Detection of Human Nerve Signals using Higher-Order Statistics

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Abstract

Afferent, whole nerve signals recorded using an implanted nerve-cuff electrode were analyzed using three detectors based on the 1st, 2nd and 3rd order statistical properties of the signals. Results based on standard Rectified, Bin-Integrated (1st order statistical) processing are compared with two algorithms based upon a Singular Value Decomposition (SVD) of the signal's 2nd and 3rd order correlation (cumulant) matrices. Due to the very low signal levels obtainable from nerve-cuff electrodes and the high levels of interference from adjacent muscles, the overall signal-to-noise ratio (SNR) is very poor. In addition, the noise level is non-stationary. The inherent properties of the 3rd order statistics of these signals yield a detector that performs better than the other two.

1. Introduction

It has been known for more than 100 years that animal muscle tissue can be made to contract through application of electrical current. More recently, this has been applied in the development of Functional Electrical Stimulation (FES) systems, with the goal of restoring lost motor function in paralyzed individuals. More than 30 years of FES development have lead to the now generally accepted conclusion that, in order to reduce muscle fatigue and increase reliability, closed-loop systems, in which some sort of "feedback" information is used to control the stimulator's parameters, yield better results than simple open-loop systems. In restoring muscle function via FES, the goal is to emulate, as best possible, the body's lost natural functionality. Given the choice of using artificial sensors (goniometers, strain-gauges, accelerometers, etc.), versus utilizing the subject's still intact sensory system, the latter is likely to provide us with the closest emulation of the body's natural control system. In order for the body's natural sensors to be used effectively, the level of information obtained from them should be comparable to that obtainable from artificial sensors. This requires a reliable, stable, implantable transducer which is able to record the sensory signals (known as "afferent" nerve signals) being passed along the body's nerve fibers, from local touch receptors, to the brain. The only appropriate such device presently suitable for use in humans (where nerve damage must be avoided) is the *nerve-cuff electrode*. Such cuffs are typically constructed from a silicone insulating tube, in which 3 non-insulated rings of stainless-steel or platinum wire act as electrodes. The cuff, which is slit longitudinally, is opened, placed around the nerve, and sutured closed. Lead wires connecting to the ring electrodes are routed to an appropriate exit site and through the skin, where they are attached to an external connector. For our purposes, these electrodes are connected to a special high-gain (110,000x), low-noise amplifier. The resulting amplified nerve signal is commonly referred to as the Electroneurogram (ENG).

We have constructed a prosthetic device utilizing this ENG signal (a "neuralprosthetic") in which a custom designed DSP-based system controls an 8-channel FES stimulator. The entire device is small enough to be easily born by the subject, and uses standard rechargeable batteries. Natural sensory information can be applied to a variety of FES tasks. We have primarily been concerned with two: Hand Grasp Restoration in Tetraplegics, and Hemiplegic Drop-foot Correction. Tetraplegic subjects, who have limited use of their arms, are typically unable to firmly grasp objects. Through stimulation of the muscles in the hand and forearm, simple grasp functions can be restored, using the processed nerve signal as a feedback signal indicating when, due to insufficient stimulation, the grasped object begins to "slip". Subjects suffering from a "drop-foot" are unable to fully activate the muscles which rotate the foot up/down. Thus, because they can not achieve adequate toe clearance, they are unable to walk normally. Stimulation of these muscles can improve such subject's gait, provided it occurs at the correct time in the gait cycle. Timing has, traditionally, been determined via a mechanical switch placed in the subject's shoe, which turns stimulation off upon closure (heel-contact) and on upon opening (heel-lift). We have previously shown that the nerve signal recorded by nerve-cuff electrodes can be used as a sort of "natural" heel-contact switch, [2]. In

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both applications, *the fundamental problem is the reliable detection of the presence of nerve signal activity in background noise*. Essentially then, the problem reduces to one of pure *endpoint* or transition detection in the drop-foot application.

