Multireference Adaptive Noise Canceling Applied to the EEG

Christopher J. James, Martin T. Hagan, Richard D. Jones, Philip J. Bones*, and Grant J. Carroll

***Abstract*— The technique of multireference adaptive noise canceling (MRANC) is applied to enhance transient nonstationarities in the electroencephalogram (EEG), with the adaptation implemented by means of a multilayer-perceptron artificial neural network (ANN). The method was applied to recorded EEG segments and the performance on documented nonstationarities recorded. The results show that the neural network (nonlinear) gives an improvement in performance (i.e., signal-to-noise ratio (SNR) of the nonstationarities) compared to a linear implementation of MRANC. In both cases an improvement in the SNR was obtained. The advantage of the spatial filtering aspect of MRANC is highlighted when the performance of MRANC is compared to that of the inverse auto-regressive filtering of the EEG, a purely temporal filter.**

***Index Terms*—Adaptive filters, electroencephalography, neural network applications, nonlinear filters.**

I. Introduction

The electroencephalogram (EEG) can be considered to consist of an underlying background process (assumed stationary and ergodic), with superimposed transient nonstationarities (TNS's) such as spike and sharp-waves (SSW's), electrode "pop," eye-blinks, and muscle artifacts. The detection of SSW's in the EEG is of particular importance in the diagnosis of epilepsy.

Methods for detecting SSW's have included mimetic methods [1], [2] and the use of template matching [3]. The lack of any definition of a SSW other than "transients clearly distinguished from background activity with pointed peaks at conventional paper speeds" [4] means that what constitutes the "ideal" SSW can vary amongst researchers. Instead of matching a single template, several authors have employed an artificial neural network (ANN) by training the ANN on a large number of known SSW's [5], [6]. Lopes da Silva *et al*. [7] used the method of modeling the (stationary) background EEG with an autoregressive (AR) prediction filter and detecting TNS's by examining the prediction error; the AR filter was calculated from a segment of the background EEG which is assumed to be stationary. The major drawback is that the stationarity assumption may not always hold true, leading to a large number of false detections.

The method described here comprises the first stage of a ANN-based system designed to detect SSW's in the interictal EEG. The system makes use of *multireference adaptive noise canceling*

Manuscript received August 16, 1995; revised April 1, 1997. The work of C. J. James was supported by the New Zealand Government under the Commonwealth Scholarship and Fellowship Plan. *Asterisk indicates corresponding author*.

C. J. James is with the Department of Electrical and Electronic Engineering, University of Canterbury, Private Bag 4800, Christchurch, New Zealand.

M. T. Hagen is with the School of Electrical and Computer Engineering, Oklahoma State University, Stillwater, OK 74075 USA.

R. D. Jones is with the Department of Medical Physics and Bioengineering, Christchurch Hospital, Christchurch, New Zealand.

*P. J. Bones is with the Department of Electrical and Electronic Engineering, University of Canterbury, Private Bag 4800, Christchurch, New Zealand (e-mail: bones@elec.canterbury.ac.nz).

G. J. Carroll is with the Department of Neurology, Christchurch Hospital, Christchurch, New Zealand.

Publisher Item Identifier S 0018-9294(97)05356-1.

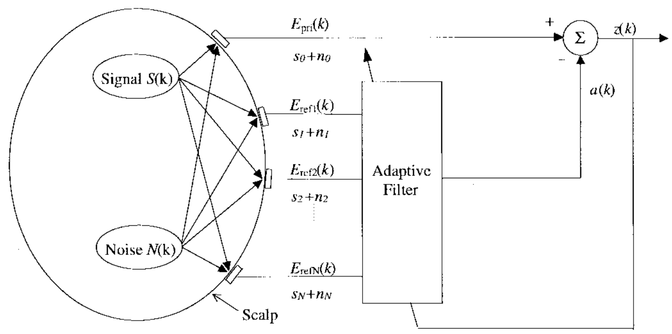

Fig. 1. Multireference adaptive noise canceller.

