OPTIMAL SPATIAL FILTERING FOR AUDITORY STEADY-STATE RESPONSE DETECTION USING HIGH-DENSITY EEG

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ABSTRACT

Using periodic auditory stimuli, it is possible to evoke so-called auditory steady-state responses (ASSRs) in the brain, which can be measured using electroencephalography (EEG). They can be used to objectively estimate frequency-specific hearing thresholds, which is especially useful for early hearing assessment in newborns. The main problem is the extremely low signal-to-noise ratio (SNR), necessitating long measurements of up to an hour for a full audiometric assessment. To speed up the detection, we apply a linear spatial filter to the multi-channel EEG measurements, resulting in a new 'virtual' channel with optimal SNR. To ensure robustness, we then consider a hybrid ASSR detection method in which the original EEG channels are complemented with this virtual channel. The addition of this virtual channel successfully speeds up the detection of ASSRs by over 15 %. Furthermore our method not only speeds up the detection, but also greatly improves its sensitivity, in particular in the (clinically most relevant) lowest SNR scenarios. This could help reduce the gap that still exists between behaviourally and objectively obtained hearing thresholds.

***Index Terms*—** Auditory steady-state responses, spatial filtering, multi-channel EEG.

1. INTRODUCTION

Auditory steady-state responses (ASSRs) are periodic electric potentials inside the brain, evoked by periodic auditory stimuli such as a sinusoidally amplitude modulated (SAM) carrier signal. These responses originate from the synchronous firing of numerous adjacent neurons in the brain and can be measured from the scalp using electroencephalography (EEG).

In the common case of SAM stimuli, the resulting ASSR is also a sinusoid, phase-locked to the modulating sinusoid, and hence also with the same frequency. Modulation frequencies are usually chosen around either 40Hz or 80Hz because these result in responses with highest SNR in respectively wakeful and sleepy states of the subject [1]. The most common carrier signals are sine waves of 500, 1000, 2000 and 4000 Hz (cfr. commonly used audiometric frequencies).

By lowering the intensity of the auditory stimulus until an ASSR can no longer be found, an objective hearing threshold (HT) can be determined. If the carrier signal is (relatively) narrowband, only part of the cochlea will be stimulated, which allows for a frequency-specific HT estimation. Although these objective HT estimations are typically about 10 dB higher than behaviourally obtained HTs, both correlate well [2–4] which makes the objective HT estimations clinically very relevant.

The main clinical use of objective HT estimation is for early hearing assessment of newborns. A correct assessment of hearing loss in the first few weeks after birth is important. It allows for early adoption and fitting of cochlear implants (CI) or hearing aids when necessary, offering the best opportunity for newborns to acquire normal communication skills [5]. Additionally ASSRs have been used in numerous audiological studies (e.g. [6,7]) as a research tool in gaining insight in the human auditory system and can even be useful to monitor anaesthesia [8]. Recently, ASSRs have also been proposed as a new possible Brain-Computer Interface (BCI) paradigm [9].

The main problem with measuring ASSRs is the extremely low Signal-to-Noise Ratio (SNR) which makes immediate detection impossible, necessitating longer measurements. Moreover, for a full HT assessment, stimuli with different carrier frequencies have to be presented at different intensities and to both ears. Although multiple carrier frequencies can be offered to the subject at the same time using different modulation frequencies (cfr. the MASTER principle [10]), the full assessment can still easily take up to an hour [11]. This is problematic as it makes the procedure costly and time-consuming. Scientific studies are often limited in depth or sample size because of this considerable time cost. Therefore, both clinical and scientific applications of ASSRs would greatly benefit from a more efficient ASSR detection. This is the main goal of this paper.

Most clinical applications historically only use one EEG channel to detect ASSRs. Nowadays however, EEG measurement devices with 64 and even up to 256 electrodes are readily available. In this paper we will leverage this availability of extra channels towards a more efficient detection.

