Comparison of Sequential Test Strategies based on Monte Carlo Simulations in the Detection of Auditory Steady-state Responses

Victor H. de S. S. Ragazzi, Alexandre G. Caldeira, Patrícia N. Vaz, Felipe Antunes, and Leonardo B. Felix

***Abstract*—Sequential testing strategies commonly reduce the time for automated detection of an auditory steady-state response (ASSR). However, repeated tests application leads to an increase of false positive rate. Monte Carlo-based strategies are used to overcome this obstacle. Despite several published papers could be found describing such strategies, no comprehensive comparison is found in the literature. Our work selects strategies based on Monte Carlo simulations to calculate critical values. To optimize each strategy, test application parameters are varied, and the Pareto frontier is discussed. The detection rate and/or the detection speed improved for every strategy, except for Stürzebecher's 2013 method, which increased the false positive rate to 15.3%. All other strategies kept the false positive rate within the desired limit. Pareto curves reveal that modified 2015 strategy had performance achieving 5.6% higher than the original parameters. The automated detection of ASSR improved with each implemented strategy, but not all of them kept a controlled false positive rate (2013 and 2015). Cebulla's 2015 modified strategy had the highest detection rate in the shortest time.**

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***Index Terms*—Encephalogram, sequential tests, critical value, false positive, optimization, Monte Carlo.**

I. Introduction

Auditory evaluation is a crucial step in diagnosing and treating hearing problems, especially in children. According to the Joint Committee on Infant Hearing [1], electrophysiological auditory evaluation through Otoacoustic Emissions (OAE) or Auditory Brainstem Response (ABR) are recommended by the third month of life, aiming to start treatment as soon as possible in case of risk of hearing loss. However, the process can be extended for several sessions due to challenges, such as patient cooperation or sleep interruptions in infants. The need to expedite auditory evaluation is evident in order to optimize the time of professionals and patients, minimizing costs and preventing hearing difficulties [2], [3].

The auditory response evaluation is an audiological procedure that aims to evaluate the integrity of the auditory pathway, covering from the auditory nerve to the brainstem. For small children, babies and uncooperative individuals, it is recommended to use objective audiometry based on OAE or ABR [4]. OAE usually does not offer a comprehensive evaluation of the entire auditory pathway, focusing mainly on the cochlear hair cells. This means that injuries that occur in the posterior parts of the auditory pathway, such as in the brainstem, may not be detected by this test alone [5], [6].

The disadvantage of ABR is both the cost of implementation and the test time, as both are higher when compared to OAE [7]. There are some cases where ABR may also depend on the subjective interpretation of specialized professionals to evaluate the presence or absence of response to the stimulus [8], therefore, the test may be influenced by the evaluator's experience [9]–[11]. Furthermore, more specific evaluations are needed when frequency range hearing loss occurs.

Within the techniques used for objective audiometry, the Auditory Steady-State Response (ASSR) emerges as a complement to the ABR and OAE [12]–[14]. ASSRs can be elicited by different sounds, and the most used stimuli are: amplitude-modulated (AM) tones, frequency-modulated (FM) tones, and combined stimuli of AM and FM. ASSR-based audiometry can estimate hearing at different frequencies simultaneously, which makes it particularly useful for identifying hearing losses at specific frequency ranges [15], [16].

The auditory brain response is described as an evoked potential, generated in the nervous system and detected in the electroencephalogram (EEG). The analysis of the EEG signals involves examining the brain's electrical activity to detect the patient's auditory response. This is achieved by presenting auditory stimuli, such as tones or clicks, and recording the corresponding brainwave patterns. By analyzing these patterns, we can determine if the auditory stimuli elicit a response, which is then used to construct the electrophysiological audiogram, a graph representing the patient's hearing thresholds across different frequencies. [17]. Electrophysiological audiogram is often used to estimate auditory thresholds, which are the minimum levels of sound intensity at which a person can detect and recognize sounds at different frequencies.