(MRANC), as described by Widrow *et al*. [8]. The background EEG on other channels in the multichannel EEG recording is used to adaptively cancel the background EEG on the channel under investigation. The use of a multilayer ANN to implement the MRANC filter provides the opportunity to model the EEG spatial distribution as nonlinear and leads to improved performance over the linear case.

II. Multireference Adaptive Noise Canceling

Multireference adaptive noise canceling [8] is illustrated in Fig. 1. The EEG signal is assumed to consist of a signal s_0 (here, modeling the TNS) contaminated by noise n_0 (here, modeling the background EEG) which is assumed to be uncorrelated with the signal. Each reference input $E_{\mathrm{refi}}(k)$ contains a noise signal n_i which is uncorrelated with s_0, but correlated with n_0. The adaptive filter adapts its parameters so as to produce an output signal a which is as close as possible to n_0. This output is then subtracted from the primary input, canceling the noise content n_0 but leaving signal s_0 intact. The adaptive filter continuously adjusts to minimize the output z. Any suitable adaptive algorithm which minimizes the output can be used; in particular, the least mean square (LMS) adaptive algorithm [8] can be used if the system is assumed to be linear. The LMS algorithm is employed in the work reported here to compare with the nonlinear ANN described below.

The reference inputs to the adaptive noise canceller may contain some signal components which are correlated to the signal at the primary input (Fig. 1). As the level of crosstalk increases, the performance of the noise canceller begins to deteriorate and the noise canceller not only cancels the noise at the primary input but begins to distort the signal component as well. It can be shown that as the number of reference channels is increased, the performance is improved, even in the presence of a limited amount of crosstalk on some of the channels [9].

Adaptation to temporal variation, as distinct from spatial variation, is incorporated by introducing a finite number p of delays at each reference input in the form of a tapped delay line. Thus for each reference channel E_{refi}, samples $E_{\mathrm{refi}}(k), E_{\mathrm{refi}}(k-1), \cdots, E_{\mathrm{refi}}(k-p)$ are input to the adaptive filter.

The adaptive filter is here implemented by means of a three-layer feedforward ANN, as an alternative to the LMS adaptive linear combiner. The ANN has $N(p+1)$ inputs (where N is the number of reference channels), an arbitrary number H of neurons in the hidden layer and a single neuron in the output layer. Each neuron

TABLE I
CHARACTERISTICS OF EEG SEGMENTS (SSW'S ARE CLASSIFIED AS DEFINITE, PROBABLE, OR POSSIBLE BY EEGER)

Patient	Montage	Duration (s)	SSW distribution	SSW classification		
				Def.	Prob.	Poss.
Patient #1	Longitudinal	24	Focal *(t5)*	3	2	5
Patient #2	Transverse	20	Focal *(t4)*	0	4	6
Patient #3	Circumferential	20	Focal *(o1)*	8	1	1
Patient #4	Longitudinal	20	Focal *(c4–p4)*	0	3	7
Patient #5	Longitudinal	20	Multifocal *(t4, c4–p4, c3)*	0	0	10
Patient #6	Longitudinal	20	Generalized	0	0	10

in the hidden layer has a log-sigmoidal nonlinear activation function while the single output neuron has a linear activation function. It can be shown [10], [11] that through the use of the backpropagation training algorithm the weights and biases of the three-layer ANN may be adjusted so as to minimize $z^2(k)$. To further optimize the performance of the ANN, the learning rate adaption procedure known as the "delta-bar-delta" learning rule is used [10].

III. METHODS

A. Data Collection

The EEG was recorded by scalp electrodes placed according to the International 10–20 system. Sixteen channels of EEG were recorded simultaneously both for referential and bipolar montages. The amplified EEG was sampled at 200 Hz, digitized to 12 bits and stored for later off-line processing.