2. Considerations Specific to this Problem

There are certain aspects of the present problem (in the use of human nerve signals) that complicate detection:

• The *noise* is some non-deterministic combination of tonic nerve firing, electrode thermal noise, and amplifier $1/f$ noise. Although, in the strictest sense, due to the presence of background (tonic) nerve firing, this isn't pure *noise*, in practice, it is dominated by the thermal and $1/f$ components of the electrodes and amplifier. In order to fully activate the paralyzed muscles using FES, it is often necessary to apply stimulation voltage pulses in excess of 140V to the skin's surface. These pulses (typically under 300msec in duration) propagate through the body (acting as a volume conductor) and induce large stimulation *artifact* impulses in the recorded nerve signal. Also, the Electromyographic (EMG) signal from adjacent muscles, either naturally occurring though voluntary activation, or stimulation induced, acts as a high level noise source. In addition, external EMF sources (typically mains power) are often of sufficient intensity to induce large noise potentials. The nerve signal amplitudes typically recorded are in the 1-10 μVolt range for common sensory stimuli. Therefore, the initial SNR of these raw nerve signals is often as low as -60dB! Fortunately, it is known that the majority of nerve signal information is confined to a narrow frequency band, from 1.0 to 3.0kHz. Therefore, an important first step in the detection process is the application of a simple (non-adaptive) bandpass filter. This filter, combined with other processing (windowing, adaptive thresholding, etc.) yields nerve signals with typical SNRs in the range from 0 to +3dB.

• The nerve signals recorded by cuff-electrodes are dominated by the activity from what are termed *fast adapting* sensory receptors. These receptors respond, primarily, to the 1st derivative (i.e. velocity) of applied force. Consequently, during a period of activity, defined by the application of a mechanical stimulus to the skin within the nerve's innervation area, *only the onset and offset of contact initiate detectably increased nerve activity*. Thus, activity occurs in short *bursts* where it is usually not possible to distinguish between force application and force removal. The practical implication of this fact for the use of afferent nerve activity in a drop-foot correction system, is a contact *onset/offset ambiguity* that must be resolved by other means.

• All methods we have tried to-date rely upon a single variable test against a fixed *threshold*. When the value of the processed ENG signal is below the threshold level, the *null* hypothesis H_0 is true, and the present *state* (gait phase) is unchanged. Upon exceeding the threshold, the *alternative hypothesis*, H_1, is indicated, and the present state is toggled (i.e., an *edge* occurred). Of particular significance is the constraint that the number of False Positives (FPs), or erroneous edge detections be, essentially, zero. The consequences of an FP are that the stimulator will be erroneously deactivated while the leg is still in motion, sufficient toe clearance will not be maintained, and the subject may fall. Thus, the detection threshold must be set sufficiently high such that the FP percentage is low. Conversely, if the threshold is too high, resulting in missed detections, the stimulator will not be turned off during the *stance* (standing) phase, the subject's muscles will tire rapidly and, again, the subject may fall. Thus, ideally, the processed ENG signal, as the input to the threshold detector, should have a very high SNR (i.e. the signal amplitude during transitions should be high, while the background level during constant force presence/absence should be close to zero). Given low SNR inputs (+3dB max.), and very non-stationary conditions (variable foot contact pressures, variable gait cycle timing, plus variable muscle and external EMF interference signals), the demands upon the signal processing algorithm for robust ENG processing are, indeed, strict!

• Finally, it is important to note that this is an unconditionally *real-time* processing application. Most ENG processing algorithms have, up until now, primarily been designed to characterize the properties of afferent nerve-cuff recordings *off-line*, and typically used inherently non-real-time methods, such as ensemble averaging, to enhance SNRs. When real-time information is desired, the standard processing method still widely used is to bin-integrate (over the inter-stimulation pulse interval) the rectified, filtered signal. Commonly referred to as the RBI (Rectified, Bin-Integrated) signal, this yields, essentially a standard lp-norm detector (or the *energy* over a window, if the squared signal is integrated), based on the signal's 1st order statistics. Unfortunately, while simple to implement (even with analog circuitry), energy detectors perform poorly on low SNR signals, with non-stationary noise. In order to improve detection reliability, specifically for the drop-foot application, an adaptive noise threshold was incorporated into the standard RBI algorithm, along with a *windowed* detector, [7]. Using these modifications, we obtained an average detection ratio of 85%, with no FPs. Since this was deemed unacceptable, we began investigating more robust detectors, in which a fundamental criterion is the ability to reject non-stationary, wide-band (essentially white) noise.

