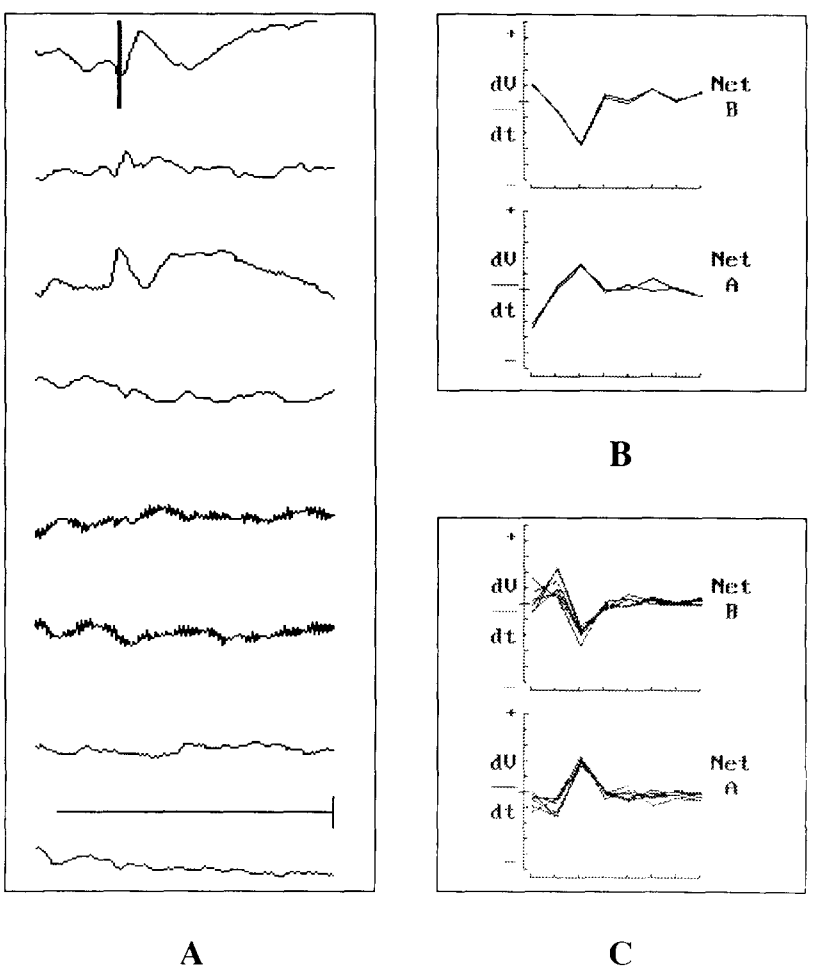

Fig. 3. Case 2. A: this is a segment of 8 EEG channels with a spike demonstrated in the top 4 channels. The times at which the voltage slope distribution was recognized by the networks are indicated by the vertical line plotted over channel 1. The level of certainty (cumulative network output) for these times was high (0.965). Cal. 1 sec, 100 μV. B: the voltage slopes recognized in A are graphically displayed (ordinate ± 0.5) as a function of the channel in which they occurred (abscissa). Pre-peak slopes were tested by net B and post-peak slopes were tested by net A. Two patterns of voltage slopes were recognized. C: the voltage slope patterns used to train each of the networks are displayed in graphic form identical to B. Six patterns are over-plotted.

training patterns (Fig. 3C). It is easy to see that voltage slope differences between the recognized patterns and the training patterns exist for several channels. For example, the voltage slopes of channel 1 are quite dissimilar comparing recognized and training patterns. The voltage slopes of the training patterns for channels 1 are fairly variable (Fig. 3C). Because of this, variation in the voltage slopes for this channel in patterns being tested is well tolerated. On the other hand, the training pattern voltage slopes of channel 3 have little variability and the sequence of voltage slopes of the training patterns is similar to that of the recognized patterns.

