

Acquisition Delay of Wireless EEG Instruments in Time-Sensitive Applications

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Abstract—The aim of this study is to characterize the acquisition delay in wireless EEG instruments and evaluate its impact on the detection of time-locked neural phenomena, such as P300 and movement-related cortical potentials (MRCP). Accurate timing is critical for both research and clinical applications, especially for real-time brain-computer interfaces (BCI). A measurement setup was thus developed to assess acquisition delays and their uncertainty. Delays were measured at both the start and stop of a reference signal generation to investigate the consistency and reliability of the devices. BCI experiments were also performed to evaluate the impact of the measured delay on the detection of the time-locked phenomena. Statistical tests confirmed significant differences in delays across devices and configurations (e.g., from few tens to a hundred ms). These delays directly impacted P300 and MRCP detection, raising concerns about potential misclassification. Nonetheless, the correction of the measured acquisition delay proved beneficial, especially with regard to the P300 latency measured through low-cost instrumentation.

Index Terms—Wireless EEG, acquisition delay, brain-computer interfaces, P300, movement-related cortical potentials.

I. INTRODUCTION

OVER the past decade, much research has been carried out concerning wearable instruments for electroencephalography (EEG) in long-term and real-world settings [1]. This has

led to a variegated landscape of wireless EEG caps. However, the uneven specifications reported by the respective manufacturers prevent a thorough comprehension of the hardware landscape [2].

A relevant but lightly treated aspect is the delay between data acquisition and reception at the processing block. Such a transmission delay was negligible for the wired systems [3], but it is expected to be significant in wireless devices because they need to manage interferences, retransmissions, and protocol overheads to maintain data integrity [4]. This would in turn impact the overall performance of a brain-computer interface (BCI) [5], [6]. Notably, delay magnitude directly impacts real-time feedback, thus compromising some BCIs' operation [6], while delay fluctuations would prevent an accurate detection of time-locked neural phenomena [3], [7].

Event-related potentials (ERPs) like P300 and movement-related cortical potentials (MRCPs) are representative and widely used time-locked phenomena in EEG-based analyses [8]. The P300 consists of an amplitude peak occurring about 300 ms after sensory stimuli over the midline electrodes (Fz, Cz, Pz). Actually, the magnitude and the latency of this potential increase from the frontal to parietal electrode sites [9], [10], [11] and, in practice, the peak can appear in the 300 ms to 600 ms time window [11].

On the other side, MRCPs are linked to overt movements and their effect appears on the EEG 2 s before, during and after the action [12], with a negative peak arising around the onset of the movement [13], as a reflection of the brain's preparation to movement.

Averaging techniques are employed in order to emphasize ERPs and isolate them from the EEG signal as a whole [8], [9], [11], [12]. In this operation, trials alignment is essential for precise ERP identification [8]. Therefore, the delay introduced by EEG acquisition system may have a detrimental impact. Indeed, any delay introduced by the instrumentation must be distinguished carefully from latencies due to the individual, which may also be pathological. This becomes relevant in clinical settings, where P300 and MRCPs are exploited in relation to cognitive [10] and motor [14] deficits or even in neurodegenerative diseases [15], [16], [17].

In addition, delay assessment appears directly relevant for BCI applications when real-time operation is demanded [18], [19]. For instance, patients with amyotrophic lateral sclerosis

