REAL-TIME DETECTION OF EPILEPTOGENIC DISCHARGES USING AUTOREGRESSIVE PREDICTION

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ABSTRACT

An algorithm that detects epileptogenic discharges from the EEG and MEG signals of an epileptic patient in real-time has been developed using autoregressive prediction in conjunction with an adaptive binomial decision rule. This algorithm has been implemented on a personal computer system that performs the data acquisition and discharge detection and extraction functions. Testing with both simulated and real patient data has shown this method to be useful for real-time epileptogenic discharge detection.

INTRODUCTION

Epileptogenic discharges that occur in the electroencephalograph (EEG) and magnetoencephalograph (MEG) of epileptic patients can be used to localize the epileptogenic sources in the brain [4]. A real-time system has been developed for the automatic detection of these discharges, which include both interictal spikes and sharp waves, from the EEG and MEG signals of a resting patient in the Magnetoencephalography Laboratory of the National Institute of Neurological Disorders and Stroke (NINDS). This paper discusses one of several real-time detection methods which have been implemented for this clinical system.

DETECTION METHOD

The algorithm consists of an autoregressive prediction measure followed by a binomial decision rule, as illustrated in Figure 1.

Figure 1: Algorithm Structure

The autoregressive prediction measure attempts to predict the source signal, taking advantage of the fact that prediction is more effective on the background activity of an EEG or MEG than on an epileptogenic discharge. The error between the actual and predicted versions of the source signal forms a useful signal that enhances and emphasizes statistical aberrations such as discharges found in the source signal. The final detection signal, from which the binomial decision is made, is directly related to this error signal.

Figure 2 presents a block diagram of the measure as implemented in the real-time system. A configurable infinite impulse response (IIR) low-pass filter

removes high frequency artifact which can lead to false positive (FP) detections, producing signal $y[n]$, $n=0 \dots N-1$. The predicted approximation of $y[n]$ uses a set of prediction coefficients $\hat{a}_m$ which are generated with the autocorrelation method [2]. An estimate of the autocorrelation sequence of $y[n]$ is taken for $p+1$ lags, where p is the prediction model order ($p \ll N$).

$$r_m = \frac{1}{N} \sum_{n=0}^{N-m-1} y[n] \cdot y[n+m], \quad m=0 \dots p \quad (1)$$

By forming a column vector and a symmetric Toeplitz matrix from the r_m , the prediction coefficients can be found as a solution of the $\hat{a}_m$ to

$$\begin{bmatrix} r_0 & r_1 & r_2 & \dots & r_{p-1} \\ r_1 & r_0 & r_1 & \dots & r_{p-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{p-1} & \dots & \dots & \dots & r_0 \end{bmatrix} \begin{bmatrix} \hat{a}_1 \\ \hat{a}_2 \\ \vdots \\ \hat{a}_p \end{bmatrix} = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_p \end{bmatrix} \quad (2)$$

Durbin's algorithm solves for the $\hat{a}_m$ in equation (2), and has been selected because it is the most efficient solution for systems of equations of this type [5].

The prediction error filter generates error signal $e[n]$ by taking the difference of the signal $y[n]$ and its predicted approximation $\hat{y}[n]$.

$$e[n] = y[n] - \hat{y}[n] = y[n] - \sum_{m=1}^p \hat{a}_m \cdot y[n-m] \quad (3)$$

The source signal $s[n]$ consists of a Gaussian distributed ergodic process superimposed with nonstationarities (NSTs) such as epileptogenic discharges [2]. The NSTs are rare events and can be considered statistical aberrations. Because both the IIR LPF and prediction error filter are linear systems, $y[n]$ and $e[n]$ are also Gaussian distributed ergodic processes, in the absence of NSTs. Furthermore, $e[n]$ has zero-mean property because $E\{y[n]\} = E\{\hat{y}[n]\}$. The squaring operator transforms the distribution so that $e^2[n]/\sigma_e^2$ is chi-square distributed with 1 degree of freedom (χ_1^2). The final step of smoothing results in a detection signal $d[n]$ which is χ_q^2 distributed, barring NSTs in $s[n]$.

$$d[n] = \sum_{t=0}^{q-1} e^2[n+t]/\sigma_e^2 \quad (4)$$

The binomial decision sets a threshold ρ for the detection signal $d[n]$, and considers for detection only those points in $d[n]$ which exceed the threshold. Those points above ρ have failed the null hypothesis that no NSTs exist in $s[n]$. The significance level of the hypothesis test is determined by the value of ρ , which is chosen by the clinician. From the chi-square tables, there exists a point probability α related to the threshold parameter ρ by

Figure 2: Block Diagram of Autoregressive Prediction Measure

$$P(d[n] \geq \rho) \leq \alpha \quad (5)$$

Figure 3 illustrates the binomial decision rule. A window of width T_L (L points) slides across $d[n]$, and if the number of points greater than ρ within the window exceeds some set minimum K , a detection is registered at time t_0 . Because the decision finds K successes within a window of L points, the overall probability of a FP can be determined using the binomial formula.

$$P(FP) \leq \binom{L}{K} \cdot \alpha^K \cdot (1-\alpha)^{L-K} \quad (6)$$

After detecting the discharge at t_0 , the decision rule jumps T_{sep} before considering the next detection in order to prevent possible redetection of the same event. The normalization stage ($1/\sigma_s$) of the measure protects against detection of muscle artifact and other unwanted NSTs.

Figure 3: Binomial Decision Illustration

The authors considered a number of criteria for choosing model order p , and settled on a modified version of the Gersch criterion [1]. Defining E_p as the mean-squared prediction error (MSE of $e(n)$) for model order p over one analysis frame of N points, this criterion chooses the highest model order for which the improvement (decrease) in E_p over E_{p-1} is at least 5%. Testing this criterion on clinical EEG data resulted in a model order choice of 9. This result agrees with empirical testing as well as other considerations. An overspecified system overpredicts the NSTs, which deteriorates detection performance. Finally, timing considerations contribute to the model order choice, as processing time increases with model order.

Figure 4: Signal Flow Example

RESULTS

The system runs on a 80386 microprocessor based personal computer using commercially available data acquisition equipment. An elaborate user interface which includes a real-time plotting display provides a valuable tool for clinical evaluations. Figure 4 demonstrates the signal flow of one analysis frame of data which includes a discharge at time 46 seconds. The system can acquire a maximum of 64 channels and analyze up to 3 of these in real-time.

Simulated data has been used to quantify detection performance of true positives. By using a synthesized signal consisting of a triggered sinusoidal pulse (one cycle) as a discharge surrounded by a continuous Gaussian noise background, a priori conditions are established which allow the measurement of the rate of false negatives (FN). Table 1 summarizes the results of this testing procedure, where the signal to noise ratio (SNR) of the pulse to the background is varied, as is the frequency of the pulse. The table lists the number of detections out of 10 manually triggered "discharges" per setting.

SNR	frequency, Hz.						
	4	8	12	16	20	30	40
2	0	0	0	0	3	2	0
3	0	1	0	3	9	5	4
4	0	1	1	4	9	7	6
6	0	1	2	8	10	10	6
9	0	2	7	10	10	10	10

Table 1: Detection rate out of 10 trials vs. SNR and frequency using $p=10$ and $q=3$.

By using the threshold parameter ρ to control the rate of FPs, clinical testing on real patient data has provided satisfactory results. At $\rho=12.6$, FPs comprise between 5% and 10% of all detections. Control over the rate of FPs allows the system to detect those true positives which are of interest for further evaluation.

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