Using a spatial filter, channels can be linearly combined into one virtual channel on which then standard one-channel detection methods can be applied. Some basic techniques have been experimented

The work of W. Biesmans was supported by a Doctoral Fellowship of the Research Foundation - Flanders (FWO). This research work was carried out at the ESAT and expORL Laboratories of KU Leuven, in the frame of KU Leuven Research Council CoE PFV/10/002 (OPTEC), Concerted Research Action GOA/10/09 MaNet, Research Project FWO nr. G.0662.13 'Objective mapping of cochlear implants', the FP7-ICT FET-Open Project (Heterogeneous Ad-hoc Networks for Distributed, Cooperative and Adaptive Multimedia Signal Processing (HANDiCAMS), funded by the European Commission under Grant Agreement no. 323944, IWT O&O Project nr. 110722 'Signal processing and automatic fitting for next generation cochlear implants' The scientific responsibility is assumed by its authors.

with so far. Source projection [12] is a means of signal maximization and offers slight SNR improvements. Another commonly uses, heuristic procedure is to select only some neurologically relevant channels and to average these [13]. Independent Component Analysis (ICA) has been applied successfully to reduce measurement times in 7-channel measurements [14]. However, ICA is computationally expensive and does not scale well with increasing number of channels. A promising approach used a two-step algorithm estimating the signal steering vector and using the eigenvalue decomposition to rotate it away from directions with high noise to obtain optimal SNR properties [15]. Results for low SNR measurements were reported to be poor however.

In this paper, we present an alternative algorithm to construct an SNR-optimizing spatial filter that is successful, even at low stimulus intensities. The spatial filter is constructed in a single step, using the generalized eigenvector decomposition (GEVD). For each subject, one measurement with high amplitude auditory stimulus is used for training of the filter, which can then be used for all further measurements on the same subject. This is different from current approaches and is key to a faster detection. Practically it fits within the clinical HT assessment protocol which records multiple subsequent ASSR measurements. To ensure robustness, the original multi-channel EEG measurement is still used in addition to the spatially filtered channel, resulting in a hybrid ASSR detection method.

The focus in this paper is specifically on low SNR measurements, resulting from stimulus intensities near the HT (22-32 dBSPL on normal hearing subjects). As detections in low SNR conditions take the longest and have the lowest detection sensitivity, they are the most relevant to optimise. Our method has been successfully applied to 64-channel EEG measurements, reducing the detection time while at the same time increasing the sensitivity of detection, hence providing a two-way improvement in the efficiency of ASSR detection.

The paper is organised as follows: In section 2 we introduce the ASSR data model and the formal problem statement. Section 3 describes the spatial filter construction and the detection method used to detect the ASSRs. Section 4 validates our approach through an experiment on real EEG data and section 5 concludes the paper.

2. DATA MODEL AND PROBLEM STATEMENT

The auditory stimulus $x(t)$ is an SAM sinusoid with modulating frequency f_m, carrier frequency f_c and amplitude A:

$$x(t) = A\,(1 + \sin(2\pi f_m * t))\sin(2\pi f_c * t). \tag{1}$$

The resulting ASSR signal component in each EEG channel can then be modelled as a sine wave with known frequency, equal to the modulation frequency f_m. Depending on this modulation frequency there can be more than one intra-cranial source that generates the ASSR [6]. However, without much loss of accuracy, one can usually assume that the ASSR is generated by one point source in the brain. Under this assumption, and since electromagnetic propagation from the source to the electrodes is instantaneous, the measured ASSR has the same phase ϕ in all of the EEG channels [12] (this has also been validated in our experimental data, as demonstrated in Figure 1). This means that the EEG signals can be described by the following m-channel signal $\mathbf{y}(t)$:

$$\mathbf{y}(t) = \mathbf{d}\ \sin(2\pi f_m t + \phi) + \mathbf{n}(t) \tag{2}$$

$$= \mathbf{s}(t) + \mathbf{n}(t) \tag{3}$$

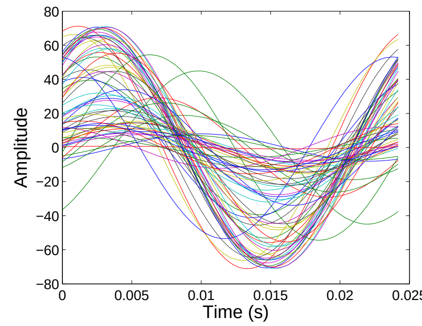

Fig. 1: ASSR waveform in all 64 EEG channels after bandpass filtering around f_m= 40 Hz and averaging over epochs with a length of $\frac{1}{f_m}$ = 25ms, i.e. one period of the modulating sine.