ASSR detection in EEG signals is conducted by statistical

This study was funded by the FAPEMIG and CNPQ institute under the scientific initiation program by the Federal University of Viçosa and carried out with the support of the Coordination for the Improvement of Higher Education Personnel - Brazil (CAPES) through the Academic Excellence Program (PROEX).

V. H. de S. S. Ragazzi, and L. B. Felix are with Federal University of Viçosa, Brazil (e-mails: victorhugosouza0@gmail.com, and leobonato@ufv.br).

A. G. Caldeira, and P. N. Vaz are with Federal University of Minas Gerais, Brazil (e-mails: alexandregomescaldeira@gmail.com, and patricia.nvaz@gmail.com).

F. Antunes is with Federal Institute of Education of Minas Gerais, Brazil (e-mail: felipe.antunes@ifmg.edu.br).

procedures in the time or frequency domain, as Objective Response Detectors (ORD) [12], used to determine response presence or absence. Single-shot strategies are methods where ORDs are applied at the end of EEG recording [18]. The test can also be performed sequentially, i.e., before the complete collection of the signal trial-by-trial, and if an immediate response is not observed, a new trial is carried out at defined time intervals. In sequential testing, the process repeats until it identifies a response or reaches a time limit. The application of these sequential approaches allows for a reduction in detection time [18]–[21].

As the number of detection trials increases, the significance of the false positive (FP) rate in relation to the true positive rate becomes increasingly critical. To enhance this analysis, metrics such as the Receiver Operating Characteristic (ROC) curve, which graphically depicts the true positive rate against the FP rate, can be utilized.

To control FP rate, the Bonferroni correction can be applied, which increases the critical value by dividing the significance level of the test by the number of times the test will be applied. However, using Bonferroni correction is considered conservative, as the probability of falsely rejecting the null hypothesis (finding a significant effect when there is none) is reduced more than necessary. A possible alternative is to make use of Monte Carlo simulations to better determine critical values for multiple tests [22], [23].

The demand for efficient auditory assessments drives the focus on automated methods for auditory response detection. This study aims at analyzing and comparing sequential methods for auditory response detection based on Monte Carlo simulations. Two approaches were conducted: a) the sequential tests were applied as closely identical as possible to how they were described in the original papers; b) a search was performed for the optimal set of parameters in each method. All methods were applied to EEG data during ASSR stimulation protocol.

II. Materials and Methods

In a sequential test, three important values must be considered: (i) the initial number of epochs for the first test (Mmin); (ii) the number of additional epochs (Mstep) required to reapply the test; and (iii) the maximum number of epochs (Mmax) that will be recorded and will be used as non-detection stopping criterion. The ORD methods were the same as those used in the original papers, namely the Modified Rayleigh Test [22], [24] and the Modified Q-sample [23], [25], which will be presented in the subsections below, as well as the sequential test strategies.

A. Strategy I — False Positive Control

A method for finding critical values that control FP rates was described by Stürzebecher in 2005 [22]. Eight million sets of simulated data were generated, each consisting of 100 epochs of random numbers. Each data set was tested using the modified Rayleigh test, starting with a Mmin equal to 10. This signal was gradually extended by one epoch (Mstep equal to 1) until all 100 epochs were included. In this way, 91 test results (91 test values) were achieved for each data set. The critical value is calculated based on the distribution of the final test values.

