A GENETIC ALGORITHM APPROACH TO THE REDUCTION OF ADDITIVE NOISE IN SINGLE TRIAL EVOKED POTENTIALS

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***Abstract* – A matching tool is introduced for use in noise reduction of single trial evoked potentials. Specific performance markers such as distortion and output SNR are investigated. Results show that the matching tool is able to significantly increase output SNR while reducing the effects of distortion. A new performance metric named the *signal improvement quotient* is also introduced. This measure represents the ratio of output SNR to distortion. It is suggested that this new metric may be a better measure of noise reduction abilities than a high output SNR. Other factors such as the limitations of the matching tool are also discussed.**

INTRODUCTION

At CMBEC32, a method for estimating the conduction velocity distributions for single trial evoked potentials (EP) was presented. This method used a physiological based EP simulator optimized with a genetic algorithm (GA) to match simulated signals to experimental recordings. Named ***SEPfit***, this method extracts conduction velocity distributions and distribution statistics from matched simulated signals to predict similar values for an input experimental recording. This worked proved successful as the authors were able to accurately predict the above mentioned parameters within a 5% significance level [1].

Following this work, efforts were made to test the robustness of the newly designed tool. This new study paid specific attention to the signal-to-noise ratio (SNR) of the input signal. In the previous study, investigations were completed using only input signals of high SNR. In the new study tests used input signals of varying SNR. The results for this study also showed promise as the method was still able to accurately predict conduction velocity parameters with input signals of low SNR (~2). During the robustness study an unforeseen phenomenon was noted. Due to the inability of the method to match the input signal's noise component, matched signals not only still predicted the conduction velocity parameters, but also presented an improved SNR as an output. It is the focus of this paper to investigate the inherent noise reduction properties of the aforementioned ***SEPfit***. Key performance metrics such as distortion and the ratio of input to output SNR will be calculated. A new metric termed the ***signal improvement quotient*** (sIQ) will also be introduced.

BACKGROUND

EPs can be used clinically to diagnose various neurological disorders. These disorders can range from the testing of carpel tunnel syndrome to the monitoring of intracranial aneurysms [2, 3]. EPs have also been used in major surgical applications such as to monitor spinal cord function in the human body during scoliosis procedures [4]. Diagnoses based on EPs are usually determined by variations in signal amplitudes and onset latency. It has been shown that a decrease in signal amplitude or an increase in latency may indicate some neurological dysfunction [5]. There is however, no single consensus to what amount of variation denotes a significant change in neurological function. Amplitude changes have been reported to be used in the order of 25 -75% of the original signal while latency changes have been reported to range from 5-10% of the original value [5]. Because these variations are so great, numbers of unexplained false positives have been reported by physicians. This means that the signal variation, whether in amplitude or latency, showed a value that would suggest a neurological dysfunction was present when in fact it was not. It is suspected that the variability in these measurements is highly due to the use of ensemble averaging (EA) as a noise reduction technique. Since the signals have very low SNRs, numerous signals must be acquired and averaged before an adequate signal can be obtained for diagnoses. If the signal at the recording site is not deterministic, a smearing effect can be introduced where the averaged signal does not give a good estimate of a single EP, but an attenuated and distorted version. Losing this single EP information is of great concern in areas attempting to show that the trial-to-trial variability in an EP waveform may be a sufficient clinical marker [6, 7]. An adequate measure of a single trial evoked potential is needed. To do this effectively, existing noise must be reduced on a single

trial basis. This means an alternative to EA must be used.

METHOD

In order to investigate and quantify the noise reduction abilities of the genetic algorithm tool, input signals of known SNR must be used. Unfortunately, data gathered from experimental procedures is contaminated with various unknown noise signals. To combat this, the existing EP simulator will be used. Noiseless signals will be generated and contaminated with different amounts of band-limited (5 kHz) additive noise. This simulates the effects of noise generated by both external equipment and other biological sources. To create signals of varying SNR the following definition will be used:

$$SNR = \frac{P_{SIG}}{\sigma_N^2} \quad (1)$$

P_{SIG}: Signal Power

σ_N^2: Noise Variance

Once the test signals are generated, each will be run separately through the matching tool, ***SEPfit***. Upon completion of each trial, output SNR measures will be taken along with a measure of distortion. The distortion measure will represent the mean squared error between the algorithm's output (the matched signal) and the ideal noiseless output. The definition of distortion is as follows:

$$Distortion = 100 \times \frac{mean\ ([S_{MATCHED} - S_{DESIRED}]^2)}{mean\ (S_{DESIRED}^2)}\% \quad (2)$$

$S_{MATCHED}$: The matched output signal of the genetic algorithm

$S_{DESIRED}$: The ideal noiseless output

Once values of output SNR and distortion are calculated, the sIQ will also be calculated. This metric, shown below, represents the ratio between the output SNR and the distortion.

$$sIQ = \frac{SNR_{OUT}}{Distortion_{OUT}} \quad (3)$$

SNR_{OUT}: SNR of resulting output signal

$Distortion_{OUT}$: Distortion of resulting output signal

The rationale behind this new metric is to take into account the deleterious effect that signal distortion can have on the clinical interpretation of the signal. For example, EA will distort the signal if there are trial-to-trial variations, however the overall SNR will be enhanced. It is suggested that a high sIQ may be a better measure of noise reduction abilities than a high output SNR. A high sIQ represents an ability to effectively reduce noise without distorting the underlying signal. It should be noted that much like the distortion measure this metric cannot be calculated with experimental recordings as the desired signal is unknown. It is simply a test measure that can be used to evaluate new single trial noise reduction techniques with simulated signals.

