THE INFLUENCE OF THE EEG RECORDING MACHINE TIME MULTIPLEX ON THE LAPLACIAN FILTER: THE SIMULATION WITH THE REAL SHAPED HEAD MODEL

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Abstract:The work analyzes the influence of the EEG recording machine time channel multiplex (TCX) on the Laplacian filter output signal-to-noise ratio. The real shaped head model is used for the analysis. The target of the analysis was to obtain a reliable answer to a question if the channel time multiplex should be compensated or not. The final answer is 'yes'.

Introduction

There are two kinds of EEG recording machines there: machines which have dedicated AD converter for each of recording channels (see Figure 1) and machines which exhibit only one AD converter time multiplexed between the channels. Our machine is of the second type and we were interested how the time channel multiplex (TCX) influences a subsequent EEG processing, mainly the surface Laplacian filter.

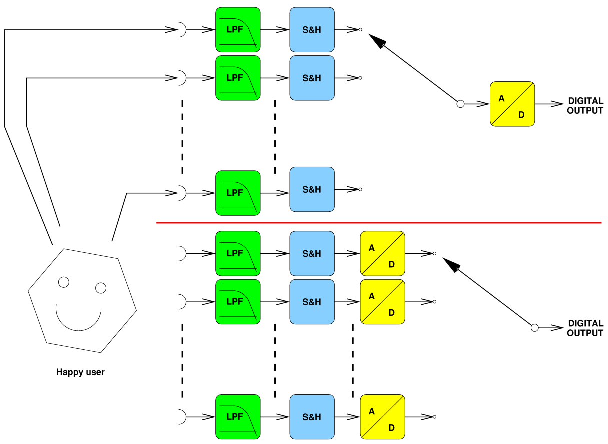

Figure 1: Two possible EEG recording machine configurations. Some EEG machines contain only one AD converter which is periodically switched between the single recording channels. The switching period is denoted as T_{ad}; obviously for the N-channel EEG recording with sampling rate f_s must be $T_{ad} \leq (fs \times N)^{-1}$.

The Laplacian filter [1] is used to enhance and sharpen the localized EEG activity and suppress the negative head tissues blurring effect. The usage of the Laplacian filter assumes that all channels are sampled simultaneously, which is not the case here.

The influence of the TCX on the surface Laplacian filter was neglected in the literature so far but [1]. We based our work on the findings of [1] and improved reached results. The theoretical analysis of the effect is presented in [2], now the results with a real head model will be presented.

Laplacian Filter

There are a few layers of head tissue in between the brain dipole sources and scalp electrodes – cerebrospinal fluid, head tissues, skull bone and scalp. The combination of these layers results in low-frequency band pass spatial filtering the EEG activity. Thanks to this the scalp potentials are blurred and any highly localized EEG activity becomes less apparent. This is in contradiction with the need of brain-computer interface experiments [6],[8] which require to record such an activity with as low signal to noise ratio (SNR) as possible.

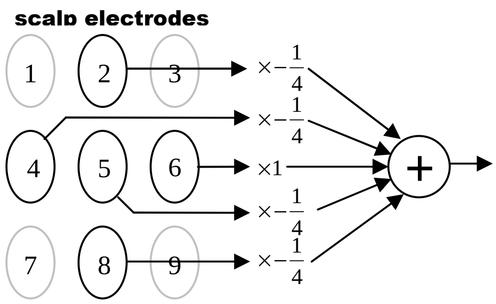

Figure 2: The simplest configuration of Laplacian filter – Small Surface Laplacian [1]. Digitized potentials from electrodes 2,4,5,6 and 8 are used to compute a new – filtered – potential at electrode no. 5. The filter itself is a simple linear combination approximating the surface derivation of the scalp potential.

The Laplacian filter helps us to compensate this blurring to some extent. The filter is the high-frequency band pass spatial filter and its frequency characteristic is

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a rough inverse approximation of the head tissues low-pass transfer function.

The Laplacian filter has some remarkable advantages – it requires only low computational power, it is easily applicable (simple linear combination of the electrode potentials – Figure 2), provides rather good results and suppresses the common-mode noise. Despite of the fact that theoretically should be the scalp electrodes placed in the vertices of a rectagonal and equidistant grid, the deviations from this have no fatal influence on the filter performance under the condition that the maximal interelectrode distance is kept less or equal 2.5cm [5] to prevent spatial aliasing (sampling theorem violation).