To define the presence or absence of a signal response, the Modified Rayleigh Test was used, which considers both the spectral phase and the ranked amplitude of each epoch of the signal during the detection strategy. The statistic of the modified Rayleigh test is calculated by:

$$R_m^* = \frac{R_m}{n\sqrt{n}}, \tag{1}$$

with:

$$R_m = \sqrt{C_m^2 + S_m^2}; \tag{2}$$

$$C_m = \frac{1}{n}\sum_{n=1}^{\infty} r_i cos(\varphi_i); \tag{3}$$

$$C_m = \frac{1}{n}\sum_{n=1}^{\infty} r_i sin(\varphi_i). \tag{4}$$

and:

φ — Angle of the spectral component of the i-th epoch;
n — Number of epochs
r — Rank number of spectral amplitude

B. Strategy II — Higher Harmonics

It was shown that the ASSR spectrum also contains higher harmonics with considerably high amplitudes. For this reason, statistical tests that consider only the first harmonic ignore a significant part of the available information. The use of a q-sample test, which, in addition to the fundamental frequency, also includes higher harmonics of the signal for better detection performance [23].

From this point on, another variable is also dealt with, the higher harmonics present in the signal. In this way, the detector was applied at the stimulation frequency and also at the frequencies of the higher harmonics (considering two higher harmonics), as proposed by Cebulla in 2006 and Stürzebecher in 1999 [12], [23]. Cebulla suggests five detectors; in the present study, it was implemented the detector that uses real phase information and ranked amplitude, named MQSTV3 (Modified Q-Sample Test V3).

C. Strategy III – Critical Value Correction

Traditionally, a constant critical value is used to determine the presence or absence of a response in the ASSR signal [22], [23]. However, it is described in [26] that this is a conservative method. At each stage of the test, the probability of mistakenly detecting a response increases compared to the previous test trial, thus the critical value of the test may also increase at each stage.

The method is based on the idea that repeated testing increases the probability of a false positive result, so the critical test value should be increased with each test step to compensate for this effect. The strategy also uses a table of pre-calculated critical values for different test steps and

signal-to-noise ratios, which are derived from Monte Carlo simulations.

It was observed that with the increase in signal size, critical values also progressively increase. One of the advantages of this strategy is the possibility of increasing the detection rate, but this can cause a consequent increase in FP.

D. Strategy IV - Mstep Variation

As observed by Cebulla in 2015, it is not necessary to keep the Mstep (epoch interval between applications of sequential tests) constant. Therefore, the Mstep was changed in each test application as shown below. The method propose the following step variation:

Epoch 21-60, Mstep = 4 (10 steps applied)
Epoch 61-108, Mstep = 6 (8 steps applied)
Epoch 109-180, Mstep = 8 (9 steps applied)

E. Strategy V – Modified Mstep Variation

Cebulla's 2015 strategy uses the variation of Mstep during sequential applications along with the variation of the critical value in each of these applications. However, as done by Cebulla in 2015 [20], a version of this strategy will also be considered where the critical value will be constant, as described in Stürzebecher's 2005 and Cebulla's 2006 strategies.

F. EEG Data

Eleven adult individuals participated in the study, consisting of two women and nine men. The age range of the participants varied between 20 and 35 years, with hearing considered normal (threshold $\leq$ 20 dB Hearing Level - HL). All patients remained awake during the recordings and were recommended to keep their eyes closed. The carrier frequencies for both ears were the same: 500, 1000, 2000, 4000 Hz, modulated respectively at frequencies 81, 85, 89 and 93 Hz for the right ear, and 83, 87, 91 and 95 Hz for the left ear. Thus, eight AM2 tones were used to evoke the ASSR. The research received approval from the local Ethics Committee (CEP/UFV No. 2.105.334), and all volunteers signed an informed consent form. Data collection took place in an acoustically isolated booth, located at the Interdisciplinary Signal Analysis Center (NIAS) at the Federal University of Viçosa (UFV). Participants were invited to relax or sleep on a bed with their eyes closed. EEG signal acquisition was performed using sixteen electrodes (m Fz, F3, F4, F7, FCz, Cz, C3, C4, Pz, P3, P4, T3, T4,T5, T6 e Oz) with reference to the back of the head and the ground in Fpz arranged on the scalp according to the International System 10-20. Recording was performed by the NIASv1 system, i.e., the RHA2216 front-end (Intan Technologies, USA) and ADS127L01 analog-digital converter (Texas Instruments, USA). A high-pass and low-pass Butterworth analog filter with a cutoff frequency of 0.5 and 300 Hz respectively was applied to each channel. The sampling frequency was 1000 Hz per channel for seven volunteers and 1750 Hz per channel for four volunteers. Each volunteer underwent three signal recording sessions with a stimulation intensity of 50dB SPL, each session lasting 5, 8 and 8 minutes respectively. The EEG signals were divided into one-second epochs and stored on disk for offline analysis, performed in Matlab R16 software (MathWorks, Natick, MA, USA). The collected database was also used in [18].