The results of testing by the networks of all cases are summarized in Table I. The length of each of the recordings analyzed varied from 9.8 min to 23.3 min. The length of the recordings was limited in part by the amount of data that could be transported from the Oxford scanning system to the processor with the networks on a single 1.44 Mbyte floppy disk. Strategies could have been devised to transport and analyze longer recordings, but it would have added little to the goals of this study. The samples were selected so as to provide adequate numbers of SSW to be tested by the network. No special effort was made to choose samples that were artifact free.

The sensitivity of the networks is represented by the mean rate of recognition of unequivocal epileptiform complexes which was 94.2% ($\pm$7.3) (range: 80–100%). The lowest sensitivity (80%) occurred in a patient (case 3) in whom only 3 SSWs were not recognized. The frequency of SSWs, however, was low and only 15 SSWs were identified by visual review of the record. In 2 other cases with low SSW frequency (2a and 5), each with 18 visually identified SSWs, all SSWs were recognized by the networks.

Reasons for non-recognition errors fell into two major categories. The most frequent reason was related to the fact that the voltage change in a channel did not reach sufficient magnitude to generate sufficiently high network certainty (Fig. 4). This occurred at times because recording was performed using 'bipolar' montages which resulted in recording of the spatial distribution of voltage field gradients rather than the spatial distribution of voltage fields. If referential montages had been used and actual voltage fields had been recorded, small shifts in the field would have little effect on the actual voltage slopes recorded in the EEG channels and the network's ability to generalize would tolerate these shifts. On the other hand, voltage field gradients could change more dramatically as a result of small shifts in field leading to a relative equipotential voltage between two electrodes situated in the field. Indeed, phase shifts in different scalp locations could alone account for dramatic changes in voltage gradient having considerably less effect on spatial voltage distributions.

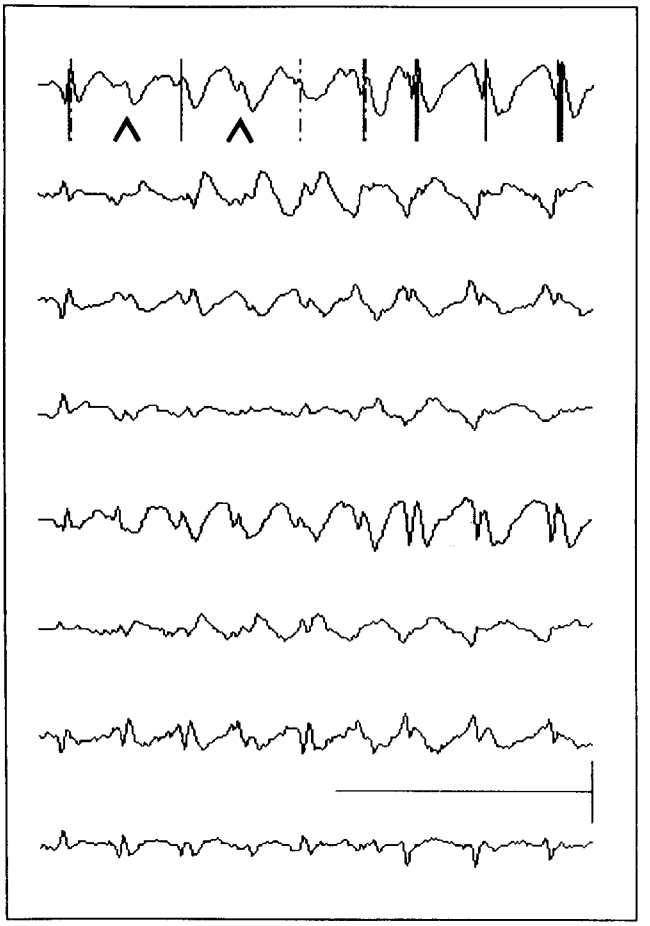

Fig. 4. Case 1. This is an example of 2 spikes (indicated by arrows) that the networks did not recognize at a level of certainty above criterion levels. In these examples the voltage change over the pre- and post-peak intervals was too small based on the training patterns chosen to train the networks (false-negative). The cumulative levels of certainty of each of the two spikes was 0.789 (left) and 0.760 (right). The lowest criterion level for recognition was 0.794 which is the same as in Fig. 1. Cal = 1 sec, 200 μV.