It has previously been shown, [4], [5], that good detection reliability is achievable using second- and higher-order statistics (HOS) on speech signals with

SNRs in the range mentioned above. This observation has prompted us to investigate the performance of detectors used for speech signals in the present problem. There are many similarities between the problems of detecting speech in noise and nerve-cuff signals in noise, indicating that similar methods may be applicable. However, one fundamental difference between speech and nerve signals is the onset/offset ambiguity issue mentioned above.

2.1 Autocorrelation-based detectors

The first, more advanced, detector investigated is based upon the signal's 2nd-order statistical properties. The method is based on the fact that the autocorrelation matrix $\mathbf{R}$ of a signal that contains only white noise is *diagonal*, with all diagonal entries equal to the variance of the noise, σ^2. All (say Q) eigenvalues of this matrix are, therefore, equal to σ^2, as well. If an information (non-white) component is also present in the signal, then $\mathbf{R}$ is no longer diagonal, and consequently its (real, positive) eigenvalues are not all equal. Testing for the presence of activity in the signal thus becomes equivalent to testing for (non)equality of the eigenvalues of $\mathbf{R}$, *under the assumption that the additive noise is white*. Given that $\mathbf{R}$ can be estimated from a record of N samples through the observation matrix $\mathbf{X}$, as $\mathbf{R} = \mathbf{X} \bullet \mathbf{X}^T$, the singular values of $\mathbf{X}$ can be used for the test. These are obtained using a Singular Value Decomposition (SVD). It has been shown that a computationally efficient method of solving the SVD problem, when the data is real-only, is the use of the Jacobi rotation algorithm, [3].

The actual test is performed by comparing the *difference* or the *ratio* of the maximum and the minimum eigenvalues, not to *zero* or *one*, respectively (as would ideally be the case), but to appropriately set *thresholds*. In theory, a significant advantage of this detection method over the RBI (or energy) method is that it is immune to the noise level (variance). This is because the white noise variance acts as a DC offset in the eigenvalue domain, which doesn't affect the eigenvalue difference. In practice, this detector is much more immune to non-stationary noise levels than the RBI detector, and yields better detection SNRs. Yet, since it primarily acts as a *whiteness versus non-whiteness* test, it is sensitive to the *color* of the noise. Note that in our case a significant proportion of the noise is due to the amplifier's colored ($1/f$) noise.

2.2 Cumulant-based detectors

In order to overcome this limitation, detectors based on the higher-order statistics (HOS) of the data were also tested. The 3rd-order statistics of a signal provide a measure of the *skewness* (difference from the Gaussian distribution) in the signal's statistical distribution, whereas the 2nd order statistics (autocorrelation and spectrum) only provide information about the signal's variance. Detectors based on 3rd-order cumulants have been successfully employed for speech signals due to the fact that *quadratic phase coupling*, present in voiced speech due to non-linearities in the vocal tract, [4], [1], can be detected using 3rd-order statistics. Although a precise model for the signals recorded by nerve-cuff electrodes has yet to be developed, it has been shown, [6], that these signals result in the non-linear combination of a series of *action potentials*, themselves modeled by a non-linear combination of sinusoidal functions. Thus it seems reasonable to assume that, in analogy with speech signals, there are significant (i.e. detectable) non-linearities in nerve-cuff electrode signals. In this case, it can be proven that the 3rd order cumulant of such signals cannot be zero for all lags. Thus a detector, using a method similar to that employed in the eigenvalue-spread algorithm, can be designed using only this diagonal vector as follows:

The 3rd order cumulant of a record of data, $x(n)$, is computed as: $c_{3x} = (1/N)\sum_n x(n)x(n+\tau_0)x(n+\tau_1)$ for an appropriate set of *lags* (τ_0, τ_1), lying on the main diagonal ($\tau_0 = \tau_1$) of the 2-D plane. This is, essentially, equivalent to computing the autocorrelation of $x(n)$ and $x^2(n)$. The $Q \times Q$ Toeplitz matrix $\mathbf{C}_3$ is formed from the first Q diagonal lags (where Q is chosen empirically) and its SVD is computed, as in the 2nd order case. In the 3rd order case, however, it is sufficient to simply use the maximum eigenvalue (rather than the difference between maximum and minimum) as the single test parameter. In this case, we are testing the matrix entries against zero as an indication of the presence of skewed components in the data (here, noise is assumed to be colored, but non-skewed). In practice, the maximum eigenvalue is compared against an empirically determined threshold.