G. Performance Measures

The detection rate, also known as sensitivity or true positive rate, is calculated by dividing the number of correctly detected detections by the total number of signals.

The FP rate represents the cases where the system erroneously identifies a positive result when it is actually negative. This metric is calculated by dividing the number of detections erroneously classified as positive by the total number of signals. In this particular study, the occurrence of false detections was determined through the analysis of the response present in the sidebands of the stimulation frequencies, using 25 neighboring frequencies.

In automated audiometry, false-negative (FN) cases indeed have more severe implications than false-positive (FP) cases. Nonetheless, the focus of this study is a step before screening applications, since we are first developing and comparing useful signal processing techniques for EEG signals. The FP rate is significant not only within the clinical context but also for verifying the correct implementation of tests, as we employ objective response detectors known as Constant False Alarm Rate (CFAR) [27]. Consequently, controlling the FP rate is essential to ensure the proper implementation of these tools, as demonstrated in the cited studies within this work. We will study FN and other metrics in a continuous work targeting clinical applications.

The average detection time is a measure of how long it takes to determine whether an auditory-evoked potential is present or not in a given recording. It is calculated by applying a ORD to the frequency spectrum of the evoked potential and finding the point at which the test reaches a certain level of confidence that the response is real and not due to noise.

In order to compare the optimizations of the proposed parameters, Pareto curves were calculated for each of the strategies. In this curve, each point represents a combination of parameters analyzed, and the position of the points on the curve indicates how favorable this combination is in relation to the others. In other words, the Pareto curve shows which combinations of parameters are the most efficient or relevant for a given problem, allowing for prioritization of actions and resources.

In order to compare whether the results of the sequential test strategies differ from each other, two different statistical methods were used. The McNemar test was used in order to compare the statistical difference of the detection rates of each strategy. The tests were performed in pairs, verifying if there is a difference in each subsequent strategy. It should be emphasized that this verification was carried out only in strategies that presented a controlled FP rate. Following the same methodology, Student's t-test was used for a comparison about the detection times of each method.

H. Parameter Optimization

The strategies mentioned before were submitted to an exhaustive search for parameters (Mmin, Mstep, Mmax) in order to improve detection rate and detection time in our database.

For Stürzebecher's 2005, Cebulla's 2006 and Stürzebecher's 2013 strategies, an algorithm was developed to generate a matrix encompassing all possible variations of parameters (Mmin and Mstep). This resulted in 1342 different sequential application possibilities, covering all possible configuration sets between Mstep and Mmin, both parameters were varied from 1 to 240 epochs. This procedure was also implemented in Cebulla's 2015 strategy. However, as this strategy has a variable Mstep parameter, the number of possible parameters grew exponentially. In order to make the process computationally feasible, the procedure was developed capable of analyze 70210 distinct parameter sets.

