LEARNING STIMULUS ARTIFACT GENERATION IN SURFACE RECORDINGS OF SOMATOSENSORY EVOKED POTENTIALS

B. H. Boudreau (1), K. Englehart (1), D. Lovely (2)
(1) Institute of Biomedical Engineering, University of New Brunswick, Fredericton, NB
(2) Department of Electrical and Computer Engineering, University of New Brunswick, Fredericton, NB

Abstract - Surface recordings of somatosensory evoked potentials pose a challenging problem as the desired signal is obscured by stimulus artifact. A widely used approach for artifact reduction is adaptive noise cancellation, where an adaptive filter is used to map a primary signal to a reference signal. A major drawback of this technique is the dependency on temporal generalization. We propose a novel approach to artifact reduction that attempts to learn the process of artifact generation as the stimulus pulse amplitude increases.

INTRODUCTION

Somatosensory evoked potentials (SEPs) propagate through central or peripheral nerves in response to external stimulation and convey valuable information about the integrity of the nervous system. An electrical pulse can provide the external stimulation required to evoke a SEP, if the magnitude is above a certain threshold level, known as supra-threshold stimulation. A SEP is not evoked if the level of the stimulating pulse is below the threshold level, known as sub-threshold stimulation. Once evoked, the SEP propagates along the nerve away from the stimulus and can be measured either invasively with needle electrodes or a nerve cuff, or non-invasively using electrodes at the surface of the skin. The non-invasive technique is preferable because it is more comfortable for the patient and has a reduced risk of infection, but poses a challenging measurement problem as the observed SEP signal is often obscured by stimulus artifact (SA). The SA is a product of the stimulation process [7], which is difficult to separate from the SEP because the SA is much larger than the SEP, is synchronous with the SEP, and overlaps the SEP in both time and frequency [4,5,7,10]. Thus, time windowing and frequency filtering cannot be used as a means of removing SA without distorting the SEP. The SA is also coherent with the SEP and therefore cannot be reduced with ensemble averaging [6,8].

A widely used approach for post-measurement SA reduction is adaptive noise cancellation [3,9]. In this approach, two channels of data are acquired: the primary channel, which contains the SEP corrupted by the SA, and the reference channel, which contains only the SA. Using the reference channel as the input to the adaptive filter, the filter predicts the SA in the primary channel. If the prediction is accurate, subtracting the adaptive filter output from the primary channel results in a clean SEP.

In order for the adaptive filter to properly predict the SA in the primary channel from the SA in the reference channel, the adaptive filter must be trained first. The training technique commonly used is known as segmented training [9], which only uses the first portion of the primary and reference channel waveforms. This is to ensure that the primary channel does not contain the SEP during training; otherwise the adaptive noise canceller would eliminate both the SA and SEP. Once training is complete, the entire reference channel waveform is provided to the adaptive filter to predict the entire SA in the primary channel. With segmented training, not only does the adaptive filter have to learn the relationship between the reference and primary channel but it must also generalize in time to portions of the waveform that were not provided during training.

The need to provide temporal generalization is a major drawback of the segmented training technique.

METHODS

This investigation proposes a novel approach to SA cancellation, addressing both the challenge of learning the nonlinear relationship between SA in the reference channel and SA in the primary channel as well as the problem of temporal generalization. Instead of mapping a reference signal to a primary signal, an adaptive filter is used to learn the relationship between the stimulus pulse amplitude and the corresponding SA waveform generated.

The input to the adaptive filter is the stimulating pulse, the target is the SA waveform observed at the recording site, and the output is an estimate of the SA waveform observed at the recording site. The first task of the SA cancellation scheme is to learn the process of SA generation during sub-threshold stimulation, where only SA is present. It has been shown [5,7,9] that the SA changes in a nonlinear fashion as the stimulus level varies, since it is known that the impedance of the skin/electrode interface changes with current density. We propose an adaptive system that will learn the nature of the nonlinear change in SA as the level of stimulus is increased from a small value, to levels that approach but do not exceed the stimulus threshold.