where the steering vector $\mathbf{d}$ contains the gains of the ASSR signal in each of the m channels, and the m-channel signal $\mathbf{n}(t)$ models the EEG background noise which is assumed to be uncorrelated with the ASSR ($E[\mathbf{n}(t)\ \sin(2\pi f_m t + \phi)] = \mathbf{0}$) and has zero mean ($E[\mathbf{n}] = \mathbf{0}$).

ASSR detection comes down to rejecting the possibility that the measurement $\mathbf{y}(t)$ originates from noise , i.e. rejecting the null hypothesis

$$H_0 : \mathbf{y}(t) = \mathbf{n}(t) \tag{4}$$

and thereby accepting the alternative hypothesis

$$H_1 : \mathbf{y}(t) = \mathbf{s}(t) + \mathbf{n}(t). \tag{5}$$

For single-channel data, some standard statistical detection methods are available, most of which have the same statistical power [16]. We will use the Hotelling T^2 (HT2) method [17] because of practical considerations. For multi-channel data no practical statistical detection method has been proposed in literature, so later in the paper we will propose our own. We will use it as a reference method that does not apply any spatial filtering but does use all 64 available channels.

Our goal is to speed up ASSR HT estimation by optimally using the available multi-channel EEG measurements. An HT estimation protocol typically consists of multiple subsequent ASSR measurements with decreasing intensity of the presented auditory stimulus. Each measurement lasts until an ASSR is detected or if, after a maximum time duration, no ASSR is found. In the latter case the protocol is halted and the objective HT is determined as the lowest stimulus intensity with a detected ASSR.

3. METHODS

To achieve a more efficient ASSR detection we construct a spatial filter using a training measurement, preferably with high SNR (i.e. resulting from a high intensity auditory stimulus). Assuming spatial coherence of signal and noise sources to remain constant, this filter can then be applied to each of the following multi-channel ASSR measurements on the same subject. This way, one new 'virtual' channel is created with a higher SNR than any of the original channels. Traditional ASSR detection methods can then further be applied to this resulting channel, which will yield faster and more sensitive detection results.

3.1. GEVD-based Spatial Filter Construction

As we are only interested in the part of the measurement $\mathbf{y}(t)$ (or $\mathbf{n}(t)$) around the modulation frequency f_m we will assume that all signals are bandpass filtered. We aim to find the spatial filter $\hat{\mathbf{w}}$ that maximizes the expected power at the modulation frequency for a signal-plus-noise measurement, while minimizing it for a noise-only measurement:

$$\hat{\mathbf{w}} = arg\ \underset{\mathbf{w}}{max} \frac{E[\|\mathbf{y}(t)^T\mathbf{w}\|_2^2]}{E[\|\mathbf{n}(t)^T\mathbf{w}\|_2^2]}. \tag{6}$$

By expanding the 2-norm, this can be rewritten as

$$\hat{\mathbf{w}} = arg\ \underset{\mathbf{w}}{max} (\frac{\mathbf{w}^T\mathbf{R}_y\mathbf{w}}{\mathbf{w}^T\mathbf{R}_n\mathbf{w}}) \tag{7}$$

where $\mathbf{R}_y = E[\mathbf{y}(t)\mathbf{y}(t)^T]$ is the signal-plus-noise covariance matrix and $\mathbf{R}_n = E[\mathbf{n}(t)\mathbf{n}(t)^T]$ is the noise covariance matrix. Because noise and ASSR were assumed to be uncorrelated, it follows that $E[\mathbf{s}(t)\ \mathbf{n}(t)^T] = 0$ resulting in $\mathbf{R}_y = \mathbf{R}_s + \mathbf{R}_n$ where $\mathbf{R}_s = E[\mathbf{s}(t)\mathbf{s}(t)^T]$. Therefore equation (7) can be rewritten as