There are some disadvantages either. The filter is sensitive to localized non-EEG related noise as it computes the estimation of the derivation only from the neighbouring samples. Further one has to pay attention not to compare Laplacian-processed EEG between experimental subjects since the results are sensitive to the head tissues conductivities which vary from person to person [5]. The precise comparison of adult and child Laplacian EEG is not possible thanks to this fact.

The filter absolutely suppresses common mode signal components under the ideal conditions. Common mode signal components are those components which are present at all electrodes used for the Laplacian computation with the same amplitude. However, this is true only if the processed signals are not mutually phase-shifted.

Real Shaped Head Model

Recently we theoretically analyzed the Laplacian filter behaviour under common mode conditions [2]. Common mode signal components might be commonly present in case we are processing video signals with Laplacian filter. However, they are rather scarce when we work with EEG. In case of EEG processing the common mode components have mostly nothing to do with the recorded EEG (power line noise, ground shift); EEG itself does not have such a character. That is why we decided to conduct a few experiments with the simulated EEG dipole and real shaped head model to know how the EEG machine time multiplex influences the recorded EEG.

The conductivity real shaped head model we have used in this study was a compound of three layers representing the three most important anatomical parts in a human head (Fig. 3, left). The volumes enclosed by these layers differ in the conductivity. There are various choices [3] of piecewise constant conductivity values, we used the conductivities (0.33, 0.02, 0.33) s/m assigned to a brain tissue, skull and scalp, respectively. Each layer in our head model consists of 1280 triangles.

A relation between a brain activity source and a scalp potential distribution was computed using boundary element method (BEM). The continuous forward problem formulae are satisfied in so called collocation points belonging to each triangle and the potential is assumed to be constant on each surface element. This solution method is known as constant collocation BEM [4]. The potential primarily expressed in the collocation points was interpolated to the real electrodes positions.

The time-sequential sampling effect was simulated on such a source arrangement that can be often observed in the real human brain activity. In our case the current dipole representing the brain activity source was placed in the primary somatosensory cortex and it had fronto-parietal (tangential) orientation (Fig. 3, right).

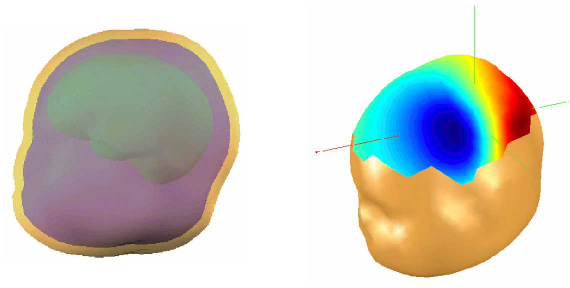

Figure 3: Geometrical arrangement of the three shell conductivity model being used (left). Potential distribution generated by the source placed in primary somatosensory cortex.

EEG Machine Parameters Measurement

Before we could start with the simulations and subsequent analysis we had to know the real parameters of our EEG machine – the time constant of the channel multiplex T_{ad} above all.

The EEG machine calibration mode was used for the T_{ad} parameter estimation. A calibration harmonic signal with f=10Hz and maximal possible amplitude is connected to all the channels in this mode. The harmonic is recorded in all the channels as if it is the real EEG; and all the channels are time multiplexed with our machine. Thanks to this we can measure the following signal in all the channels

$$y_e[n] = A_e \sin(2\pi f \frac{n}{f_s} + \Psi_e + T_{ad} e f 2\pi) \qquad (1)$$

$$\varphi_e = \Psi_e + T_{ad} e f 2\pi \qquad (2)$$

where e is the channel number, Ψ_e is the general calibration harmonic phase shift and $T_{ad} ef 2\pi$ is the phase shifted caused by the EEG channel time multiplex. The magnitude A_e and phase φ_e of the recorded harmonic are not known but it is possible to estimate them with the least-square method from the measured signals. At first we have to rewrite the calibration harmonic (1) and express it with the help of its orthogonal components

$$y_e[n] = a_e \cos(2\pi n \frac{f}{f_s}) + b_e \sin(2\pi n \frac{f}{f_s}), \qquad (3)$$

where

$$A_e = \sqrt{a_e^2 + b_e^2}, \varphi_e = -arctg\left(\frac{b_e}{a_e}\right). \qquad (4)$$

With the help of the MSE criterion (least squares method) we can derive the following linear equation