In order to make the process computationally feasible, an algorithm was developed capable of simulating 70210 sets of distinct parameters, varying the Mmin frIom 0 to 240 epochs, and the values of Mstep varied only between even numbers (2, 4, and 6) as shown in the following example:

Set 1 (Mmin = 2):

- Epoch 2-230, Mstep = 2 (115 steps applied)
- Epoch 230-234, Mstep = 4 (1 step applied)
- Epoch 234-240, Mstep = 6 (1 step applied)

Set 2 (Mmin = 2):

- Epoch 2-226, Mstep = 2 (113 steps applied)
- Epoch 226-234, Mstep = 4 (2 steps applied)
- Epoch 234-240, Mstep = 6 (1 step applied)

Set 3 (Mmin = 2):

- Epoch 2-224, Mstep = 2 (112 steps applied)
- Epoch 224-228, Mstep = 4 (1 step applied)
- Epoch 228-240, Mstep = 6 (2 steps applied)

Defining the method, continue using all step variations with these Mstep values. When all sets have been used, the values of Mstep vary to (4, 6, and 8), and in this way, until reaching the maximum value being this (78, 80, and 82).

III. Results and Discussion

A. Comparison using Original Papers' Guidelines

Initially, it is important to emphasize that the size of the signals used in the original papers may differ in the number of epochs to our database. Stürzebecher et al. (2005) and Cebulla et al. (2006) have 100 epochs, while the others have 180. So, the same Mmin and Mstep parameters from the original papers were adopted, only changing the number of test applications on each signal. For example, in Cebulla's 2005 strategy, the authors propose an application with Mmin = 10 and Mstep = 1 on a signal of 100 epochs, resulting in 91 applications. In this study, although the values of Mmin and Mstep have been kept the same, since our database has 240 epochs, 231 test applications were performed.

The detection rates, FP rates, and detection time were calculated in order to evaluate the strategies employed. These results are presented in Table I.

The strategies were compared in pairs with the strategy developed later (2005 was compared with 2006, then 2006 was compared with 2013) to check if there is a significant difference in detection times, and all of them showed a significant difference between them. However, in Stürzebecher‘s 2013 strategy, there was a showed a critical increase in the false positive rate. It is worth noting that this increase persisted in Cebulla's 2015 strategy, as the strategies were incorporated cumulatively. To correct the increase in the number of false positives, Cebulla's 2015 strategy was applied without the progressive increase of the critical value, as shown in Cebulla et al. (2015) resulting in the so-called 'Cebulla's 2015 Modified'. With this modification, there was a 6.9% increase in the detection rate in relation to Cebulla's 2006 strategy, being the second-best strategy that presented controlled rates of false positives.

B. Pareto Frontier Comparison from Exhaustive Search

After analyzing the methods that were replicated, optimizations were carried out to find the best possible set of parameters for each of strategy. It was found that it was possible to control the FP rate of nearly 100% of tests with the parameters of Strategies I, II and V in the confidence interval used (FP equal to 5%). However, it was not possible to control the FP rate for Stürzebecher's 2013 and Cebulla's 2015 strategies, as they presented an uncontrolled FP rate (greater than 10%) in 57% and 99% of the parameter sets, respectively. In the 2006 Cebulla strategy, the FP rate was under control. However, when implementing the progressive increase of the critical value (referring to Stürzebecher's 2013 strategy), the parameter sets that use many test applications, caused the FP to increase more than expected.

In order to perform a direct comparison of the optimization of the parameters of each of the strategies, Pareto curves were calculated in Fig. 1. In this sense, it is seen that each point on the curve represents a set of parameters, while the axes represent the detection rate and the detection time. Stürzebecher‘s 2013 and Cebulla's 2015 strategies were not shown since their FP rate were mainly out of control amongst the sets of parameters.

It is notable that the curve corresponding to Stürzebecher's 2005 strategy is above the others, indicating a longer detection time for equivalent detection rate values compared to other strategies. This strategy reaches a maximum detection rate of 65.9%, while subsequent strategies reach this value 70 seconds earlier.

Additionally, it is important to note that the curves related to Cebulla's 2006 and Cebulla's 2015 Modified strategies display a notable proximity, suggesting a similarity in the detection rate and detection time. This consistency can be attributed to the fact that both strategies use the same response objective detector. In contrast, Stürzebecher's 2005 strategy employed another detector, which may explain its distinct differences compared to the others.

