TIME-VARYING EVOKED POTENTIALS: MONITORING AND SIGNAL PROCESSING

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ABSTRACT

New monitoring instrumentation and signal processing methods are needed to record and analyze time-varying evoked potentials (EP) in neurological critical care environments. A personal computer-based data-acquisition system is used to deliver repetitive stimulation and digitize the EP signals continuously over several hours. Traditional signal processing approaches are moving window averaging and exponentially weighted averaging. Recently we have proposed adaptive signal processing methods: adaptive impulse correlated filtering, and adaptive Fourier and Walsh function modeling. These methods enhance the signal-to-noise ratio, and simultaneously track time-varying changes. The Fourier and Walsh function modeling approaches also identify incidence of injury from transient changes in the model parameters. Implementation of these algorithms in a real-time system would be useful in detecting injury to brain in neurosurgery and neurological critical care.

INTRODUCTION

Evoked potential (EP) monitoring is now being considered for continuous monitoring in neurological critical care environments [1]. Applications can be found in neurological surgery where for example, accidental occlusion of a cerebral artery or clipping of a nerve, may result in immediate injury to the brain. Continuously monitored EP signals may capture such an event and prevent permanent injury to brain.

Traditional approaches to EP signal processing utilize ensemble averaging or a posteriori Wiener filtering [2]. To monitor time-varying events, the signal processing algorithm must not only enhance the signal-to-noise ratio (SNR) rapidly but also adapt to time-varying changes and indicate those changes in the signal that may be of diagnostic significance. We have proposed adaptive filtering and adaptive signal modeling techniques for such applications [3-7].

METHODS

In the experiments reported here, the stimulator is programmed to repeatedly deliver stimuli over a span of several hours under the control of a personal computer. The EP signals are digitized sweep-by-sweep. Raw sweeps are then analyzed using a number of conventional and modern methods.

Moving window averaging (MWA) - An ensemble of desired number of sweeps is averaged to increase the SNR (ΔSNR = N, where are N are the number of sweeps). As each new sweep is acquired, the oldest sweep in the memory is discarded and a new average is obtained. A trade-off exists in that as more sweeps are averaged the SNR increases, but this also slows the adaptation time. A distinct disadvantage is that all N sweeps must be stored in the computer at any given time.

Exponentially weighted averaging (EWA) - A weighted proportion of each new sweep is added to the previous result. As each new sweep is added, the contribution of the older sweeps is proportionally weighed less and less. The weighting or the forgetting factor μ governs the SNR enhancement as well as the capability to follow time-varying changes:

$$\Delta SNR = (1-\mu/\mu)/[(1-(1-2\mu)^N)^2 / (1-(1-2\mu)^{2N})]$$

Adaptive filtering - The adaptive filter helps reduce noise by minimizing the MSE between two channels that have uncorrelated noise components. Thakor [3] used a noisy EP sweep as the primary input, and either a second noisy sweep or a previously ensemble averaged, relatively noise-free signal as the reference input (Fig. 1). The filter weights are adapted by the method of steepest descent (also called the least mean squares (LMS) algorithm): $\underline{W}_{k+1} = \underline{W}_k - \mu[\delta\varepsilon_k/\delta\underline{W}_k]$, where the filter weights at time k+1 are adapted from their past weights $\underline{W}_k$ and the gradient of the instantaneous error in the estimate ε_k (μ governs the adaptation rate). The filter simultaneously improves the SNR and adapts to transient changes. However, the overall performance is degraded at very low SNR and ensemble averaging is necessary to enhance the SNR.

Adaptive impulse correlated filtering (AICF) - A single unit impulse coincident with the stimulus is used as the reference for the filter in Fig. 1 [4]. The adaptation is by the LMS algorithm, as before. As a result, the filter acquires the impulse response of the EP signal generator. The improvement in the SNR is: $\Delta SNR = (1/M)[(1-(1-2\mu)^N)^2 / (1-(1-2\mu)^{2N})$, where M is the misadjustment error of the adaptive filter which tends to μ when $\mu << 1$. Therefore, the AICF performs in a manner very similar to the EWA method. However, the adaptive formalism allows very robust analysis of the adaptation properties and the steady-state errors resulting from this filter.

Adaptive Fourier series modeling (AFSM) - In order to obtain parametric description of the changes in EP signals, Vaz and Thakor [5] present the idea of modeling by a Fourier series. The reference input to the adaptive filter are the sine and cosine

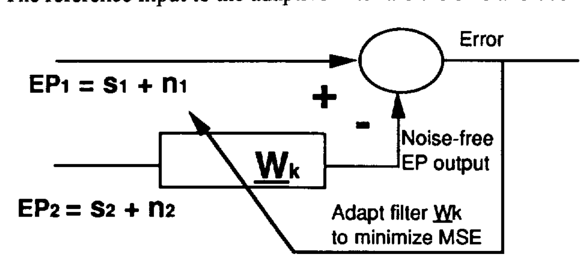

Fig. 1. Adaptive filter structure in [4]. For AICF, the reference input EP2 is only a unit impulse (stimulus) correlated in time with S1.