Because supra-threshold responses contain SEPs they cannot be used for training. Indeed, it is the supra-threshold response that is used to recover the SEP, once the adaptive element has been trained to learn the relationship between the stimulus pulse and the resulting SA. The assumption here is that, having seen many (five to fifteen) examples of stimulus pulse/SA pairs in the sub-threshold training set, the adaptive element will be able to generalize this relationship to stimulus pulse/SA pairs at supra-threshold levels. This, we believe, is a reasonable assumption, as there is no reason to expect that the process of SA generation at supra-threshold levels differs from that at sub-threshold levels. This approach has some distinctive advantages to the segmented training approach:

1. The entire sub-threshold waveform is used in adaptation. This means that no temporal generalization is necessary;
2. Several sub-threshold level stimulus pulse / SA pairs are given to the adaptive element, as compared to a single example sub-threshold in the segmented training approach. This allows the adaptive element to learn much more about the nonlinear nature of SA generation; and
3. Occasionally, the interference due to the SA can exhibit odd characteristics, such as an extended DC offset or oscillatory behavior. Previous cancellation methods are ill-suited to remove these effects, but the proposed approach should be capable of modeling, and therefore, removing this interference.

The choice of adaptive element is essential to the success of the proposed method. The problem is that of modeling an impulse response of a system that changes nonlinearly with the amplitude of the impulse. This suggests a class of adaptive systems collectively referred to as *dynamic neural networks*, which explicitly incorporate memory in their architecture. These dynamic networks are particularly well suited to modeling temporal structure in dynamical systems. The most widely used form of dynamic neural network is the time-delay neural network (TDNN), which incorporates memory in the form of a filter structure in the input layer of the network. The TDNN architecture has shown exceptional performance as pattern classifier and as a time-series predictor [12,11,2]. The architecture and the training regimen of dynamic structures under investigation must be optimized for this application. This includes the number of hidden layers, the number of neurons in these layers, the training algorithm, and schemes that may enhance performance, such as weight elimination and data pre-processing.

Prior to applying the proposed method to actual data, a simulated data set was used [1]. This was done to develop a preliminary architecture for the TDNN estimator and to quantify the estimation error since this is not possible with real data, as the true SEP waveform is unknown. The data were applied to a two-layer TDNN and the performance measure of the residual error of the SEP waveform after SA cancellation was calculated to validate the effectiveness of the TDNN to cancel SA. The performance was then compared to the segmented training technique [3], with a neural network adaptive element.

After the analysis on the simulated data, real data were acquired from seven healthy subjects with no known neuromuscular disorders, both female and male, between the ages of 20 and 33. The general setup of SEP acquisition is depicted in Figure 3, in this case illustrating the measurement of a SEP from the median nerve.

At least ten SA waveforms were acquired at sub-threshold stimulation for each subject as the stimulus pulse amplitude increased by 1mA. Between five and ten SA waveforms were acquired at supra-threshold stimulation for each subject as the stimulus pulse amplitude increased by 2mA. The data were sampled at 25.6KHz and 400 exemplars were collected for each stimulus level. The results were then ensemble averaged to reduce most of the uncorrelated noise, including EMG, instrumentation noise, and 60Hz interference [6,8].

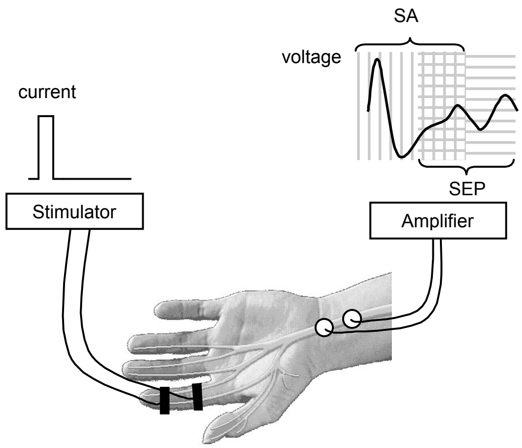
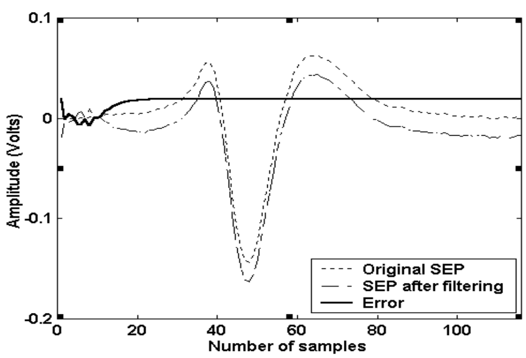