TABLE I
STRATEGY PERFORMANCE MEASURES USING ORIGINAL PAPERS GUIDELINES. ASTERISKS SHOW THAT THERE WERE SIGNIFICANT DIFFERENCES BETWEEN A STRATEGY COMPARED TO THE PREVIOUS ONE

Strategies	Single Shot	Detection Rate	False Positives	Average Detection Time
2005 (I)	64.7%%	51.1%	3.6%	166s
2006 (II)	63.6%	54.5%	6.2%	158s*
2013 (III)	63.6%	61.4%	15.3%	139s*
2015 (IV)	63.6%	65.9%	11%	139s*
2015 (V) Modified	63.6%	61.4%	3.3%	164.5s*

Through a comparison between the values in Table I and Fig. 1, an improvement is noted in both the detection time and the detection rate of the strategies implemented with optimized parameters. The test results faithful to the guidelines of the papers show a performance progression between the implementations of the strategies, but this progression is better observed during the search for better parameters, where it is possible to see the strategies improving.

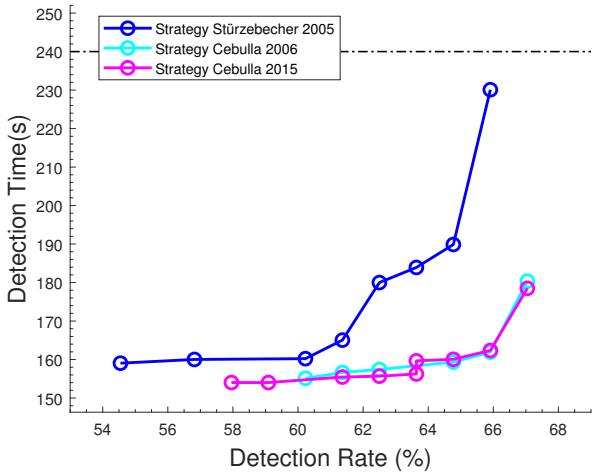

Fig. 1. Pareto curve of the parameter optimizations of the strategies. The points on the curves represent a parameter set which presents a detection rate (represented on the horizontal axis) and a detection time in seconds (represented on the vertical axis). The dotted lines represent the Single-Shot performance measures of the detectors. Only strategies that maintained controlled levels of false positives were plotted.

IV. CONCLUSIONS

Based on the analysis of the results presented in Fig 1, it is possible to establish a direct relationship between an increase in the detection rate and the detection time, as the strategies progress. However, the application of Stürzebecher's 2013 and Cebulla's 2015 strategies showed significant limitations. Stürzebecher's 2013 strategy demonstrated little reliability, as less than half of the optimized parameter sets fell within the established confidence interval. This limitation was also observed with Cebulla's 2015.

Among all the strategies evaluated, the implementation modified Cebulla et al., (2015) stood out as the most advantageous in terms of cost-benefit ratio. The optimization of this strategy resulted in a higher detection rate relative to the detection time, with its parameters remaining within the established confidence interval. Cebulla's 2015 Modified strategy surpassed other approaches, including Cebulla's 2006 strategy in some scenarios, having a significant standout in mean detection time.

The results of this study demonstrate that Cebulla's 2015 Modified stands out as the most reliable and effective, offering a combination of high detection rate and parameter control within the confidence interval. This suggests that's strategy is the most recommended option for the analysis of sequential tests in objective audiometry.

This study aimed to validate the theory of sequential tests in computerized audiometry for enhanced clinical performance, including the potential application to infant EEG capture. Future studies will consider separate investigations for comparing EEG data, particularly given the challenges associated with obtaining EEG data from children.

ACKNOWLEDGMENTS

The authors thank mainly the NIAS research group for the ideas discussed and proposed during the development of the research.