RESULTS

Using the EP simulator, noiseless bipolar test signals were generated to simulate experimental recordings acquired along the median nerve. Randomly generated band-limited noise was added to each signal in order to vary the test set SNR values from approximately 0.2 to 20. Each signal was then run through ***SEPfit*** for 5000 iterations/generations. This was done multiple times for each signal in the test set. Figure 1 shows a sample output comparing an input signal of unity SNR to both the output of ***SEPfit*** and the desired noiseless signal. Here, the output signal shows an improved SNR (~9) and distortion measure of ~12% (sIQ ≈ 0.75).

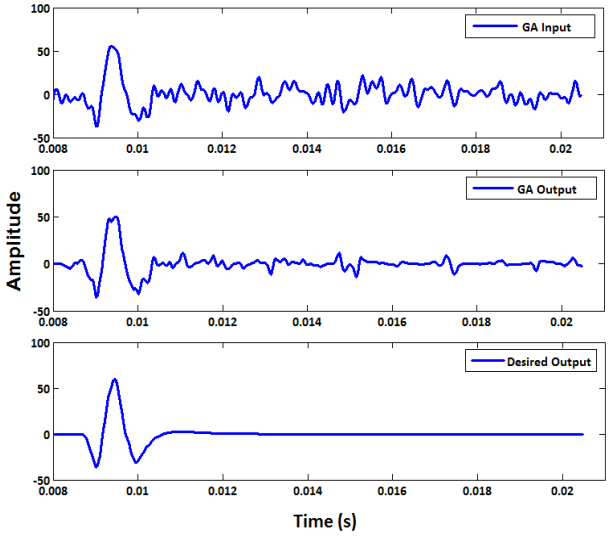

Figure 1: A sample output comparing an input signal of unity SNR (top) to the ***SEPfit*** output (middle) and the desired noiseless signal (bottom).

Once all signals in the test set were matched performance metrics were calculated. Figure 2 shows the comparison between input SNR and output SNR. Here it can be seen that the output signal benefits greatly from the matching procedure along the whole test set. The increasing variability in the SNR improvement at each ends of the SNR input values can be explained by the tools incapability of improving both significantly high (greater than 15) and significantly low (less than 0.5) SNR signals. It is also suggested that output SNR variability with a low SNR input may be reduced with an increase in the GA generations of the ***SEPfit*** routine.

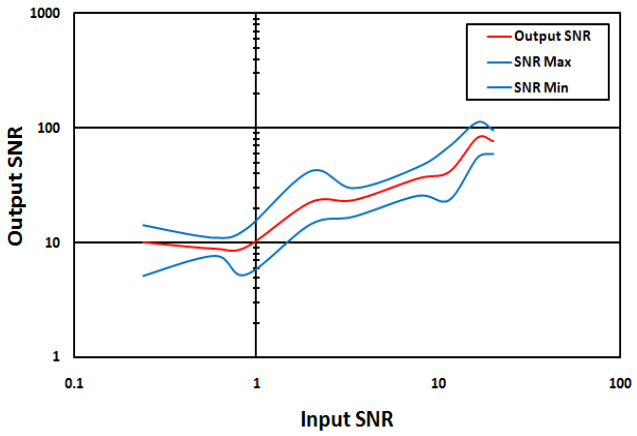

Figure 2: Comparison of input SNR to output SNR. Maximum and minimum envelops of the data are also highlighted.

To coincide with Figure 2, a comparison between input and output distortion is shown in Figure 3.

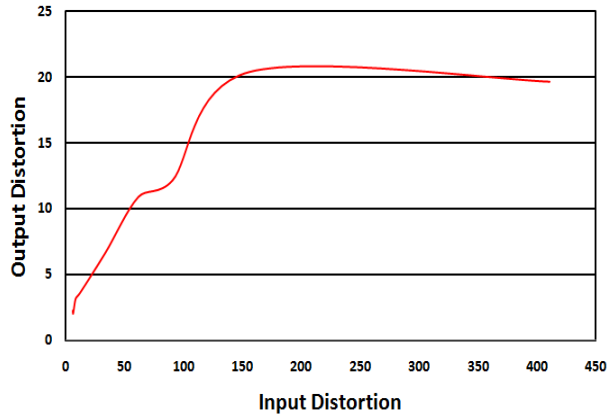

Figure 3: Comparison of input distortion to output distortion.

