AN ADAPTIVE MULTI-LEVEL WAVELET DENOISING METHOD FOR 40-HZ ASSR

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ABSTRACT

This paper presents a novel method for extracting auditory steady state response (ASSR) signals from background electroencephalogram. 40-Hz ASSR signals are sensitive to subject's state of consciousness and can be used as a monitor for the depth of anaesthesia. The suggested method is a multi-level adaptive wavelet denoising scheme that extracts ASSR cycles faster than the currently used averaging schemes and can monitor depth of anesthesia with minimum delay. It estimates the variance of noise and adapts the threshold at each denoising level. The algorithm benefits from the fact that wavelet transform preserves temporality and takes into consideration the correlation of the neighbor wavelet coefficients. Our method extracts ASSR from small number of epochs in a short time moreover, it does not neglect the variations of the signal from one epoch to the other and outperforms averaging. The performance of the proposed scheme is evaluated on the synthetic and on real data recorded during induction of anaesthesia ASSR signals in the paper.

***Index Terms*—** 40-Hz ASSR, monitoring depth of anaethesia, wavelet denoising

1. INTRODUCTION

Auditory steady state response (ASSR) is the electrical changes in the ear and brain of a normally hearing person in response to a periodic acoustic stimuli. The ASSR is called 40-Hz ASSR if the stimuli has 40 Hz repetition rate. ASSR signal shows how neural information propagates from the acoustic nerves in the ear to the cortex [1]. ASSR signal was originally used for audiometry tests. The signals are extracted from electro encephalograph (EEG) [2].

The amplitude in 40-Hz response varies by the subject's level of arousal [3, 4, 5], and consciousness [6, 7]. 40-Hz response can be used as a measure of depth of anesthesia [7, 8, 9, 10]. In almost all cases in the literature, ensemble averaging is used for extracting 40-Hz ASSR signals from the background noise [8, 11, 9]. Long durations of time and high number of epochs are needed for extracting ASSR by averaging. In our previous paper we used a window of 300 epochs for extracting each ASSR cycle [10]. Plourde et al. used 1000 epochs [8], which took 132.8 seconds of recording to extract an ASSR cycle. In his other paper, Plourde used 34.25 to 47.95 seconds of recording. Picton [9] used 100 seconds of recording for extracting ASSR during sleep and Bohorquez et al. averaged over 2219 sweeps [12]. Besides, the long duration of time averaging is based on the assumption that the buried-in noise ASSR signals do not vary between epochs which may not always be the case. Specifically during induction and emerging from anaesthesia, important information regarding the fast variations of ASSR may be lost due to this assumption.

Wavelet transform is a time-frequency decomposition method with optimal resolution on both domains. Wang et al. suggested in [13] that wavelet analysis is more suitable than FFT analysis for neurophysiological signals due to the non-stationary nature of the signals. Although wavelet transform had been used for extracting evoked potentials [14, 15, 13, 16], it has never been used to extract 40-Hz ASSR signals except by Ikawa et al. in 2012 [17]. Their proposed wavelet denoising method consisted of decomposing the signals with stationary wavelet transforming [18] and inverse transform of just the forth scale (D4) in order to keep the desired frequencies. Their method, however, is incapable of removing the noise in the same frequency band. Later in [19] they suggested that the frequency band was too wide to extract the 40-Hz ASSR.

For denoising evoked potentials Quiroga et al. [14] and [16] proposed a wavelet denoising scheme but their methods use prior information about the previous cycles for denoising the next ones. Wang et al. [13] used conventional wavelet denoising method for recorded from rhesus monkey intracortical evoked potential which has much higher signal to noise ratio (SNR) than recorded from scalp evoked potentials.