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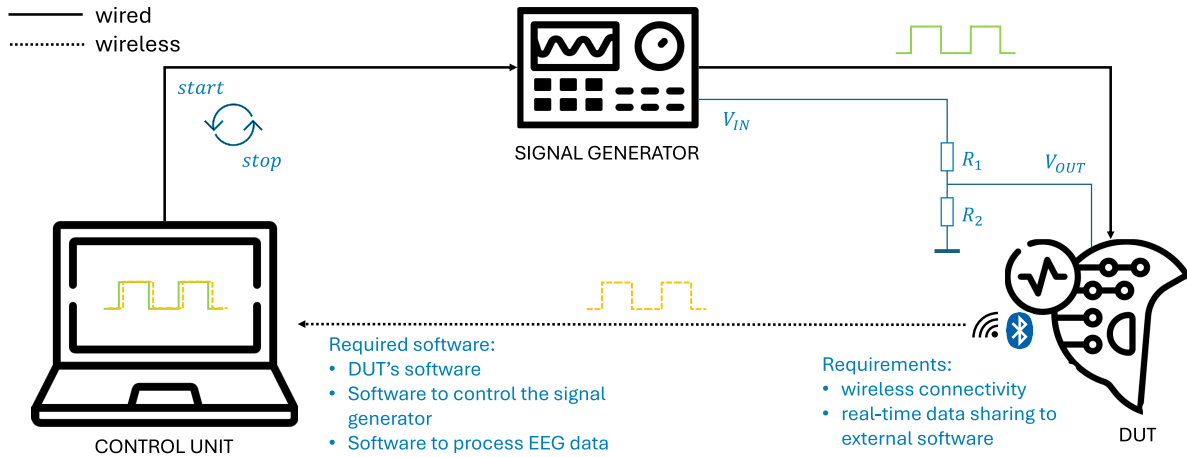


Fig. 1. Block diagram of the proposed measurement setup: a control unit starts and stops the generation of a voltage that, once lowered to the μV range by a resistive divider, is applied to the wireless EEG device under test (DUT). The control unit then receives the data to process through wireless communication.

rely on P300-based BCIs for communication [20] and it is already known that pathological trial-by-trial latency jitter affects the operation [21]. Moreover, BCIs that rely on MRCP detection to provide neurofeedback in rehabilitation [19] require a short latency [14]. In this context, it is again essential to account for the delay (and associated uncertainty) introduced by the EEG acquisition and prevent further detrimental effects, which add to the variability of the P300 peak worsening the performance of the BCI.

Despite the relevance for the mentioned technologies, there is currently not much investment in the assessment of the acquisition-transmission delay. Indeed, existing literature tends to focus on the synchronization of a signal related to the stimulus triggering the ERPs [22], evaluating the delay of the marker in relation to the acquired EEG, without adequately accounting for the delay caused by the acquisition system [6], [23]. Other studies propose on-purpose hardware solutions with a controlled delay [3]. However, the development of customized hardware with the requisite specifications for the analysis of the phenomenon in consideration, which would effectively bypass the market for wearable EEG instruments, is not a feasible option for all BCI end-users.

The present study proposes a methodology for assessing the acquisition delay in EEG instrumentation along with related uncertainty. It then considers an on-field BCI experiment to illustrate how delays can affect the detection of time-locked neural phenomena. The article is structured as follows: Section II presents the setup and related data analysis for the delay measurement, Section III introduces a case study for demonstrating the delay impact, Section IV reports the results, and Section V discusses the inherent findings.

II. ACQUISITION DELAY MEASUREMENT

A. Setup Design

The delay from the acquisition and transmission of data was assessed with a measurement setup as illustrated in Fig. 1. The measurement includes a signal generator, a control unit, and the device under test (DUT), namely the wireless EEG instrument for signal acquisition.

The control unit drives the signal generator to stimulate the DUT with a reference voltage waveform. The DUT transmits the measured signal to the control unit via wireless connection. Meanwhile, the relevant events of the reference waveform are also recorded by the control unit itself. The transmission delay at the control unit can be thus assessed by comparing the signal received via cable from the generator with the signal acquired from the DUT. It is worth noting that also the generator and the DUT are connected via cables. It was reasonably assumed that the delay of the wired connection is negligible with respect to the wireless one. The proof of this fundamental assumption is reported in Sec. II-B.

The proposed measurement station must satisfy some conditions to ensure accurate and reliable measures. Firstly, the control unit has to jointly execute the software for the signal generator control, the software to acquire EEG data in real-time, and the eventual proprietary software of the DUT. The first two may be the same software. Moreover, the temporal distance between consecutive relevant events of the reference waveform needs to exceed the expected acquisition delay in the worst case. Hence, a preliminary delay estimation appears necessary.