As shown above, as the input distortion ranges from 0 to 150, due to the additive noise, there is a significant improvement in output distortion. Beyond input distortion of 150 the output distortion seems to become somewhat constant. This can be linked to a limitation of the GA matching tool. The GA operates by manipulating input parameters to a physiological based EP simulator. Because it is possible to have *a priori* knowledge of some physiological parameters, limitations can be set within the GA interface. Here, simulated signals represented recordings taken from the median nerve. Since the number of velocities used to create the signal is representative of the number of active fibres within a nerve, a maximum number of possible velocities was set. It is speculated that at input distortion levels greater than 150 the matched signal is reaching its maximum possible output distortion. It should be noted that these input distortion levels are characteristic of input SNR levels below 0.5.

A comparison of input SNR and sIQ is shown in Figure 4. Results are as expected as we see a significant improvement to sIQ as the input SNR increases. Slight variability in the sIQ at each end of the input SNR values can be linked to the variability discussed for the output SNR results.

Although there are no defined values for adequate SNR or distortion measures, the author suggests that SNR values greater than 5 and distortion values less than 5% may be considered adequate for clinical interpretation. This suggests that a sIQ value greater than unity represents a significant improvement. From Figure 4 it is shown that using this method such an sIQ can be achieved at input SNR values greater than unity.

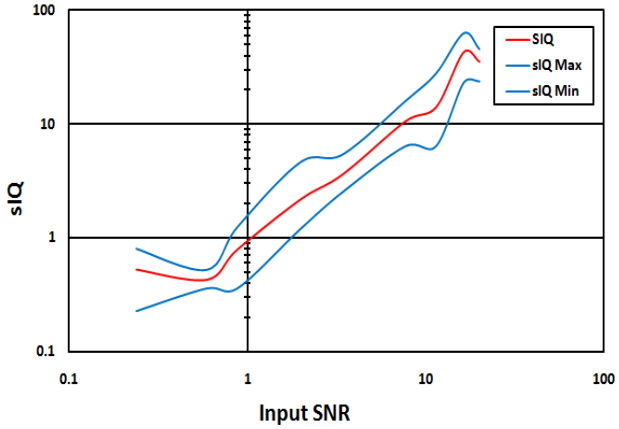

Figure 4: Comparison of input SNR to sIQ. Maximum and minimum envelops of the data are also highlighted.

A final investigation to quantify the matching tool's performance led to the study of how the sIQ varies with the number of GA generations. Shown in Figure 5, the sIQ has a relatively high peak value after completing only 250 generations. This value however, is misleading. After examining the results found in Figure 5 it was discovered that at iterations less than ~1000 the signal distortion was significantly high (greater than 25%). This implies that although the sIQ is high, the signal has not been adequately matched. This suggests that the GA tool must stabilize before the sIQ is measured. Further investigation is needed to fully comprehend how and why the sIQ is affected by the number of GA generations. Finally, it was noted that the time taken to complete 5000 GA generations on a standard personal computer was approximately 90 minutes.

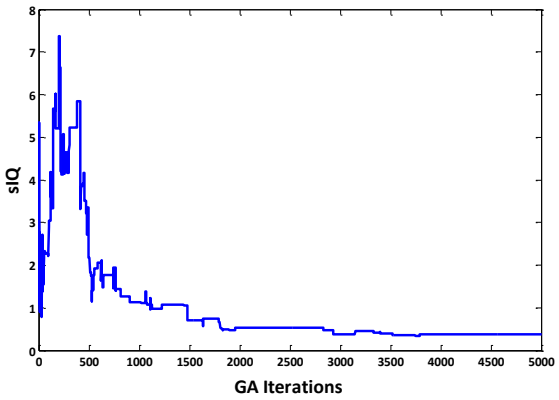

Figure 5: sIQ improvement with GA iterations (input SNR ≈ 1)

CONCLUSION

Using a test set of input signals with varying SNR, it was shown that the introduced matching tool, ***SEPfit***, can significantly increase output SNR while reducing the effects of distortion. Input SNR levels with values greater than 5 were shown to have the best performance. Other factors such as the limitations of the matching tool were also discussed. These limitations included the necessary number of iterations needed before a reliable signal could be reached and how using *a priori* knowledge of the number of active nerve fibres can set a maximum possible output distortion for the output signal.

FUTURE WORK

The overall aim of this research is to develop an effective tool for reducing noise in single trial surface recorded evoked potentials. Although this study has shown major steps towards this goal, more work is still needed.

As discussed earlier, the time taken to run this procedure may exceed 1 hour. Although this may not be detrimental to the proposed method, as it is all post-processing, analysis of the computational load to improve the associated run-time is needed.

In addition to run-time issues, comparisons with existing noise reduction methods are also needed. Most importantly it is necessary to compare the proposed method with EA. Again, common performance metrics would need to be explored. Values of sIQ would also be of particular interest. Other noise reduction methods that may also warrant an investigation are both wavelet and Fourier analysis [8]. This is due to both methods being developed on the same decomposition techniques as GA tool.

Finally, as mentioned previously, further investigation into how and why the sIQ is affected by the number of GA generations is needed.

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