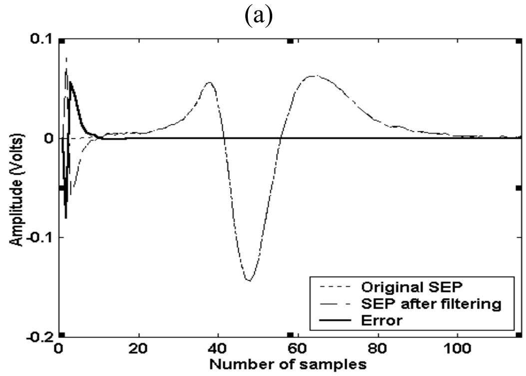
Figure 3 – SEP acquisition, and SA interference

RESULTS

To assess the performance of SA reduction in the stimulated data set, a qualitative analysis was conducted on the output waveform. The original SEP waveform was subtracted from the SEP waveform acquired after filtering and the error produced was plotted. Results when using both approaches is shown in Figure 5.



(a)



(b)

Figure 5 – SA cancellation on simulated data: (a) segmented training technique (b) TDNN

It can be seen that the TDNN was more successful in reducing SA than the segmented training technique because the error was closer to zero when using the new training scheme.

The mean squared error (MSE) between the known SEP and the predicted SEP was computed using the proposed method and the segmented training technique. The new approach, using SA waveform modeling, outperformed the segmented training approach for every level of stimulus. As one might expect, as the stimulus amplitude increases, both schemes experienced higher MSE, as they must generalize SA behavior at stimulus levels that are further from what they have seen during training.

Preliminary results demonstrating the ability of the TDNN to cancel SA on real data are shown in Figure 6. So far, it can be seen that this technique does quite well in reducing SA. The MSE cannot be computed on real data, as the true SEP waveform is not known. Assessment can take the form of a subjective visual inspection, or surrogate quantitative methods [9].

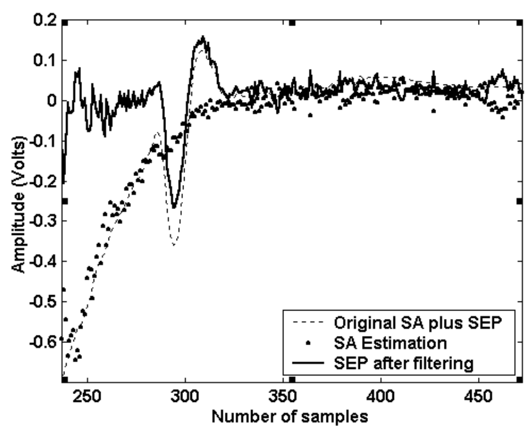


Figure 6 – SA cancellation on real data

DISCUSSION

The non-linear nature of the process of SA generation justifies the use of dynamic adaptive filters for the purpose of learning this process. The TDNN has shown to have better SA cancellation abilities than the segmented training technique on simulated data for all of the stimulus amplitudes.

A three-dimensional representation of the process of SA and SEP generation is shown in Figure 7. The non-linear nature of the SA generation can be seen on the right of the figure as the stimulus amplitude varies. It is interesting to note that as the stimulus pulse amplitude during supra-threshold stimulation, the SEP increases in amplitude, signifying that a greater number of nerve fibers are being activated. Also, as the stimulus pulse increases, the onset of SEP arrives earlier in time, indicating that some of the nerve fibers activate earlier.