$$\hat{\mathbf{w}} = arg\ \underset{\mathbf{w}}{max} (1 + \frac{\mathbf{w}^T\mathbf{R}_s\mathbf{w}}{\mathbf{w}^T\mathbf{R}_n\mathbf{w}}) \tag{8}$$

$$= arg\ \underset{\mathbf{w}}{max} (\frac{\mathbf{w}^T\mathbf{R}_s\mathbf{w}}{\mathbf{w}^T\mathbf{R}_n\mathbf{w}}). \tag{9}$$

This shows that optimizing the signal-plus-noise to noise ratio (as in (7)) is equivalent to optimizing the SNR (as in (9)).

It is known that the solution to the optimization problem stated in (7) is given by the principal generalized eigenvector ($\mathbf{GEVec_1}$) of the matrix pencil $(\mathbf{R}_y, \mathbf{R}_n)$ [18]:

$$\hat{\mathbf{w}} = \mathbf{GEVec_1}(\mathbf{R}_y, \mathbf{R}_n). \tag{10}$$

Once the spatial filter $\hat{\mathbf{w}}$ is constructed, it can be applied to subsequent measurements on the same subject to speed up the rest of the HT assessment. Spatial filtering of a measurement results in a new, virtual channel $y(t) = \mathbf{y}(t)^T\ \mathbf{w}$. Statistical detection can then be applied to this single virtual channel, the same as if it were a real channel.

3.2. Estimation of the Covariance Matrices

To calculate the spatial filter $\hat{\mathbf{w}}$ as in (10), the covariance matrices $\mathbf{R}_y$ and $\mathbf{R}_n$ have to be estimated first. The straightforward way to do this, is to use two measurements: one with and one without auditory stimulus, for the calculation of respectively $\mathbf{R}_y$ and $\mathbf{R}_n$. In practice however, we will not record such a second measurement but rather estimate both $\mathbf{R}_y$ and $\mathbf{R}_n$ from the same measurement, using different frequency ranges through spectral filtering.

For estimation of $\mathbf{R}_y$ we will use the frequency range

$$[f_m - \delta, \quad f_m + \delta] \qquad \text{(ASSR present)} \tag{11}$$

while for $\mathbf{R}_n$ we will use

$$[f_m - \delta - \Delta, \quad f_m - \delta] \qquad \text{and} \tag{12}$$

$$[f_m + \delta, \quad f_m + \delta + \Delta] \qquad \text{(only noise present)} \tag{13}$$

for some bandwidths δ and Δ. This assumes the noise spatial coherence to be constant in a limited frequency range $2(\delta + \Delta)$ around the modulation frequency. Estimating the necessary covariance matrices this way is more practical as it requires only one training measurement instead of two, saving time.

3.3. ASSR Detection

As mentioned before we will use the HT2 test for detection. To this end, a single-channel measurement (or virtual channel such as $y(t)$) first has to be split in epochs of equal length (typically 1s), where this length is also a multiple of the modulation period $\frac{1}{f_m}$. Then these epochs are all transformed to the frequency domain using the Fast Fourier Transform (FFT). For each epoch only the frequency bin corresponding to the modulation frequency is retained. Note that the resulting sequence of complex numbers has an expected average of zero for noise-only measurements, and a non-zero expected average for measurements containing an ASSR. In fact, phase and amplitude of this average FFT bin are good estimators of the ASSR phase ϕ and amplitudes (elements of $\mathbf{d}$).

The HT2 test then takes the aforementioned sequence of complex numbers as an input and computes a significance level s, with $0 \leq s \leq 1$. This number equals the likelihood that these (or more extreme) observations can be explained by zero mean Gaussian noise. Finally the null hypothesis H_0 is rejected (= 'successful detection') if the obtained significance level is lower than a pre-defined threshold T, i.e. $s < T$. It should be noted that on top of normal thresholding the channel was required to stay below this threshold for 15 subsequent seconds to avoid possible artefacts in the data to trigger a detection.