B. Performance Index

As a means of measuring the performance of the system, the signal-to-noise ratio (SNR) is defined as the ratio of the peak-to-peak value of the SSW to the root mean square (rms) value of the background EEG for a number of samples on either side of the SSW, excluding the SSW itself. As the duration of SSW's is 70–200 ms [4], we have assumed a typical duration of 135 ms, corresponding to 27 samples at 200 samples/s. The peak-to-peak value S_{pp} is calculated from samples within the range ± 14 samples from the maximum negative peak. Finally, 30 samples (150 ms) on either side of the 27-sample-wide SSW are chosen to describe the immediate background EEG and to calculate the background rms value B_{rms}. The SNR is calculated by SNR $= S_{\mathrm{pp}}/B_{\mathrm{rms}}$. The primary performance index used is the percentage increase in SNR defined as

$$\Delta\mathrm{SNR} = \frac{\mathrm{SNR}_{\mathrm{new}} - \mathrm{SNR}_{\mathrm{old}}}{\mathrm{SNR}_{\mathrm{old}}} \times 100\% \tag{1}$$

where subscripts "old" and "new" refer to before and after filtering, respectively.

C. MRANC and ANN Parameters

Experiments were performed to determine the number of reference channels N, the number of delays to be considered for each reference channel p, and the number of neurons H in the single hidden layer of the ANN. To remove crosstalk it is preferable to choose reference channels as far as possible from the primary input channel. Conversely, the more distant a reference channel lies from the primary input channel, the less correlated the background EEG becomes with the primary channel and hence the more MRANC performance deteriorates. To determine the optimal combination of reference channels, the reference channels were put into three groups, N was varied for each group, and a number of tests carried out for each case. The channel containing the highest amplitude SSW's was made the primary channel. The reference channels were then grouped as follows: group A comprised the three channels closest to the primary channel, group B the four channels furthest from the primary channel, and group C all channels other than the primary channel.

A number of tests were carried out with H set at 2, 5, 10, and 20. Preliminary testing indicated that system performance was optimal for $p = 2$ and, hence, this was used for all subsequent tests.

D. Subjects

The system was tested on the epileptiform EEG's of six patients. Single segments of bipolar EEG, each containing ten SSW's (classified by an electroencephalographer as definite, probable or possible), were chosen from each patient (see Table I). The SNR of each SSW was calculated in the original recording. So as to test the system on a range of different SSW's, the EEG's chosen included both focal SSW's and generalized SSW's.

E. Autoregressive Prediction

For comparison with MRANC, the technique of autoregressive (AR) prediction as described by Lopes da Silva *et al.* [7] was applied to the primary channel EEG of each patient. In this method the EEG is considered as being the output of an AR filter having an input of white noise (normally distributed). Passing the EEG through the inverse of the estimated AR-filter should therefore result in normally distributed (white) noise, the prediction error. At any point at which the prediction error deviates from a normal distribution (at a certain probability level) a TNS is assumed to be present at the input.

The coefficients of the AR model were estimated by Durbin's algorithm (see Makhoul [12]) on the first 800 samples (4 s). The order of the estimated AR filter was set at $p = 15$, corresponding to that used by Lopes da Silva *et al.* [7]. The SNR of the known TNS's was measured (as in Section III-B) at the output of the inverse AR-filter and the percentage increase in performance calculated. Also calculated was a detection function [7] $d(k) = \sum_{m=k-2}^{k+2}[\frac{\hat{e}(m)}{\hat{\sigma}}]^2$, where $\hat{e}(k)$ is the prediction error of the inverse AR filter and $\hat{\sigma}^2$ is the variance of the prediction error. For a normally distributed $\hat{e}(k)$, $d(k)$ would have a χ^2 distribution with five degrees of freedom (d.f.)

