18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam 1996
5.7.5: Nerve and Muscle Action Potentials

SVD and Higher-Order Statistical Processing of Human Nerve Signals

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ABSTRACT

Human, afferent, whole nerve signals recorded using an implanted nerve-cuff electrode were analyzed using two algorithms based on the statistical properties of the signals. The processing method typically described in the literature (Rectification and Bin-Integration - RBI) has serious shortcomings in processing these signals, which have very poor signal-to-noise ratios. Algorithms based on a Singular Value Decomposition (SVD) of the signal's 2nd and Higher-Order Statistics (HOS) have resulted in more robust signal detection. Reliable detection of afferent nerve signals is essential if such signals are to be of use in artificial sensory-based Functional Electrical Stimulation neuralprosthetics.

INTRODUCTION

It has been demonstrated that afferent nerve signals can be used as a replacement for artificial sensors (switches, strain gauges, etc.) in Functional Electrical Stimulation (FES) neuralprosthetic devices, [1]. Unfortunately, these signals are difficult to use in practice since they are plagued with high background noise levels, resulting in poor overall signal-to-noise ratios (SNRs). We present two advanced signal processing algorithms, both based upon signal and noise subspace orthogonal decompositions using the signal's statistical distribution. The first algorithm, which is based on a 2^{nd} order signal statistic (autocorrelation), is quite similar to the well known "super-resolution" algorithms (MUSIC, for example). The second algorithm is based on a Higher Order Statistic (HOS) of the data. Both utilize a Singular Value Decomposition (SVD) to perform an orthogonal decomposition and derive an eigen-spectrum. As a baseline, both are compared to the standard processing method most frequently employed in nerve signal analysis.

METHODS

Afferent, whole nerve signals were recorded from the *calcaneal* nerve of a patient afflicted with a mild, Multiple Sclerosis induced "drop-foot", using an implanted nerve-cuff electrode, in accordance with the guidelines suggested by the local ethical committee. These nerve signals are intended to be used as a replacement for an external heel-contact switch in controlling a drop-foot correction FES neuralprosthetic. The output of this switch and the raw (unprocessed, amplified) nerve signal were recorded simultaneously, during stimulation assisted gait. The raw signal was digitally filtered, and stimulation artifacts removed, as described in [2]. This signal was Rectified and Bin-Integrated (RBI) to produce the baseline signal for comparison. In addition, an estimate (using the first 10 lags) of the standard, Toeplitz, autocorrelation matrix, **R**, was computed using a block of 512 data samples. It is well known that, if an orthogonal decomposition of this matrix is performed using a Singular Value Decomposition (SVD), then the resulting singular (eigen) values provide an ordered measure of the relative importance (in a least-squared energy sense) of the principal signal components in the eigen-spectrum domain, [3]. The eigenvalue-spread (the difference between the largest and smallest eigenvalues) can be used as a measure of the separation of the signal and noise subspaces. A small spread means that there is little statistical difference between the orthogonal signal components, indicating a purely stochastic (i.e. noise-only) signal. Conversely, a large spread points to the presence of a signal component (i.e. the signal+noise case). This is readily explained by noting that an eigen-decomposition of a purely "white-noise" signal yields a single degenerate eigenvalue. Thus, in the ideal noise-only case, there is no spread. Due to the linearity property, the noise component simply adds an offset (corresponding to the noise variance) to all of the eigenvalues when a signal (non-stochastic) component is present, and is, therefore, removed when the eigen-difference is computed.

Unfortunately, this separation of noise and signal+noise subspaces is complicated when the noise is "colored" (non-white). Although methods for modifying the standard 2^{nd} order decomposition methods have been described (pre-whitening, for example), another solution is the use of a higher-order (greater than 2^{nd}) statistic of the signal as a basis for a subspace decomposition. It can be shown that the 3^{rd} order cumulant (which is equivalent to the 3^{rd} moment for zero-mean signals) is immune to the contribution of all symmetrically distributed signals (Gaussian, or otherwise), [4]. Thus, 3^{rd} order cumulants provide a measure of the "skewness" (difference from a symmetric distribution) of a signal. Like 2^{nd} order statistics, cumulants are also linear operators (i.e. additivity holds). Therefore, the 3^{rd} order cumulant of a signal+noise space is equal to the sum of the individual cumulants of the signal and noise subspaces. However, if the distribution of the noise subspace is symmetric, as is the case with the ENG signals analyzed (where the noise follows a Gaussian distribution), then it is suppressed in the 3^{rd} order cumulant domain. It is important to note that this noise suppression also holds for colored noise sources, such as the typical amplifier's $1/f$ noise.

As with the 2^{nd} order subspace decomposition method, it is possible to use an estimate of the true 3^{rd} order cumulant value, obtained by selecting an appropriate subset of the 2-D cumulant matrix. First, a vector, c_{3x}, is computed from the first Q *lags* (τ_0, τ_1), along the main diagonal ($\tau_0 = \tau_1$), where Q is determined empirically (typically $10 \leq Q \leq 20$), using:

$$c_{3x}(\tau_0,\tau_1)=(1/N)\sum_n x(n)x(n+\tau_0)x(n+\tau_1)$$

This is equivalent to computing the autocorrelation of $x(n)$ and $x^2(n)$, when $\tau_0=\tau_1$ (N=512). Next, a Toeplitz matrix $\mathbf{C}_3$ is formed (analogously to the 2nd order **R** matrix), and it's maximum eigenvalue computed. Since, given an accurate estimate of c_{3x}, the minimum eigenvalue (corresponding to the noise subspace) should, ideally, be zero, it is sufficient in this case to compute only the maximum eigenvalue for use in discriminating the noise-only and signal+noise cases, [5].