Regarding the EEG instruments, the fundamental requirements for inclusion in the analysis are wireless connectivity and the capability to share data in real time out of their proprietary software. Finally, the signal generator has to generate voltage waveforms with amplitudes compatible with EEG, namely from $0.5 \mu\text{V}$ to $100.0 \mu\text{V}$ [24]. A voltage divider could be considered to this aim. This prevents saturation of the DUT and potential damages.

B. Implementation

The present study aimed to explore wireless and low-density EEG technology available on the market. To this end, three representative EEG devices were chosen: one with the possibility to use either wet or dry electrodes (hybrid), one with only dry electrodes, and one with only wet electrodes. All of them were wireless instruments with up to eight electrodes. They will be referred to as Device 1, Device 2,

TABLE I
MAIN CHARACTERISTICS OF THE EEG DEVICES UNDER TEST

	Device 1	Device 2	Device 3
sample rate	250 Sa/s	512 Sa/s or 1024 Sa/s	125 Sa/s
EEG channels	8 monopolar Fz, C3, Cz, C4, Pz, PO7, PO8, Oz	8 monopolar Fp1, Fp2, Fz, C3, Cz, C4, O1, O2	3 bipolar and 5 monopolar FC3-CP3, FCz-CPz, FC4-CP4, Pz, P3, Pz, P7, O1, Oz
Simulink API	Yes	No	Yes

and Device 3, and their characteristics are summarized in Tab. I. Devices 1 and 2 acquire the EEG signal via eight monopolar channels, while Device 3 can exploit a combination of five monopolar channels and three bipolar channels. These devices have different sample rates ranging from 125 Sa/s to 1024 Sa/s as reported in Tab. I. Device 1 and Device 3 are sold with an API that allow the real-time acquisition of EEG data in different software, while Device 2 requires a proprietary software to acquire the EEG signal before sending it to an external software via the Lab Streaming Layer (LSL) protocol. Simulink (by MathWorks) was used as the software for data reception and processing as it is commonly used in many BCI applications.

The employed signal generator was the Agilent 33220A. Its amplitude range spans from 20 mV_{pp} to 20 V_{pp} in High-Z mode. To generate signals compatible with typical EEG amplitudes, a voltage divider was thus added. The partitioned voltage was obtained through:

- $V_{IN} = 500\text{ mV}_{pp}$
- $R_1 = 1\text{ M}\Omega$
- $R_2 = 100\Omega$

The measured output voltage had an amplitude of about $(47.5 \pm 0.1)\mu\text{V}$. Square wave generation was set because its sharp rising and falling edges could be taken as meaningful events of the reference waveform. Notably, the employed generator has a rise/fall time in the order of nanoseconds, which practically corresponds to instantaneous transitions in measuring latencies with milliseconds accuracy.

The signal generator was driven by a custom LabVIEW model. A single measurement cycle consisted of switching the generator on, acquiring with the DUT for a fixed time window, and then switching the generator off. Preliminary estimations were obtained from a single “switch on” event and they suggested that the acquisition delay could be around 200 ms in the worst-case scenario. Therefore, the generation time windows was fixed at 120 s (time between consecutive on-off commands) as it is significantly higher than the delay to be measured. Such a long measurement time even allowed to mitigate the effect of eventual packet loss, as well as to observe slower phenomena (e.g., thermal effects) at regime.

To assess the mean transmission delay and estimate its uncertainty, repeated measures were necessary. Hence, the signal generator was turned on and off several times. It stayed on for 120 s and then also off for another 120 s. The

measurement began with the DUT battery fully charged and continued for the entire battery duration with the aim to observe eventual drifts due to the discharge. The total duration of the test thus depended on the DUT, but no drift caused by battery discharge was observed.