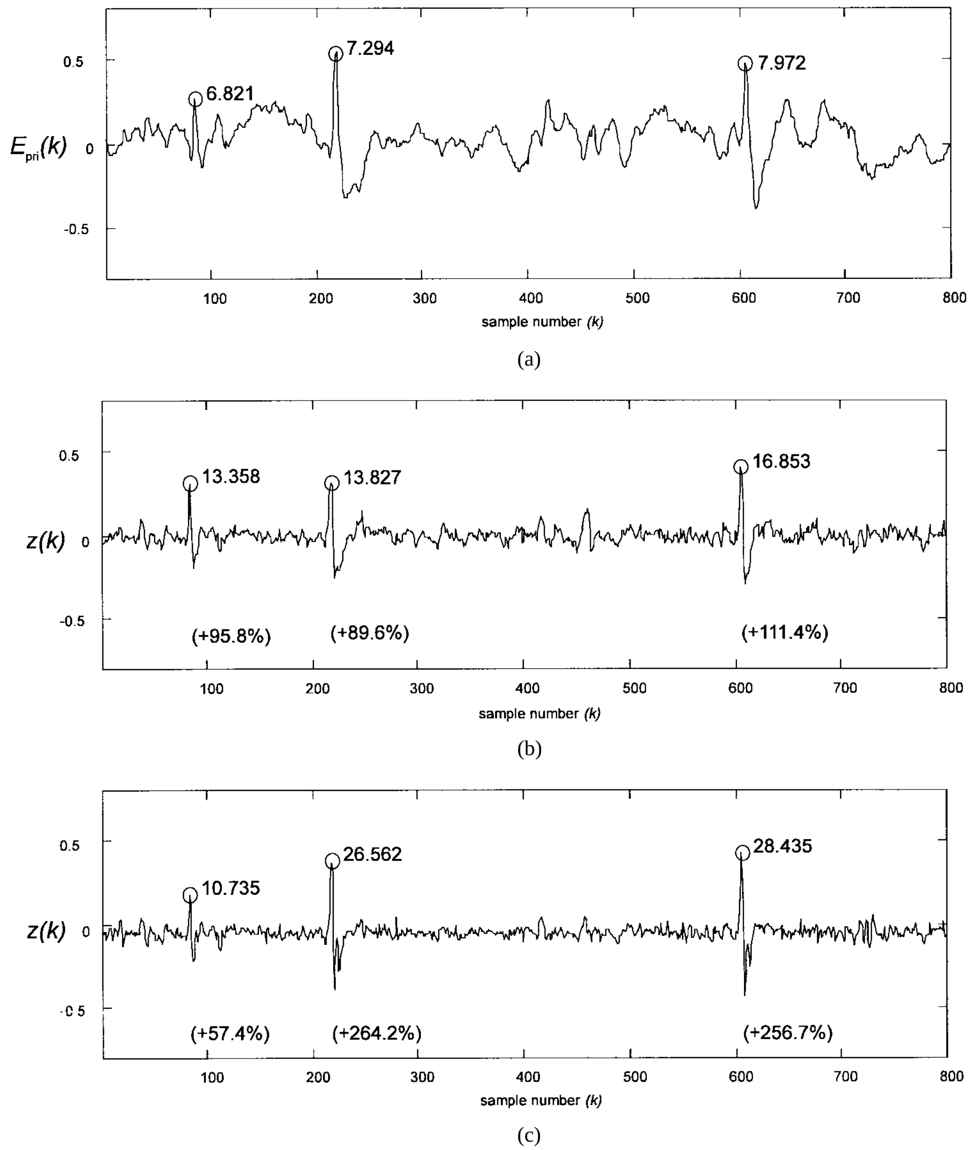

Fig. 2. Results of processing an 800 sample (4 s) epoch of signal for Patient #1 containing three SSW's. The primary signal was recorded at $t5$–$o1$ and references at $c3$–$p3$, $p3$–$o1$ and $t3$–$t5$. (a) The original signal and primary input to the MRANC filter—the SNR's of SSW's are indicated. (b) The output of the linear MRANC filter and (c) the nonlinear MRANC filter $(p = 2, H = 2)$. The percentage increase in SNR is indicated by the values in brackets.

[7]. A threshold D was set for $d(k)$ on the basis that $P(d(k) > D) < 0.001$; from tabulated values, $D = 20.5$.