As true EEG background noise might not be perfectly Gaussian, the computed significance s might differ from the true likelihood that these observations can be explained by EEG background noise (as opposed to Gaussian noise). Typically an a-specificity or false positive (FP) rate of 5% is desired. We can experimentally determine the corresponding threshold T by 'detecting' ASSRs in measurements without ASSR present and adjusting the threshold until 5% of these ASSR-less measurements trigger a detection. In practice however, we will re-use our EEG measurements with ASSRs present, but test at frequencies other than the modulation frequency.

More generally we will construct a full Receiver Operating Characteristic (ROC) curve that plots the sensitivity, also known as the True Positive (TP) rate, versus the a-specificity (FP rate), while varying the threshold from zero to one. By constructing this curve both for the reference method (explained below) and our own method we obtain an objective comparison of the detection performance. Also, the threshold corresponding to the point of clinical interest with 5% a-specificity can easily be found by this method.

3.4. Reference and 'Hybrid' Method

We will compare our method with a reference method (denoted by 'MC ref'): it uses the full multi-channel measurements, but does not apply any spatial filtering. The channels are combined at the detection level through a simple, heuristic method: for a successful detection, 8 out of the 64 available channels are singly required to be significant ($s < T$) for a period of 15s. We will denote the threshold used for this reference method by $T_{MC_{ref}}$.

To benefit both from the improved sensitivity and detection speed on the spatially filtered channel and from the robustness of the multi-channel reference method, our method will be devised as a hybrid of both (denoted by 'MC + SC spat'). A detection is considered successful when one of both detection methods detects a response. Our hybrid method therefore uses two thresholds, denoted respectively as $T_{SC_{hybrid}}$ and $T_{MC_{hybrid}}$.

4. EXPERIMENTAL RESULTS

4.1. Set-up

Eight normal hearing subjects aged 18-24 were asked to sit and relax in an electromagnetically shielded and soundproof room. Their EEG was measured with a 64-channel BioSemi ActiveTwo set-up. Electrodes were placed on the subjects' head according to the international 10 - 20 system. Subjects were presented an auditory stimulus as in (1) with modulation frequency $f_m = 40$ Hz. Auditory stimuli were presented at different intensities A; one measurement at 82dBSPL (high intensity, used for training) and two at respectively 34 and 22dBSPL (near-HT intensities, challenging for ASSR detection). This procedure was performed twice for different carrier frequencies f_c: 500 and 2000 Hz. The 16 training measurements lasted only 150s each, the 32 evaluation measurements lasted 600s each. The EEG was sampled at 8kHz and the measurements were downsampled to 500Hz and notch filtered at 50 Hz to remove power-grid noise.

Each training measurement was duplicated and each copy was bandpass filtered differently as described in section 3.1, with second order sinc filters ($\delta = \frac{1}{8}$ Hz, $\Delta = 12$ Hz), to allow the construction of $\mathbf{R}_y$ and $\mathbf{R}_n$. The spatial filter $\hat{\mathbf{w}}$ was calculated as $\hat{\mathbf{w}} = \mathbf{GEVec_1}(\mathbf{R}_y, \mathbf{R}_n)$. This spatial filter was then applied to all other measurements on the same subject at the same carrier frequency, resulting in one virtual channel for each of these measurements.

Finally, a hybrid detection (as explained in section 3.3) was performed on the virtual channels together with the original 64-channel measurements, for 50 different values of the thresholds ($T_{SC_{hybrid}}$ and $T_{MC_{hybrid}}$). Note that this would result in 2500 different threshold pairs. As most of these are suboptimal, we only retained the threshold pairs which give the highest sensitivity for each value of the a-specificity.

The results of the multi-channel reference method were calculated as explained in section 3.3, again for 50 different values of $T_{MC_{ref}}$.