In this paper we present a new multi-level denoising algorithm for fast denoising of low SNR ASSR signals. The method uses a window of 64 epochs for denoising ASSR cycles in 6 levels of wavelet denoising. Thresholds which have an important role in the performance of the algorithm are calculated adaptively at each level of denoising and for each wavelet scale. The time correlation between the neighbor wavelet coefficients on the same scale, parent and children coefficients in different scales are taken into consideration while thresholding. The method is built on the Cyclic Shift tree denoising (CSTD) algorithm [15, 20] for denoising auditory evoked potentials. The modified denoising algorithm with adaptive thresholding, performs better than weighted averaging in very low SNRs. The algorithm is applied to synthetic signals, and signals recorded from human subjects during surgery before and after induction of anaesthesia. The denoised 40-ASSR can show the decrease in the signals amplitude during induction of anaesthesia.

2. METHOD

2.1. Data acquisition

The 40-Hz ASSR signals were recorded for the purpose of monitoring depth of anaesthesia after getting ethics approval from University of Toronto and "Research Ethics Board" of Trillium Health Partners (where the surgical procedures were conducted). Volunteer participants who were going under general anaesthesia for primary reasons unrelated to and independent of this project were recruited. Participants had no history of hearing loss or neurological problems, were more than 18 years old and had American Society of Anaesthesiology score (ASA) below or equal to III.

Signals were recorded before and after anaesthesia induction, and after emerging from anesthesia. In all surgeries general anesthesia was induced by Fentanyl and Propofol, the depth of anesthesia was then maintained by the volatile anesthetic, Sevoflurane. Muscle relaxant Rocuronium was also injected in some cases. The auditory stimuli were generated with Vivosonic Integrity$^{\text{TM}}$ V500 as an AM-ASSR stimulus with the modulation frequency of 40.68 Hz as carrier and center frequency near 2 KHz. The stimuli was presented binaurally to the ears of the subjects by ER-3A-ABR insert earphone (Etymotic Research) at the level of 60 dB HL, loud enough to generate an ASSR but not too loud to cause discomfort to the study participants. The signals were recorded in presence of normal auditory noise and no earmuff was used for recoding. EEG signals were recorded in 8 channels from 11 electrode sites placed on international 10-20 electrode sites. EEG was recoded by Nicolet$^{\text{TM}}$ Wireless 32 amplifier with 12 KHz sampling frequency. The stimuli was also recoded on one of the EEG channels for synchronization purposes.

2.2. Data pre-processing

After recording the EEG signal and the stimuli with Nicolet$^{\text{TM}}$ Wireless 32 amplifier, the signals were downsampled from $f_s = 12$ KH to $f_s = 2.4$ KHs and the outlier samples (with more that 3×standard deviation away from the mean value) were removed. The signals were then filtered with third order butterworth low pas and high pass filters to remove the frequencies out of 35 Hz $\leq f \leq 45$ Hz and 75 Hz $\leq f \leq 85$ Hz. Afterwards the EEG signal channels were synchronized with the stimuli cycles in the second round of outlier removal epochs with variance more that 3×standard deviation away from mean variance were discarded.

After synchronization each epoch of the EEG signal can be modeled as

$$x_i[n] = s_i[n] + r_i[n] \tag{1}$$

where $x_i[n]$ is the ASSR in response to the i_{th} sweep of the stimuli and $r_i[n]$ is the EEG and noise from other sources. Under the assumption that $s_i[n]$ is phase locked to the stimuli, noise $r_i[n]$ is zero mean, $E(r_i[n]) = 0$, has constant variance, $var(r_i) = \sigma^2$ and is uncorrelated from one sweep to another, $E(r_i[n]r_j[n-k]) = \rho_r[k]\delta(i-j)$ ensemble average $\hat{x}[n]$ will be

$$\hat{x}[n] = \frac{1}{N}\sum_{i=0}^{N-1} x_i[n] = s[n] + \frac{1}{N}\sum_{i=0}^{N-1} r_i[n] \tag{2}$$

which is an unbiased estimator: $E(\widehat{x}[n]) = E(s_i[n]) = s[n]$, and decrease the variance of the noise to $var(r_i) = \frac{\sigma^2}{N}$. In this paper we compared the performance of weighted ensemble average, equation 3, for extracting ASSR cycles with our proposed denoising algorithm.