REFERENCES

[1] "Position statement: priniciples and guidelines for early hearing detection and intervention programs. pediatrics," 2007. https://doi.org/10.1542/peds.2007-2333.
[2] "Diretrizes de atenção da triagem auditiva neonatal," 2012.
[3] Y. S. Sininger, L. L. Hunter, P. A. Roush, S. Windmill, D. Hayes, and K. M. Uhler, "Protocol for rapid, accurate, electrophysiologic, auditory assessment of infants and toddlers," *J Am Acad Audiol*, 2020. 10.3766/jaaa.19046.
[4] T. Picton, M. S. John, A. Dimitrijevic, and D. Purcell, "Human auditory steady-state responses," *International Journal of Audiology*, 2003. 10.3109/14992020309101316.
[5] W. Wagner and P. Plinkert, "The relationship between auditory threshold and evoked otoacoustic emissions," *Eur Arch Oto-Rhino-Laryngology*, 1999. 10.1007/s004050050136.
[6] S. Norton, M. Gorga, J. Widen, R. Folsom, Y. Sininger, and B. Cone-Wesson, "Identification of neonatal hearing impairment: Evaluation of transient evoked otoacoustic emission, distortion product otoacoustic emission, and auditory brain stem response test performance," *Ear & Hear*, 2000. 10.1097/00003446-200010000-00013.
[7] M. Leigh, "Hearing screening: Oae vs automated abr," *www.interacoustics.com*, 2022.
[8] Y. H. Tarawneh, R. H. Sohrabi, H. A. M. W. Mulders, N. R. Martins, and M. P. D. Jayakody, "Comparison of auditory steady-state responses with conventional audiometry in older adults," *Front. Neurol.*, 2022. 10.3389/fneur.2022.924096.
[9] A. Canale, M. Lacilla, L. A. Calalot, and R. Albera, "Auditory steady-state responses and clinical applications," *Eur Arch Otorhinolaryngol*, 2016. 10.1007/s00405-006-0017-y.
[10] M. A. Chesnaye, L. S. Bell, M. J. Harte, and M. D. Simpson, "Objective measures for detecting the auditory brainstem response: comparisons of specificity, sensitivity and detection time," *International Journal of Audiology*, 2017. 10.1080/14992027.2018.1447697.