4.2. Results

Figure 2 shows the ROC curve comparing the hybrid method's (MC + SC spat) detection performance with the reference method (MC ref) in terms of sensitivity for all 32 evaluation measurements. Additionally the green dashed lines with triangle markers show what would happen if only the spatially filtered channel would be considered and no hybrid detection would take place, i.e. $T_{SC_{hybrid}} = 0$ (denoted by 'SC spat'). Figure 3 shows the same ROC curve, but now zoomed in around the clinically relevant 5% a-specificity.

It is clear from the figures that the hybrid method outperforms the reference method by a fair margin concerning sensitivity. Figure 3 also reveals that although detection on the single spatially filtered channel (SC spat) and the multi-channel measurement (MC ref) have similar results, combining them still offers significant improvement (MC + SC spat), demonstrating complementarity of both methods.

Method	T_{MC}	T_{SC}	Sensitivity	Measure Time(s)
MC + SC spat	0.007	0.005	0.75	309
SC Spat	//	0.01	0.66	338
MC ref	0.006	//	0.59	382

Table 1: Detection times, thresholds and sensitivity results at 5% a-specificity.

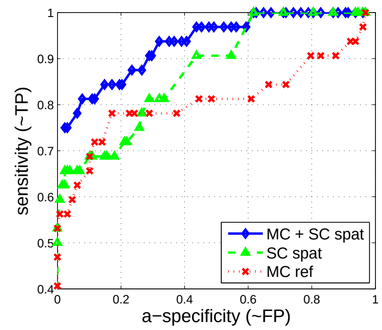

Fig. 2: ROC curve comparing detection performance

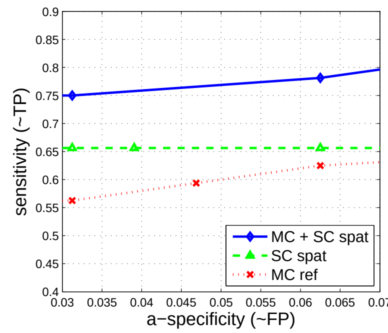

Fig. 3: Same ROC curve as Figure 2, but now zoomed in at the clinically relevant 5% a-specificity

We interpret this performance increase as the result of combining the improved sensitivity of the former method with the robustness of the latter.

In practice, as mentioned before, only the thresholds and detection times at the optimal points at 5% a-specificity are of clinical interest. These can be found for the different methods in table 1. If detection was not successful, the detection time was set to the maximum measurement time, i.e. 600s. The table shows that the average measurement time of the hybrid method is more than 15% lower than without spatial filtering.

Finally we would like to note that the increase in sensitivity was very apparent, certainly at the 22dBSPL measurements (at 32dBSPL less so because both methods did well). The decrease in measurement time however seems to be very measurement-specific and therefore has a high variance.

5. CONCLUSIONS

In this paper we have presented an algorithm for linear spatial filtering that, when applied to multi-channel EEG measurements containing ASSRs, optimizes the SNR in the resulting channel. We have shown on real EEG measurements that our hybrid detection method using both the spatially filtered channel and the original multi-channel measurement successfully improves detection efficiency, both in terms of an improved detection sensitivity and a reduced measurement time.

6. ACKNOWLEDGEMENTS

The authors would like to thank Michael Hofmann for the many fruitful discussions and Maaike Van Eeckhoutte for providing the experimental data.

7. REFERENCES

[1] M. Aoyagi, T. Kiren, Y. Kim, Y. Suzuki, T. Fuse, and Y. Koike, "Optimal modulation frequency for amplitude-modulation following response in young children during sleep," *Hearing Research*, vol. 65, no. 12, pp. 253 – 261, 1993.

[2] T. Picton, A. Durieux-Smith, S. Champagne, J. Whittingham, L. Moran, C. Gigure, and Y. Beauregard, "Objective evaluation of aided thresholds using auditory steady-state responses," *Journal of the American Academy of Audiology*, vol. 9, pp. 315–331, October 1998.

[3] O. G. Lins, P. E. Picton, T. W. Picton, S. C. Champagne, and A. DurieuxSmith, "Auditory steady-state responses to tones amplitude-modulated at 80 to 110 Hz," *The Journal of the Acoustical Society of America*, vol. 97, no. 5, 1995.