$$\hat{x}[n] = \frac{1}{N}\sum_{i=0}^{N-1} \omega_i x_i[n], \text{ where } \sum_{i=0}^{N-1} \omega_i = 1 \tag{3}$$

Here the weights are inversely proportional to the variance of each epoch.

$$\omega_i = \frac{\alpha}{E(x_i - E(x_i))^2} \tag{4}$$

2.3. The estimator

The ASSR signals are buried in the background EEG and noise and have a very low SNR. The ASSR signals which are recorded for the purpose of monitoring depth of anaesthesia are noisier than the ones recoded for audiometry.This is because the these ASSR signals are recorded in the very noisy environment of the operation rooms with noise from other instruments and equipments and the patients body movements.

Conventional wavelet denoising method is a fast estimator of signals that are corrupted by low level noise. It operates on a single frame of signal by performing a single wavelet transform, setting the coefficients below a defined threshold to zero, and performing inverse wavelet transform. This approach is not suitable for signals with very low SNR since most of the signal energy will be lost by setting the wavelet coefficients to zero.

For extracting ASSR signals we modified the Causevic et al. method of CSTD that uses an array with N frames for extracting one cycle of the clean signal [15, 20]. In the CSTD method, information from N individual frames (which consists of an epoch) is used to produce an estimator that denoise the signal in $K = \log 2(N)$ levels. CSTD performance exceeds that of linear averaging process and conventional wavelet denoising. The algorithm recombines the original low SNR frames in a tree like fashion and creates $M > N$ frames. Defining the thresholds plays a very important role in the CSTD. While a very high threshold sets too many coefficients to zero, a very low threshold does not omit the noise coefficients. The un-denoised frames will be averaged at each level of denoising; hence, the method will change into an ensemble averaging estimator. In this paper we used two different adaptive schemes for calculating threshold adaptively as function of estimated noise variance, wavelet scale and denoising level. The decision is made taking into consideration the correlation between the coefficients of the same and different wavelet scales [16].

At the first denoising level each two adjacent frames in the original array are averaged to form $N/2$ frames, another $N/2$ frames are generated by cyclicly shifting the array of frames by one frame, and averaging over each two adjacent frames. Wavelet coefficients are calculated for each frame and denoising threshold is defined as a function of estimated noise variance, wavelet scale and denoising level as

$$\delta_{j,l} = (\sqrt{2})^l \times \widehat{\sigma}_l^2 (2\ \ln(n)) \qquad (5)$$

where n is the number of coefficient at the scale j, and sigma is the estimated noise level at level l calculated as

$$\begin{aligned} \widehat{\sigma}_l &= \mathrm{MAD}/0.6745 && (6) \\ \mathrm{MAD} &= \mathrm{Median}\{|X_{J,1} - \overline{X}_J|, \ldots, |X_{J,n} - \overline{X}_J|\} && (7) \end{aligned}$$

On the decision making stage Cai and Silverman [21] and Shapiro [22] denoising schemes are used as presented in Ahmadi's paper [16]. In scheme 1, information from the neighbor coefficients are incorporated to form a new thresholding criterion. Wavelet transform preserves temporality and the neighbor coefficients are close in time and should be highly correlated; hence, a sudden increase can be an indication of noise. In this scheme some of squares of each coefficient, $X_{j,k}$, and its immediate neighbors, $X_{j,k-1}$,$X_{j,k+1}$, in the same scale are compared with the threshold for denoising.

$$X_{j,k} = \begin{cases} X_{j,k} & \text{if } X_{j,k-1}^2 + X_{j,k}^2 + X_{j,k+1}^2 > \delta_{j,l} \\ 0 & \text{if } X_{j,k-1}^2 + X_{j,k}^2 + X_{j,k+1}^2 \leq \delta_{j,l} \end{cases}$$

In scheme 2 we added an additional step to scheme 1 based on Shapiro's method [22]. In this scheme if a coefficient is detected as noise and omitted at a wavelet scale most probably its children coefficients at the finer wavelet scales are noise coefficients and should be omitted as well. Therefore if a coefficient is set to zero the two parent coefficients at the lower wavelet scale will be set to zero too.