[11] M. A. Chesnaye, "The convolutional group sequential test: reducing test time for evoked potentials," *IEEE Transactions on Biomedical Engineering*, 2019. 10.1109/TBME.2019.2919696.
[12] E. Stürzebecher, C. M., and W. K.-D, "Objective response detection in the frequency domain: Comparison of several q-sample tests," *Audiol Neurootol*, 1999. 10.1159/000013815.
[13] H. Luts, B. Van Dun, J. Alaerts, and J. Wouters, "The influence of the detection paradigm in recording auditory steady-state responses," *Ear and Hearing*, 2008. 10.1097/AUD.0b013e318174f051.
[14] W. D'haenens, M. B. Vinck, L. Maes, A. Bockstael, H. Keppler, B. Philips, F. Swinnen, and I. Dhooge, "Determination and evaluation of clinically efficient stopping criteria for the multiple auditory steady-state response technique," *Clinical Neurophysiology*, 2010. 10.1016/j.clinph.2010.03.008.
[15] D. Ehrmann-Muller, W. Shehata-Dieler, A. Alzoubi, R. Hagen, and M. Cebulla, "Using assr with narrow-band chirps to evaluate hearing in children and adults," *European Archives of Oto-Rhino-Laryngology*, 2020. 10.1007/s00405-020-06053-0.
[16] Y. S. Sininger, L. L. Hunter, D. Hayes, P. A. Roush, and K. M. Uhler., "Evaluation of speed and accuracy of next-generation auditory steady state response and auditory brainstem response audiometry in children with normal hearing and hearing loss," *Ear & Hearing*, 2018. 10.1097/AUD.0000000000000580.
[17] R. Galambos and S. Makeig, "The cerp: Event-related perturbations in steady-state responses," *Brain Dynamics*, 1981. https://doi.org/10.1007/978-3-642-74557-7_30.
[18] T. Zanoteli, F. Antunes, M. D. Simpson, E. Mazoni, A. Marçal, and F. L. Bonato, "Faster automatic assr detection using sequential tests," *International Journal of Audiology*, 2020. 10.1080/14992027.2020.1728402.
[19] N. P. Vaz, A. F., E. Mazoni, and F. L. Bonato, "Automated detection of auditory response: nondetection stopping criterion and repeatability studies for multichannel eeg," *Computer Methods In Biomechanics And Biomedical Engineering*, 2023. https://doi.org/10.1080/10255842.2023.2232071.
[20] M. Cebulla and E. . Stürzebecher, "Automated auditory response detection: Further improvement of the statistical test strategy by using progressive test steps of iteration," *International Journal of Audiology*, 2015. 10.3109/14992027.2015.1017659.
[21] M. A. Chesnaye, "A group sequential test for abr detection," *International Journal of Audiology*, 2019. 10.1080/14992027.2019.1625486.
[22] E. Stürzebecher, C. M., and C. Elberling, "Automated auditory response detection: Statistical problems with repeated testing," *International Journal of Audiology*, 2005. 10.1080/14992020400029228.
[23] M. Cebulla, E. Stürzebecher, and E. C, "Objective detection of auditory steady-state responses: Comparison of one-sample and q-sample tests," *J Am Acad Audiol*, 2006. 10.3766/jaaa.17.2.3.
[24] B. Moore, "A modification of the rayleigh test for vector data," *Biometrika*, 1980. https://doi.org/10.2307/2335330.
[25] K. Mardia, "Statistics of directional data," *Academic Press*, 1975. https://doi.org/10.1111/j.2517-6161.1975.tb01550.x.
[26] E. Stürzebecher and C. M., "Automated auditory response detection: Improvement of the statistical test strategy," *International Journal of Audiology*, 2013. 10.3109/14992027.2013.822995.
[27] S. M. Kay, *Fundamentals of Statistical Signal Processing*. Prentice-Hall, 1993.

Victor Hugo de Souza Singulani Ragazzi Undergraduate student in Electrical Engineering at the Federal University of Viçosa, Brazil. Currently in the third year of research in biomedical engineering, investigating detection methods in electroencephalograms (EEG) and heart rate analysis in tachograms."

Alexandre Gomes Caldeira M.Sc. graduate student in Electrical Engineering at UFMG. He obtained his B.Sc. in Electrical Engineering from UFV in 2024 and an Electrotechnics Technical degree from CEFET-MG in 2022. His research and interests focus on Signal Processing, Linear and Nonlinear Systems, Modeling, Statistics, and Machine Learning applications to tasks in Neuroscience, Biomedical Engineering, and Robotics.

Patricia Nogueira Vaz Electrical Engineer from the Federal University of Viçosa, she earned her D.Sc. in 2023 with a focus on auditory response detection in electroencephalograms at the Federal University of Minas Gerais. Currently, she works as a teacher at the education institute in Minas Gerais.

Felipe Antunes Electrical Engineer from the Federal University of Viçosa, he earned his M.Sc. in 2018 with a focus on modeling and control at the Federal University of São João Del Rei, Brazil. Currently, he works as a professor of basic, technical, and technological education at IFMG.

Leonardo Bonato Felix Electrical Engineering at the Federal University of São João del Rei in 2002. MSc (2004) and DSc (2006) from UFMG. PhD (2020) from the University of Southampton, Inglaterra. Currently, a professor, researcher, and advisor at the Federal Universities UFV, UFSJ, and UFMG. Head of the Biomedical Engineering Research Laboratory, NIAS.