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system for the unknown parameters estimation $\tilde{a}_e$ and $\tilde{b}_e$

$$\begin{bmatrix} \sum_{n=0}^{N-1} \cos(\frac{2\pi fn}{f_s})\sin(\frac{2\pi fn}{f_s}) & \sum_{n=0}^{N-1} \sin^2(\frac{2\pi fn}{f_s}) \\ \sum_{n=0}^{N-1} \cos^2(\frac{2\pi fn}{f_s}) & \sum_{n=0}^{N-1} \cos(\frac{2\pi fn}{f_s})\sin(\frac{2\pi fn}{f_s}) \end{bmatrix} \begin{bmatrix} \tilde{a}_e \\ \tilde{b}_e \end{bmatrix} = \begin{bmatrix} \sum_{n=0}^{N-1} x[n]\sin(\frac{2\pi fn}{f_s}) \\ \sum_{n=0}^{N-1} x[n]\cos(\frac{2\pi fn}{f_s}) \end{bmatrix}. \quad (5)$$

The equation system might be solved with the help of the elementary linear algebra. Substituting values into (3) and (4) we will get the appropriate estimations of the calibration harmonic signal magnitude $\tilde{A}_e$ and phase $\tilde{\varphi}_e$. The parameters might be computed for all the electrodes and plot into a graph along the electrode number – see Figures 4 and 5.

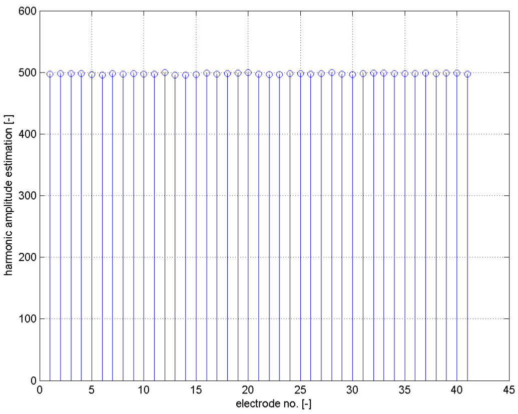

Figure 4: Calibration harmonic magnitudes estimation for the used electrodes. Please note that the magnitude is nearly constant for all the electrodes and approximately equal to the AD converter full scale – 512LSBs for the used 12bit AD converter.

Table 1: T_{ad} estimation accuracy for the various number of calibration harmonic samples used for the estimation.

No. of calibration signal samples[-]	**T_{ad} estimation [μsec]**	**Relative accuracy [%]**
256	7.53	3.6
1024	8.00	2.4
2048	7.86	0.6
4096	7.80	0.1

Now we can apply the least-square estimation for the second time and obtain the slope of the phase trend – see Figure 5 – to get the T_{ad} estimation. We got $T_{ad} = 7.80\mu s$ with our measured calibration signal. This is in a good compliance with the expected value

$$T_{ad} = \frac{1}{f_{s\max} * N_{electrodes}} = 7.81\mu s \quad (6)$$

where f_{smax} is the maximal sampling frequency of the EEG machine (1024Hz) and $N_{electrodes}$ is the maximal available number of EEG channels (125).

The accuracy of the T_{ad} estimation grows with growing number of calibration harmonic samples used for the estimation – see Table 1.

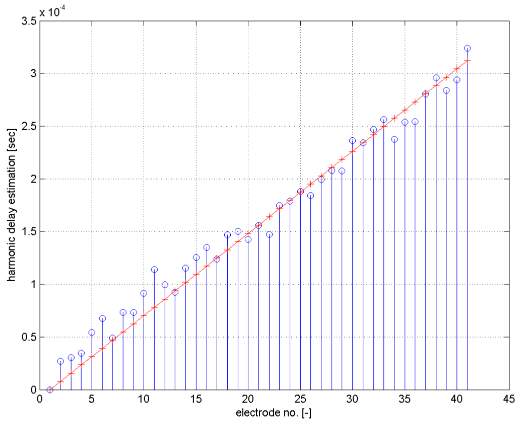

Figure 5: Calibration signals phase estimations. Estimated phases clearly forms the linear trend depending on the electrode number. The trend is further emphasized with the line. Its slope is estimated with the second least-square method application.

Measurement Method

Our EEG machine is able to record up to 125 channels at $f_s \leq 1024$Hz (we use 256Hz), 12bit ADC. The TCX channel switch rate was determined as T_{ad}=7.81μs.