On the next level of denoising the new frames are generated by averaging over the previous level frames and, averaged in the same manner to generale new array of frames. Denoising is performed with the new thresholds. As we go from one level to the next level of denoising, each frame is generated by averaging over more frame from the original N frame array and expected to have a higher SNR [15, 20]. Thus, at each level of denoising the threshold is scaled down by $\sqrt{2}^{l/2.5}$. After the N_{th} level of denoising the coefficients will be averaged and inverse wavelet transform is applied to obtain the denoised ASSR cycle.

Original	Ens. Averagin		Scheme1		Scheme2	
SNR	64 fr	128fr	6lv	7lv	6lv	7lv
-12dB	6.09	9.02	11.47	13.54	11.82	12.83
-11dB	7.11	10.11	12.19	14.54	12.31	13.59
-10dB	8.19	11.13	13.22	15.17	13.11	13.92
-9dB	9.21	12.18	13.97	15.81	13.53	14.27
-8dB	10.13	13.14	14.65	16.54	14.18	15.01
-7dB	11.22	14.18	15.41	17.14	14.67	15.35
-6dB	12.16	15.14	16.02	17.73	15.00	15.92

Table 1: signals SNR before, and after denoising with weighted ensemble average, and adaptive multi-level wavelet denoising schemes(scheme1 and 2).

3. RESULTS

The performance of the proposed method is presented in this section. First the estimator is applied on a simulated signal with different noise levels. To simulate the signal a clean 40-Hz ASSR signal is extracted by ensemble averaging over 1000 epochs then white Gaussian noise is added to the signal to generate the signal with the desired SNR. The simulated signals are denoised with both schemes in 6 and 7 levels of denoising. Hence an array of 64 and 128 frames are used for estimating ASSR. Daubechies's spline biorthogonal filter is used for the wavelet transform. Each denoising window consists of two cycles with 118 samples which is zero padded with 10 zeros at the boundaries and transformed by wavelet into 7 scales. Table 1 presents the signal SNR before and after denoising with both schemes. The SNRs presented on the table are the mean SNRs calculated over 100 trials of denoising ASSR cycles with random noise.

Adaptive CSTD with similar parameters and 6 level of denoising is used to estimated ASSR signals from recorded EEG signals. The 4 ASSR cycles extracted from recorded $Cz - A_1A_2$ and $C4 - A_1A_2$ channels of two subjects are shown in figure 1 and 2. ASSR cycles denoised with scheme 1 and 2 adaptive CSTD and weighted averaging are plotted on the same figures for comparison. ASSR cycles are extracted with both schemes with 6 levels of denoising, hence 64 epochs are used for extracting each cycle. The performance of the schemes are almost identical in this case and outstandingly smoother than the same cycle denoised by weighted averaging. The

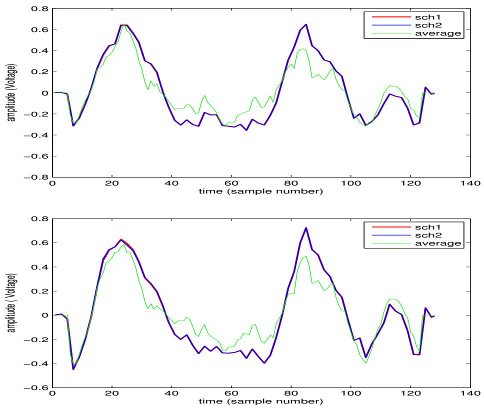


Fig. 1: ASSR cycles in subject 110 denoised with adaptive multi-level wavelet denoising schemes(sch1 and 2) and weighted ensemble averaging.