Changes in the time-course of the epileptiform complex was the next most frequent reason causing non-recognition. If the network had been trained exclusively with relatively fast spikes, slower sharp waves with smaller rates of change before and after the peak may well remain unrecognized (Fig. 5).

The selectivity of the networks was dependent on the user selected recognition threshold (level of certainty). When the network recognition threshold was high (output $\geq$ 0.9), the mean false-positive recognition rate was low (3.7% $\pm$ 6.8). False-positive recognitions increased (20.9% $\pm$ 22.6) at the lower recognition threshold (output $\geq$ 0.825). In the worst case this represented over 50% of the total recognitions by the network as compared to 3.6% in the best case. In 5 of the 7 cases false-positive recognitions did not exceed 10% at low recognition thresholds.

False-positive recognitions were most frequently encountered as a result of muscle activity. This was due

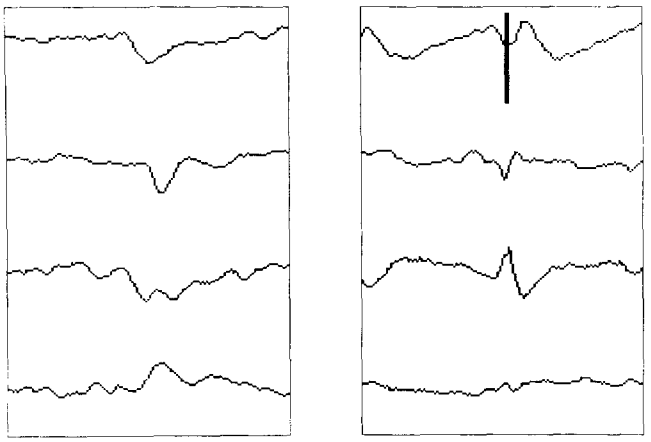

Fig. 5. Case 2. 1 sec segments of the same 4 EEG channels. A: example of a sharp wave unrecognized by trained network. B: example of a spike recognized by network with high level of certainty (> 0.900). The pre- and post-peak voltage slopes of the sharp wave in A are not as steep as those of the spike in B. The spatial distribution of the sharp wave is also a bit different from that of the spike. The difference in distribution has less effect on network output than the difference in slope.

in part to the inherent low pass filtering (40 Hz–3 dB) characteristics of the recording system. Low pass filtering results in integration of the signal which in practical terms changes very fast voltage changes into an envelope of slower voltage change. These slower potentials may have slopes similar to the SSW the networks are trying to identify.

Muscle potentials tend to occur in groups and it is usually during bursts of muscle activity that the voltage integration leading to false recognition occurs. Although several false recognitions may occur in one 3.5 sec data epoch it is likely that all the false recognitions are due to the same prolonged burst of muscle activity. When the number of epochs with only false-positive recognitions was compared to the total number of epochs recognized, the percent of epochs with only false-positive recognitions due to muscle activity was small (mean 3.3% $\pm$ 2.5).

Electrode artifacts due to electrode movement or imperfections ('pops') only rarely were recognized as epileptiform activity. So long as these artifacts did not occur in EEG channels manifesting the main portion of the epileptiform voltage field, false recognition occurred only exceptionally. If these artifacts were manifest in the electrodes recording from the most active epileptiform voltage field false recognitions did occur but represented less than 1% of the false recognitions.

Discussion

This study was designed to test the utility of artificial neural networks applied to automated identification of epileptiform activity in the EEG. Preprocessing of raw data was kept to a minimum to permit estimating the degree to which the network could apply its generalizing and variability tolerance properties to unmanipulated raw data. One major concession was made however, in order to reduce processing time. Features characteristic of the SSWs were calculated prior to presentation to the network.