A series of harmonics was generated for frequency 1-40Hz, without (ideal case) or with (TCX EEG recording) linear phase shift (electrode#×T_{ad}) for each electrode. Amplitude was determined on the base of the real-head model. These harmonics simulated the outputs of the EEG recording machine w/o TCX.

The surface Laplacian filter with 8 neighbouring electrodes was used [8]. Filter coefficients were derived from the known inter-electrode distanes. If d_{ij} is the distance between i-th and j-th electrode, then the coefficients c_j for the Laplacian filter with central electrode *60* and surrounding electrodes *S={46, 47, 48, 59, 61, 72, 73, 74}* are to be computed [8] as follows:

$$c_j = \frac{1}{d_{60,j}} \sum_{i \in S} \frac{1}{d_{60,i}}, \quad (6)$$

The following output signals were computed by laplacian-filtering the harmonics: ideal $x_i[n]$, no TCX; real with TCX $x_R[n]$; real with TCX + compensation – linear interpolation [1] $x_{RL}[n]$; real with TCX + compensation – quadratic interpolation [2] $x_{RQ}[n]$. Then signal to noise introduced by the TCX ratios were computed as follows:

- first we compute the RMS of the error signal:

$$\sigma_{errR} = \sqrt{D\{x[n] - x_R[n]\}}, \quad (7)$$

where D is the variance operator,

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- then the ideal output RMS was estimated

$$\sigma_{ID} = \sqrt{D\{x[n]\}}, \qquad (8)$$

- and finally we estimate the output SNR:

$$SNR_R = 20\log_{10}\frac{\sigma_{ID}}{\sigma_{errR}}. \qquad (9)$$

The SNR_{RL} and SNR_{RQ} estimations were similar, only $x_{RL}[n]$ and $x_{RQ}[n]$ were used in equation (7) instead of $x_R[n]$.

Estimated SNRs across the whole EEG frequency band of interest are shown in Figure 6..

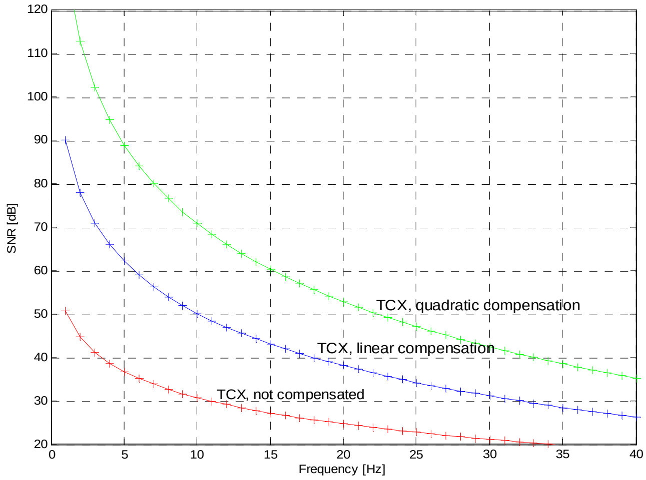

Figure 6: SNRs for electrode 60 (≈C3) filtered output in the EEG frequncy band of interest; RMS of the ideal output electrode harmonic was 9.4e-3. Please note that the SNR of the Laplacian filter output without compensation („TCX, not compensated“ curve) at f=35Hz is only about 20dB (worst case from EEG analysis point of view). The linear interpolation proposed in [1] improves the SNR for approx 10dB at 35Hz („TCX, linear compensation“ line); another 10dB might be gained with quadratic interpolation resulting in 40dB worst case SNR_{RQ} (at 35Hz, „TCX, quadratic compensation“ line).

Conclusion & Future Work

Despite of the fact the our EEG machine has rather low T_{ad} (7.81µs compared to 122µs in [1]) the SNR of the simulated signal falls below 20dB at f≥35Hz. We found that compensation might suppress the TCX introduced noise by 10-70 dB here (Figure 6). With the help of the proposed quadratic interpolation we might get as much as 40dB SNR at 35Hz. This should be enough since our machine utilizes only 12bit ADC (40dB is equivalent of slightly more than 6bits of dynamic signal range). The linear interpolation proposed in [1] helps as well but reaches lower SNR (30dB at 35Hz; the difference is bigger at lower frequencies).

Even with our time-multiplexed EEG machine with low T_{ad} the interpolation compensation clearly helps to get better results out of the Laplacian filtration and we recommend it to any one who uses an EEG machine with the recording channel time multiplex.

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