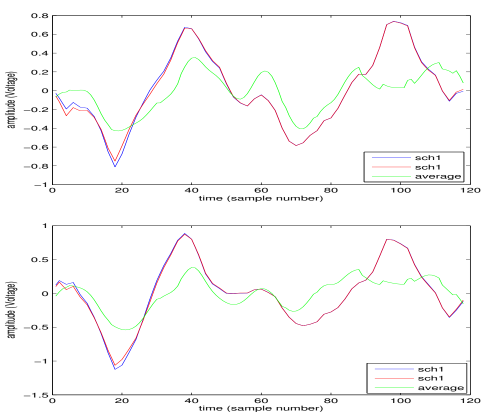


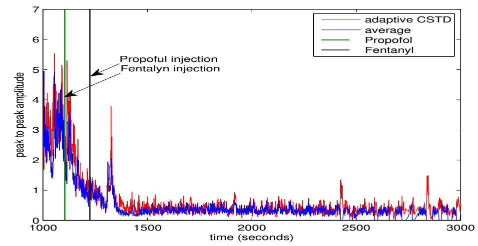
Fig. 2: ASSR cycles in subject 104 denoised with adaptive multi-level wavelet denoising schemes(sch1, and 2) and weighted ensemble averaging.

decrease in the amplitude of ASSR can be observed in the denoised ASSR cycles before and after injection of anaesthetics. Figure 3 shows the variation of peak to peak amplitude in 40-Hz ASSR cycles before, and after injection of the anesthetics in the same two channels for the two subjects shown in figures 1 and 2. The difference in the reaction time to injection of the anaesthetics can be explained in differences in the weight and height of the subjects and dose of anaesthetics (Table 2). The sudden increase and decrease after induction in subject 110 coincides with a neuroexcitatory phenomena which was the jerking movement of the hand. Figure 3.c shows the trend in peak to peak amplitude for multi-level extracted ASSRs and Averaged ASSRs in subject 104. The trend is estimated for windows of 100 seconds by fitting a polynomial of order 5. It can be seen that the trend of the peak to peak amplitude for

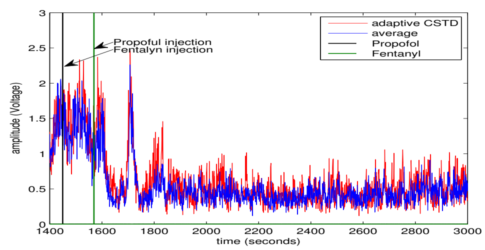
subject	Height	Weight	Fent. Dose	Prop. Does
104	153 Cm	67 Kg	200 μ g	110mg
110	179 Cm	123 Kg	150 μ g	250mg

Table 2: Subjects weight, height,and dose of anaesthetic agents.

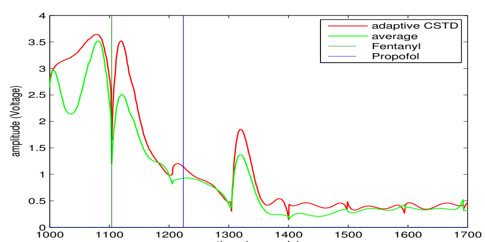
the ASSRs that are extracted with the proposed method shows the reduction after anesthetic injection more clearly.



(a)



(b)



(c)

Fig. 3: Amplitude variations before, and after the induction of anaesthesia. (a) subject 110 , (b) subject 104 (c)estimated trend in subject 104.

4. CONCLUSION

Adaptive multilevel wavelet denoising method is presented in this paper for denoising very low SNR synthetic and recorded 40-Hz ASSR signals. It is shown that the method outperforms the currently used ensemble averaging and extract ASSR cycles with higher SNR. The method applied on the recoded signals over the coarse of a surgical operation and shown that the fast extracted ASSR cycles can well capture the induction of anesthesia.

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