IV. Results

On calculating the average performance of the MRANC over all six patients with each group of reference channels, with the number of neurons in the hidden layer varying from 2 to 20, for both linear and nonlinear implementation of MRANC, the following was observed: MRANC achieved an increase in the average SNR of SSW's in all patients for both linear and nonlinear configurations. However, in virtually every SSW tested over the six patients, the nonlinear MRANC configuration resulted in a significant improvement in performance over the linear configuration. Overall, increasing the number of neurons in the hidden layer above ten resulted in no significant improvement in performance. These results also show that performance increased slightly as more channels were included in the reference groups. Fig. 2 depicts a particular example of three SSW's in the EEG segment of patient #1.

Overall, linear MRANC resulted in an average performance of 76% ($p = 2$, Group C) and nonlinear MRANC 121% ($p = 2$, $H = 10$, Group C).

The performance of MRANC was superior to the inverse AR-filter output in terms of enhancement of SSW's by an average 18%. Fig. 3 illustrates inverse AR-filtering (with $p = 15$) applied to a single 3-s segment. The same segment was MRANC filtered (using reference group C, $H = 10, p = 2$) and subsequently inverse AR filtered, producing its corresponding prediction error and detection function. A threshold was set for the detection function of each case, Fig. 3(c) and (f), corresponding to a probability level of 0.001 for detecting the presence of TNS's. While the known TNS was detected in both cases, numerous false detections occurred for the "raw" EEG case. The SNR of the known TNS (SSW in this case) is shown in Fig. 3 both for the inverse AR-filtered EEG and the MRANC filtered EEG, along with ΔSNR in each case.

The MRANC filter can be considered to converge to a highpass filter (HPF) the characteristics of which varies with time and between EEG's of different patients. Fig. 4 shows the frequency response of