RESULTS

Figure 1 compares the performance of the 3 algorithms when applied on human nerve signals recorded during FES assisted gait. The traces, from the top show: 1) the output of a mechanical heel-contact sensor placed in the subject's shoe where a "high" level indicates stance phase; and the outputs from the 2) RBI, 3) 2nd order, and 4) 3rd order detectors, respectively. Note that, because the cuff-electrode primarily records signals from Fast Adapting (FAI) receptors, the raw signal contains short "bursts" of activity, corresponding to the change (derivative) of the applied mechanical stimuli. This is evident in the output from all three processing algorithms as a marked increase in level within a short window around the onset/offset of heel contact (the "edges" on the top trace, indicated with dashed lines). It is also important to point out that it is possible to obtain a real-time implementation of all three of these processing algorithms using a portable neuralprosthetic system based upon a commercial Digital Signal Processor (DSP), [2].

DISCUSSION

It is evident from Fig. 1 that the RBI (1st order) algorithm has very poor noise rejection ability, which results in a poor SNR in the processed signal (i.e. the activity "peaks" which occur during edges are not much greater in amplitude than the "background" activity). This is as expected, since there is no separation of signal and noise spaces using this method (i.e. signal and noise contribute with equal weighting to the final result). The situation is improved in the 2nd order case, where signal and noise subspaces are, in the ideal case, completely separated (orthogonal). In practice, as can be seen, this is not the case. Although the noise floor is lower (or, conversely, the signal peaks higher), resulting in a correspondingly higher SNR, noise is not completely rejected. This can be explained by 1) the non-ideal (non-white) nature of the noise, and 2) the use of a subset (approximation) of the complete subspace decomposition. These limitations are, largely, overcome by the 3rd order algorithm. It's output closely resembles the ideal case (the derivative of the "square-wave" heel-contact signal). Here, the noise floor is negligible, resulting in a very high SNR, which, in turn, yields more reliable detectors. Such detectors can either be based upon a threshold comparison (the simplest case), or more complex analysis methods (Adaptive Neural or Logic Networks, Hidden Markov Models , etc.).

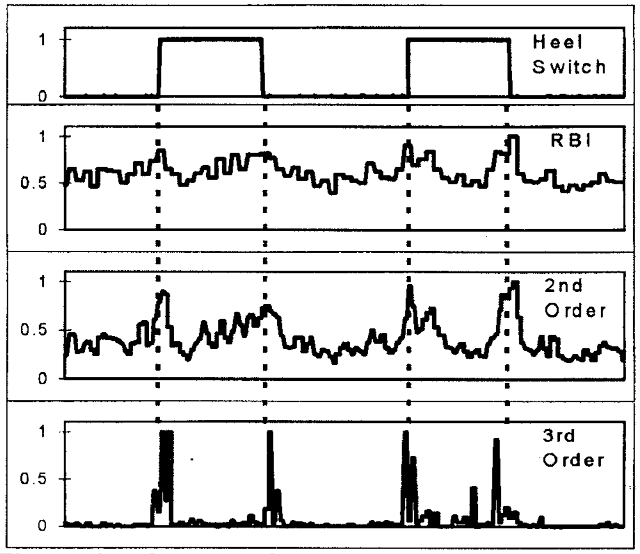

Figure 1 - A comparison of the results from the three algorithms using data from FES assisted gait.

CONCLUSION

In order for natural sensory signals to be truly applicable in FES neuralprosthetic devices, robust signal processing algorithms must be developed to cope with poor SNRs and non-stationarity, yielding reliable signals under a variety of "real-world" conditions. Such devices should simply "work", without requiring frequent parameter adjustments or user interaction. Given the state-of-the art of cuff-electrodes, and the "poor" signals obtainable from them, standard processing methods prove inadequate. We have demonstrated that subspace decomposition methods based on the statistical properties of nerve signals can be used to improve the situation markedly, yet are simple enough to be implementable within a realistic hardware and power consumption budget on commercial or custom DSP devices.

ACKNOWLEDGEMENTS

Special thanks to *The Danish Foundation for Physical Disability*, *The Danish National Research Foundation*, and *The Danish Ministry of Industry* for their financial support.

REFERENCES

[1] Haugland M., Hoffer J., Sinkjær T., "Skin Contact Force Information in Sensory Nerve Signals Recorded by Implanted Cuff Electrodes," *IEEE Transactions on Rehab. Engineering*, vol. 2, no. 1, pp. 18-28 (1994).

[2] Upshaw B., Sinkjær T., "Natural vs. Artificial Sensors Applied in Peroneal Nerve Stimulation", *Proc. of 5th Vienna International Workshop on Functional Electrostimulation*, pp 239-242 (1995).

[3] Haykin S., "Adaptive Filter Theory," 2nd Edition, pp. 418-428, Prentice Hall (1991).

[4] Nikias C., Petropulu A.., "Higher-Order Spectra Analysis," pp. 7-122, Prentice Hall (1993).

[5] Rangoussi M., Carayannis G., "Adaptive Detection of Noisy Speech using Third-Order Statistics," *Intl. J. Adapt. Contr. & Sig. Proc.*, Special Issue on HOS, Dec. 1995.