We sought to identify a feature that reflected voltage magnitude and polarity as well as the change in voltage magnitude as a function of time that could be represented by a single value. The average slope of the voltage change over an interval indexed to the peak of the SSW fulfilled these requirements. Each input node of the networks then represented the spatial distribution of the average voltage slopes (over the user selected interval) of the recording channels.

In contrast, raw digital voltage values were used by an earlier application of artificial neural network technology to EEG pattern recognition. This required 210 nodes to evaluate 4 channels of EEG data (Eberhart et al. 1989). By comparison the current strategy utilizing preliminary feature preprocessing uses 2 networks with 17 nodes in each to evaluate 8 channels of EEG.

The pre- and post-peak voltage slopes have been recognized as one of the more reliable characteristics of epileptiform transients (Gotman and Gloor 1976; Gotman et al. 1979; Frost 1985) and have been successfully applied to non-network spike and seizure recognition strategies. The transition of the pre-peak slope to the post-peak slope has also been shown to be important (Saltzberg et al. 1967; Frost 1979) and sensitive. The transition at the peak or 'sharpness,' usually calculated as the second derivative of raw EEG data, is the difference of two sequential slopes. The sequential testing of pre- and post-peak slopes to determine cumulative network output was sufficient to determine whether the slope change at the peak was similar to the training patterns and a separate feature for sharpness was not calculated.

A different network was used for each spatial slope pattern for two reasons. First, and most importantly, this permitted independent manipulation of network parameters (number of nodes, different activation functions, organization of connections) and permitted the user (or program designer) to select the weight that each network would have in determining the cumulative level of certainty of recognition. Second, the use of two networks rather than one large network reduced the number of connections between nodes by almost one half (144 connections for two networks compared to 272 connections for one network) and thereby reduced computation time.

The benefits of being able to adjust the weighting of the output of each network was confirmed by sensitivity testing of the trained networks. Only rarely was the

sensitivity of the two networks to small changes of input very similar. Most of the time one network was more sensitive than the other in the range of $1:1 \pm 0.5$. Network sensitivity reflects, in part, the consistency of the feature used for training; in this case the voltage slope before or after the peak. As feature variability increases, the sensitivity decreases. Most of the time the pre-peak slope was more consistent (from one training pattern to the next) than the post-peak slope. This is intuitively satisfying because the onset of the epileptogenic event at the cellular level, as examined in animals with experimental epilepsy (the paroxysmal depolarization shift (PDS) (Matsumoto and Ajmone Marsan 1964)), is highly stereotyped while the duration and offset of the PDS is less predictable over time and in different neurons. In any case, it is not possible to predict which slope of the SSW will be most consistent in any particular patient. If there is any practical diagnostic significance to determining which slope is most consistent this is yet to be defined.

The program currently identifies a single pair of voltage slope distributions. Modifications of program design to test for 4 or more voltage slope distributions (for 2 or more spike foci) would require only duplication of existing strategies. The time required to test one time window would of course increase by approximately 0.4 msec per pair of voltage slope distributions. An increase in the number of recording channels would require only increasing the number of input and hidden nodes also increasing processing time.

The advantage of being easily able to select EEG features that are unique to specific patients carries with it the disadvantage of having to first identify a few wave forms to train the networks. This may be a time consuming task if relatively few epileptiform complexes are present in a prolonged recording. Identification of potential candidates for training patterns may be automated however, by utilizing a network structure and a training strategy that is designed to recognize SSWs in each of the channels (using multiple output nodes), but does not take spatial distribution into account resulting in poor specificity. Such a network has been designed and is currently being tested. As expected, these networks produce a relatively high number of false-positive recognitions since spatial features are not used as recognition constraints. Hierarchical constraints to differentiate artifact from SSW could replace in part spatial representation of the SSW. The need to identify only a handful of training patterns would make this process useful even if 50% of epochs containing recognized wave forms were epochs with only false-positive recognitions.

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