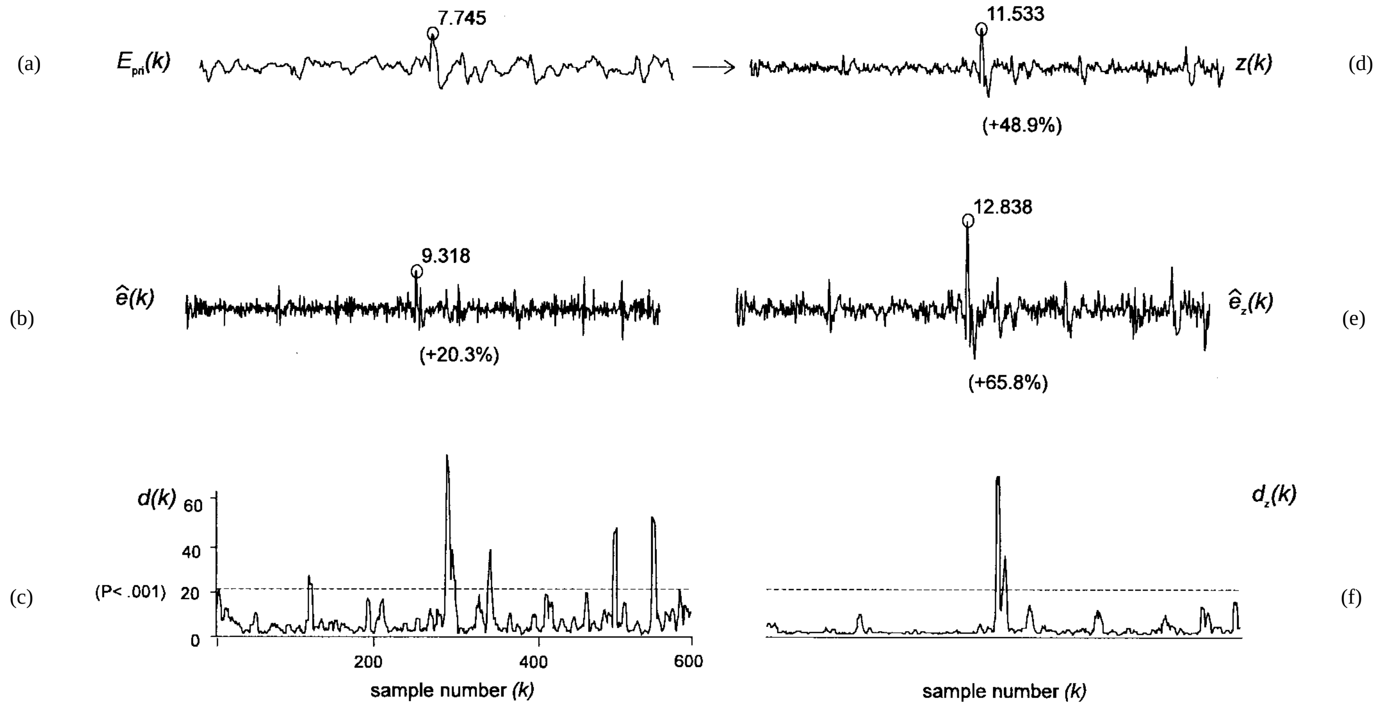

Fig. 3. Nonlinear MRANC and inverse AR filtering applied to a 3-s EEG segment. (a) The original EEG segment. (b) The prediction error from inverse AR filtering the "raw" EEG ($p = 15$), and (c) the detection function calculated from (b) with 5 d.f. (d) The MRANC filtered version (nonlinear) of the EEG (ref. group C, $H = 10, p = 2$). (e) The corresponding prediction error due to inverse AR filtering the MRANC filtered EEG ($p = 15$) and (f) the detection function from (e) with 5 d.f.

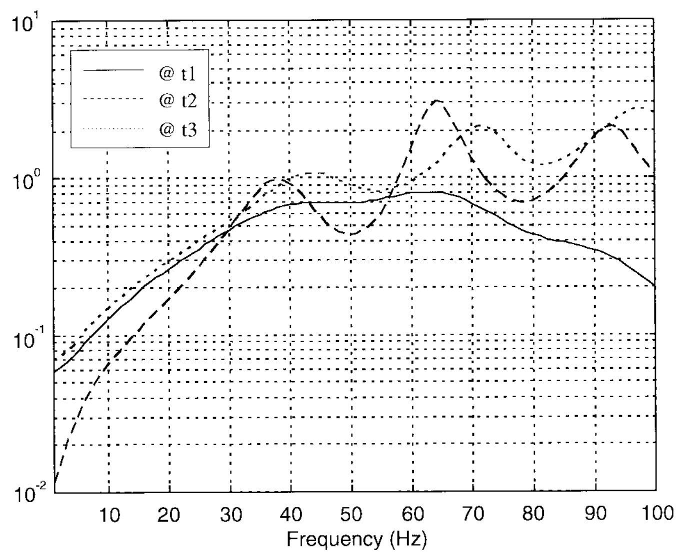

Fig. 4. Amplitude response of nonlinear MRANC filter (reference group C, $H = 10, p = 2$) at times $t1 = 500$ ms after SSW #1, $t2 = 900$ ms after SSW #2 and $t3 = 200$ ms after SSW #3 (see, Fig. 2).

the MRANC filter (with $H = 10$ and utilizing reference group C) at different instances in time through the EEG segment of Fig. 2. The figure highlights the variability with time of the filter characteristics.

V. Discussion

Implementing MRANC by means of an ANN allows the process to be modeled as nonlinear which has been shown to yield considerably better results than its linear counterpart (LMS). The adaptive nature of the MRANC filter also allows for variations in the background EEG's of different patients to be accommodated. Classification of the enhanced TNS's into epileptiform and nonepileptiform events is to be performed by a following stage. Our contention is that the classification process will be rendered considerably more accurate in terms of both sensitivity and selectivity by the prior attenuation of the background EEG.

The presence of signal crosstalk between the primary and reference channels is a significant factor affecting the performance of MRANC. In the case of EEG, maximum crosstalk is seen with generalized epileptiform activity such as, for example, in patient #6. Nevertheless, although MRANC did not perform as well for patient #6 as for the other patients, a substantial improvement in SNR was still achieved.