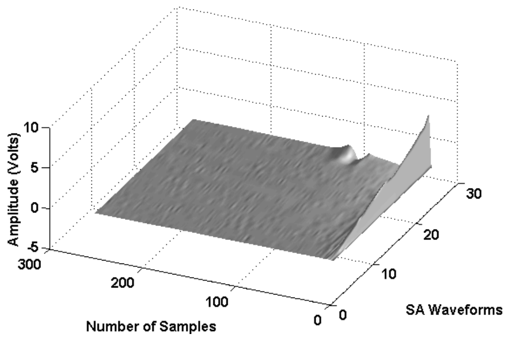


Figure 7 – Process of SA generation

From the results seen thus far, the TDNN approach to SA cancellation appears to work very well. Further analysis must be done on the data to see whether this method of SA cancellation is much better than that of the segmented training technique.

CONCLUSION

A novel approach to SA cancellation using a TDNN to learn the relationship between the stimulus pulse amplitude and the corresponding SA waveform generated is described here. This technique addresses both the problem of segmented training as well as temporal generalization of other SA reduction techniques. Preliminary results using simulated and real data demonstrate that the TDNN outperforms the segmented training approach to adaptive noise cancellation.

REFERENCES

1. B.H. Boudreau, K. Englehart, "Novel adaptive filter training scheme for reducing stimulus artifact in non-invasive somatosensory evoked potential measurements", *XIV Congress of the International Society of Electrophysiology and Kinesiology,* Vienna, Austria, June, 2002.

2. K. Englehart, B. Hudgins, M. Stevenson, and P.A. Parker, "Classification of transient myoelectric signals using a dynamic feedforward neural network," *World Congress of Neural Networks,* Washington, DC, July, 1995.

3. R. Grieve, P. A. Parker, B. Hudgins, and K. Englehart, "Nonlinear Adaptive filtering of Stimulus Artifact," *IEEE Trans. Biomed. Eng.,* vol.47, pp.389-395, March 2000.

4. S.B. Harrison and D.F. Lovely, "Identification of noise sources in surface recordings of spinal somatosensory evoked potentials", *Med. Biol. Eng. Comp.,* vol. 33, pp. 299-305, 1995.

5. K.C. McGill *et al*, On the nature and elimination of stimulus artifact in nerve signals evoked and recorded using surface electrodes. *IEEE Trans. On BME,* 29:129-137, 1982.

6. C.D. McGillem, J.I. Aunon, and D.G. Childers. Signal processing in evoked potential research: Applications of filtering and pattern recognition. *CRC Critical Reviews in Bioengineering,* 9F:225-265, October 1981.

7. L. McLean, An investigation into the waveform characteristics of the spinal somatosensory evoked potential, Ph. D dissertation, University of New Brunswick, Fredericton, NB, Canada, 1995.

8. E.L. Morin. Investigation of surface-recorded spinal somatosensory evoked potential. *M.Sc.E thesis, University of New Brunswick,* 1984.

9. V. Parsa, P. A. Parker, and R. N. Scott, "Adaptive stimulus artifact reduction in noncortical somatosensory evoked potential studies," *IEEE Trans. Biomed. Eng.,* vol.45, pp.165-179, Feb. 1998.

10. D. Regan. *Human Brain Electrophysiology.* Elsevier Science Publishing Co., New York, 1989.

11. A. Waibel, T. Hanazawa, G. Hinton, K. Shikano, and K. Lang, "Phoneme recognition using time-delay neural networks,"*IEEE Transactions on Acoustics, Speech and Signal Processing,* Vol. 37, No.3, pp.328-339, 1989.

12. E. Wan, "Finite impulse response neural networks with applications in time series prediction", Ph.D dissertation, Stanford University, Stanford, CA, USA, 1993.

ACKNOWLEDGEMENT

The authors would like to acknowledge the financial support of NSERC (PGS-A scholarship and grant #217354-99).