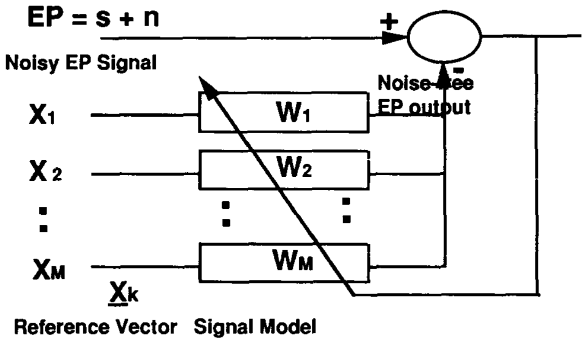

Fig. 2. Adaptive signal modeling. The reference vector is composed of sine and cosine functions in AFSM and cal and sal functions in AWFM. The signal model is constructed from the filter coefficients.

functions ($\underline{X}_k$), and the weights $\underline{W}_M$ of the filter are the Fourier coefficients to be adapted. Since the eigenvalues of $\underline{X}_k$ are identical, the adaptation is uniformly governed by μ ($\tau=1/2\mu$). The mean-square error (MSE) in estimation at the steady-state is approximately given by MSE $\simeq \mu\, \Sigma_m S(2\pi m/T)$ where S is the noise power spectral density at harmonic m, and T are the number of samples per sweep [5]. The output of the filter is the reconstructed EP signal in the time domain, while the weights of the filter are the Fourier coefficients. Time-varying changes in the Fourier coefficients provide the diagnostic information.

Adaptive Walsh function modeling (AWFM) - Another orthonormal set of functions, Walsh functions (cal and sal), may also be used as the reference vector [6]. The primary benefit of the Walsh functions is that they require significantly fewer calculations (M multiplications instead of 2M+1 needed by AFSM, where M are the number of coefficients employed). Simulations show that the steady-state error for AWFM is higher than for AFSM, but surprisingly, the adaptation time is slightly better for the same value of adaptation parameter μ.

APPLICATIONS

We have conducted several experimental studies to evaluate the performance of these algorithms. Thakor et al. [7] report a study of the transient neurological response of etomidate anesthetic in human subjects. They discovered that the EP signal amplitudes rose by 200-500% in about 100 s (Fig. 3). Poon and Thakor [8] report the application of adaptive filtering to monitor transient changes in EP signals when cerebral arteries are occluded in anesthetized animals. These experiments indicate that the signal processing methods will be valuable in neurosurgical procedures where acute injury to brain may occur due to inadvertent trauma to nerves or blood vessels. Timely detection may lead to actions that may reverse such injury.

In a recent study, we recorded response to progressive cerebral hypoxia in cats. The oxygen content in inspired gases was reduced from 100% down to 9%, after which the animal was returned to normal room air. Analysis using the AFSM technique shows that, as expected, the amplitude declined due to hypoxia and returned under normoxia (Fig. 4). However, the EP signals also show characteristic changes in spectral content. Specifically, the relative energy in the fundamental and the second harmonic was greatly increased during *early stages* of hypoxia. The lower harmonics also recovered most rapidly upon reoxygenation. We hypothesize that time-varying changes in the signal model, such as relative energy in various harmonic bands, may be used as an early predictor of neurological injury.

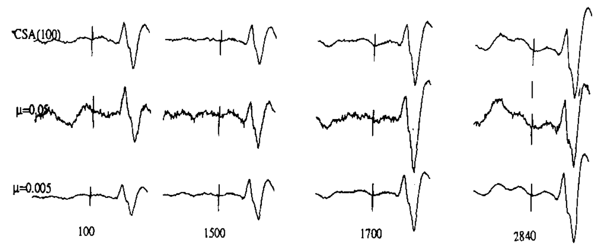

Fig. 3. Time-varying EP signals in response to etomidate anesthetic. The results from EWA (top trace) and ICAF (μ = 0.05 and 0.005) are compared.

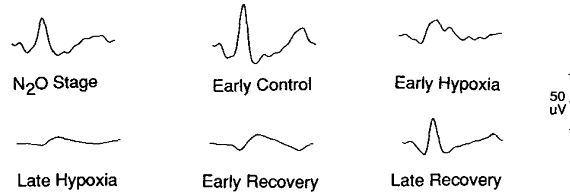

Fig. 4. EP signals recorded in response to progressive hypoxia and recovery. Analysis is done using the AFSM technique.

SUMMARY

Ensemble averaging still remains the method of choice due to its simplicity, robustness, and vast clinical experience gained with it. MWA and EWA may be used for time-varying EP signals, although EWA is preferred as it requires less memory for data storage. Adaptive filtering approaches allow SNR enhancement while also capturing time-varying changes in the signal model. The AICF is analogous to EWA but allows the use of the LMS formalism to govern its performance. FSM and WFM improve on these methods because they help detect changes in the signal model that may be indicative of neurological injury. These algorithms are well suited for implementation in real-time patient monitoring systems.

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