Another factor affecting MRANC performance is the correlation of the noise source between the input channels. Designating all channels other than the primary channel as reference channels (i.e., reference group C), confers a practical advantage in that it eliminates the need for arbitrary selection of reference groups dependent on a primary channel and montage for a particular EEG segment. Initially, it was thought that the choice of reference channels would prove the most important factor in the application of MRANC to the EEG, but this turned out not to be the case. Although increases in performance were seen as more reference channels were added, these were slight.

MRANC (with $H = 10$ and utilizing reference group C) performed better than the inverse AR-filtering method. The fundamental difference between the two approaches is that the AR-filtering method utilizes purely temporal information and relies on the nonstationary properties of TNS's to enhance their presence in the otherwise stationary background EEG, whereas MRANC utilizes spatial as well as temporal information (but, particularly the former) to enhance TNS's in the primary channel, with no prior knowledge of "signal" or "noise" characteristics required.

In conclusion, it is clear that MRANC can considerably enhance the presence of focal activity in the EEG and that the use of a nonlinear ANN in the application of MRANC improves the effectiveness of the process. By enhancement of transient nonstationarities, in particular spikes and sharp-waves, MRANC should provide an important first stage in the detection of epileptiform activity in the interictal EEG.

REFERENCES

[1] A. A. Dingle, R. D. Jones, G. J. Carroll, and W. R. Fright, "A multistage system to detect epileptiform activity in the EEG," *IEEE Trans. Biomed. Eng.*, vol. 40, pp. 1260–1268, 1993.

[2] J. R. Glover, Jr., N. Raghavan, P. Y. Ktonas, and J. D. Frost, Jr., "Context-based automated detection of epileptogenic sharp transients in the EEG: Elimination of false positives," *IEEE Trans. Biomed. Eng.*, vol. 36, pp. 519–527, 1989.

[3] J. Gotman, "Automatic recognition of interictal spikes," in *Long Term Monitoring in Epilepsy EEG,* Supplement no. 37, J. Gotman, J. R. Ives, and P. Gloor, Eds. New York: Elsevier, 1985, pp. 99–114.

[4] G. E. Chatrian, L. Bergamini, M. Dondey, D. W. Klass, I. Peterson, and M. Lennox-Buchtall, "A glossary of terms most commonly used by clinical electroencephalographers," *Electroenceph. Clin. Neurophysiol.*, vol. 37, pp. 358–548, 1974.

[5] A. J. Gabor and M. Seyal, "Automated interictal EEG spike detection using artificial neural networks," *Electroenceph. Clin. Neurophysiol.*, vol. 83, pp. 271–280, 1992.

[6] W. R. S. Webber, B. Litt, K. Wilson, and R. P. Lesser, "Practical detection of epileptiform discharges (ED's) in the EEG using an artificial neural network: A comparison of raw and parameterized EEG data," *Electroenceph. Clin. Neurophysiol.,* vol. 91, pp. 194–204, 1994.

[7] F. H. Lopes da Silva, A. Djik, and H. Smits, "Detection of nonstationarities in EEG's using the autoregressive model—An application to EEG's of epileptics," in *CEAN: Computerized EEG Analysis*, G. Dolce and H. Künkel, Eds. Stuttgart: Gustav Fischer Verlag, 1975, pp. 180–199.

[8] B. Widrow, J. R. Glover, J. M. McCool, J. Kaunitz, C. S. Williams, R. H. Hearn, J. R. Zeidler, E. Dong, and R. C. Goodlin, "Adaptive noise canceling: Principles and applications," *Proc. IEEE*, vol. 63, pp. 1692–1716, 1975.

[9] E. R. Ferrara and B. Widrow, "Multichannel adaptive filtering for signal enhancement," *IEEE Trans. Acoust, Speech, Signal Processing*, vol. 29, pp. 766–770, 1981.

[10] S. Haykin, *Neural Networks: A Comprehensive Foundation*. New York: Macmillan, , 1994.

[11] M. T. Hagan, H. B. Demuth, and M. Beale, *Neural Network Design*. Boston, MA: PWS, 1996.

[12] J. Makhoul, "Linear prediction: A tutorial review," *Proc. IEEE*, vol. 63, pp. 561–580, 1975.