The 3rd order method requires slightly more computations than the 2nd order case; yet, it is substantially less sensitive to additive (non-stationary) noise variance than either the RBI or 2nd order methods. This is important in a neuralprosthetic application where noise levels (and signal properties in general) vary not only amongst applications (i.e. the nerve used, its size, the size of the cuff electrode, etc.), but also amongst patients, and even with the time after implantation. Finally, the storage requirements of both the 2nd and 3rd order algorithms are well within the bounds of the *on-chip* memory of most commercial DSPs in contrast to most frequency domain (FFT or wavelet) methods, which generally require the addition of external memory. This is an important consideration for portable (or implantable) systems, where low power consumption is essential.

3. Results, Discussion and Conclusion

Figures 1 and 2 show a comparison of the 3 algorithms described, under non-stationary noise conditions. In Figure 1, linearly increasing white-noise (up to 100% of nominal) was added to a typical afferent nerve-cuff (ENG) signal in the region from 6000 to 10000 samples. The increased amplitude between samples 3000 and 5000 corresponds to increased nerve activity resulting from a single mechanical stimulation of the skin in the innervated area. This is also indicated by the arrow in Figure 2. The ordinate is in Volts. The nerve-cuff output signal was amplified by 220,000, filtered with a 4th order Butterworth bandpass (500Hz-3kHz) filter, and digitized to 12-bits (±5V range) using a sampling frequency of 10,000Hz.

Figure 2 shows detection results when the 3 detectors are applied on the noisy signal in Figure 1. Note that all three detect the true ENG activity (arrow), although the noise baseline, which defines the SNR of the detector (since the data is normalized to the peak value), is highest for the RBI detector and lowest for the cumulant detector. Thus the cumulant detector yields the highest SNR and the RBI detector the lowest, with the eigen-spread detector's SNR falling in between. As is evident in Figure 2, the SNR of the RBI detector decreases markedly with increased noise power. Both the eigen-spread and cumulant detectors continue to function at 100% added noise power.

In order for a natural sensory based device to be accepted in clinical applications, the amount of parameter adjustment required by the user (or physiotherapist) must be minimal. This has proven to be a severe drawback with RBI based detectors. Although we have obtained reasonable success by adding adaptive noise thresholding to the basic algorithm, we have not yet achieved a truly robust RBI implementation that does not require frequent parameter adjustments. Although it cannot be claimed that HOS offer the best solution for all types of signals, our preliminary results show that they hold great promise in the detection of afferent nerve signals in noise. Further improvements are anticipated through the use of (i) automatic thresholding based on a fixed, specified FP ratio, or (ii) a bi-frequency domain bi-coherence magnitude/phase detector, [1]. Further characterization of the statistical properties of nerve-cuff signals will be required to fully optimize future detection algorithms.

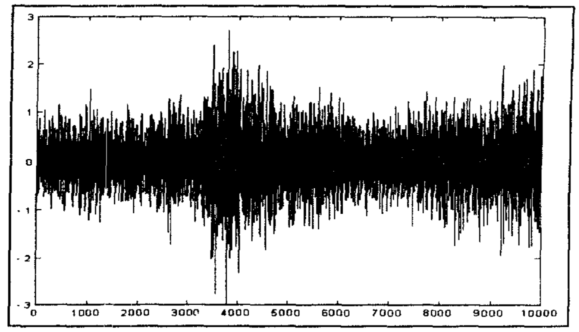

Figure 1. ENG signal plus white noise

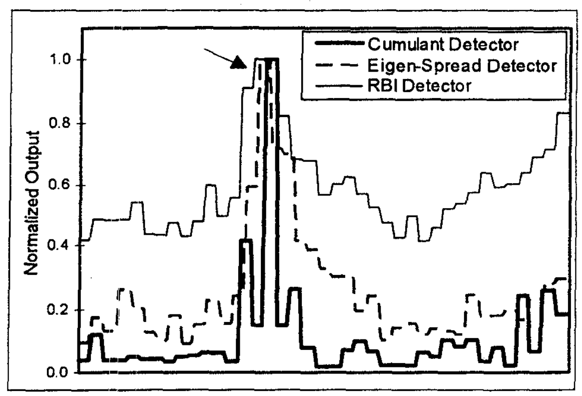

Figure 2. Results from the three detectors

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