[4] G. Rance, R. Roper, L. Symons, L.-J. Moody, C. Poulis, M. Dourlay, and T. Kelly, "Hearing threshold estimation in infants using auditory steady-state responses," *Journal of the American Academy of Audiology*, vol. 16, no. 5, pp. 291–300, 2005-05-01T00:00:00.

[5] R. A. McConkey, Koch, Osberger, Zimmerman-Phillips, and Kishon-Rabin, "Effect of age at cochlear implantation on auditory skill development in infants and toddlers," *Archives of Otolaryngology, Head and Neck Surgery*, vol. 130, no. 5, pp. 570–574, 2004.

[6] A. Herdman, O. Lins, P. Van Roon, D. Stapells, M. Scherg, and T. Picton, "Intracerebral sources of human auditory steady-state responses," *Brain Topography*, vol. 15, no. 2, pp. 69–86, 2002.

[7] M. John and T. Picton, "Human auditory steady-state responses to amplitude-modulated tones: phase and latency measurements," *Hearing Research*, vol. 141, no. 12, pp. 57 – 79, 2000.

[8] T. W. Picton, M. S. John, D. W. Purcell, and G. Plourde, "Human auditory steady-state responses: The effects of recording technique and state of arousal," *Anesthesia & Analgesia*, vol. 97, no. 5, pp. 1396–1402, 2003.

[9] H. Higashi, T. Rutkowski, Y. Washizawa, A. Cichocki, and T. Tanaka, "EEG auditory steady state responses classification for the novel BCI," in *Engineering in Medicine and Biology Society,EMBC, 2011 Annual International Conference of the IEEE*, pp. 4576–4579, Aug 2011.

[10] M. S. John, O. G. Lins, B. L. Boucher, and T. W. Picton, "Multiple auditory steady-state responses (MASTER): stimulus and recording parameters," *International Journal of Audiology*, vol. 37, no. 2, pp. 59–82, 1998.

[11] H. Luts and J. Wouters, "Hearing assessment by recording multiple auditory steady-state responses: the influence of test duration," *International Journal of Audiology*, vol. 43, no. 8, pp. 471–478, 2004.

[12] T. W. Picton, M. S. John, A. Dimitrijevic, and D. Purcell, "Human auditory steady-state responses: Respuestas auditivas de estado estable en humanos," *International Journal of Audiology*, vol. 42, no. 4, pp. 177–219, 2003.

[13] S. Vanvooren, H. Poelmans, M. Hofmann, P. Ghesquire, and J. Wouters, "Hemispheric asymmetry in auditory processing of speech envelope modulations in prereading children," *The Journal of Neuroscience*, vol. 34, no. 4, pp. 1523–1529, 2014.

[14] B. Van Dun, J. Wouters, and M. Moonen, "Improving auditory steady-state response detection using independent component analysis on multichannel EEG data," *Biomedical Engineering, IEEE Transactions on*, vol. 54, no. 7, pp. 1220–1230, 2007.

[15] B. Van Dun, J. Wouters, and M. Moonen, "Multi-channel wiener filtering based auditory steady-state response detection," in *Acoustics, Speech and Signal Processing, 2007. ICASSP 2007. IEEE International Conference on*, vol. 2, pp. II–929, IEEE, 2007.

[16] J. L. Valdes, M. C. Perez-Abalo, V. Martin, G. Savio, C. Sierra, E. Rodriguez, and O. Lins, "Comparison of statistical indicators for the automatic detection of 80 Hz auditory steady state responses," *Ear and hearing*, vol. 18, no. 5, pp. 420–429, 1997.

[17] T. W. Picton, J. Vajsar, R. Rodriguez, and K. B. Campbell, "Reliability estimates for steady-state evoked potentials," *Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section*, vol. 68, no. 2, pp. 119 – 131, 1987.

[18] G. H. Golub and C. F. Van Loan, *Matrix computations*, vol. 3. JHU Press, 2012.