The waveform events taken as relevant were the time instants when sending on/off commands to the signal generator. In addition to that, the generator’s state (i.e., on/off) was also queried by Simulink through the User Datagram Protocol (UDP). This was needed to check the correct setting of the generator and hence properly record the first and last edge of the reference waveform. Repeated ping-pong tests were carried out to assess the delay in this LabVIEW-Simulink communication and the half round-trip time resulted equal to $(30 \pm 2)\mu\text{s}$. It was thus concluded that, when using the same PC for both LabVIEW and Simulink, their communication delay would not affect the proposed measurement system. Meanwhile, the delay introduced in the communication with the signal generation through USB (Hi-Speed) is in the order of $100\mu\text{s}$ [25].

Overall, the developed Simulink model consists of two main components: a UDP read block that receives the generator states from LabVIEW and a block for receiving the signal from the EEG instrument. For Devices 1 and 3, this block uses the provided API, while for Device 2, a Level-2 MATLAB® S-function was implemented to receive the EEG signal. Although an open-source Simulink library for LSL signal acquisition (SimBSI) was developed [26], it was not used in this work due to stability issues. Finally, the signals from these blocks were sent simultaneously to a scope, with the received data saved for offline processing.

To ensure synchronization of the two signals, the Simulink model was started first, followed by the LabVIEW model. This setup allowed for precise measurement and characterization of the acquisition delay in the data processing software for wireless EEG instruments.

C. Data Analysis

The acquisition delay in wireless EEG instruments and the associated uncertainty were calculated offline using MATLAB®. After data acquisition, a file was available for each DUT. It contained the on/off status of the signal generator for each time sample (values equal to +1 and −1, respectively) and the signal acquired by the DUT in the same time samples. Regarding the signal generator status, the transitions from −1 to +1 were identified as the “start” timestamps and those from +1 to −1 were identified as the “stop” timestamps. Correspondingly, the signal acquired by the DUT contained alternatively 120 s of baseline (generator off) and 120 s with a square waves (generator on).

The transitions from baseline to square waves were identified through thresholds. Notably, the baseline was observed to be between the 45th and 55th percentiles of the acquired signal. This range contains the most frequent values, which are predominantly noise. Instead, the extremes of the square wave were observed to be below the 5th or above the 95th percentiles of the acquired signal. Therefore, positive transitions were identified when going above the 75th percentile (half way

between 55th and 95th percentile), while negative transitions were identified when going below the 25th percentile (half way between the 45th and 5th percentile). The delay was quantified by comparing the time samples of the detected transitions in both the signal generator and the signal acquired by the DUT.

III. ON-FIELD EXPERIMENT

This section presents a BCI experiment to demonstrate the impact of acquisition delay in EEG signals analysis. Specifically, the three DUTs were employed within a BCI based on right and left-hand movements detection. The executed movement was the squeezing of a soft ball. The neural phenomena taken into account were the P300 and the MRCP. The experiments were conducted on a 31-year-old right-handed male subject at the University of Naples Federico II. Before participating in the study, the involved subject signed an informed consent in accordance with the Ethical Committee of University of Naples Federico II (Ethical Committee of Psychological Research, protocol number 24/2024).

A. Overview of the BCI System

In this study, the BCI system includes two main hardware components: (i) the DUT, namely one of the EEG instruments, and (ii) a control unit consisting of a personal computer. The EEG instrument sends data to the personal computer via Bluetooth. The personal computer runs the proprietary software where needed, MATLAB®/Simulink 2021b for EEG data acquisition and processing, and Unity¹ 2022.3.16f1 for the paradigm timing. Communication between Simulink and Unity was handled using the UDP protocol. As previously reported, the delay due to UDP communication is negligible and is in the order of 30 μ s.

A synchronous paradigm was chosen to highlight the impact of the delay under investigation. Indeed, in a synchronous paradigm, the timing of events is pre-determined and externally paced. This is essential for measuring time-locked neural phenomena that occur in response to specific events. The acquired EEG signals were synchronized with the cues. During each trial, the Unity application displays a fixation cross for 2.00 s, followed by a visual cue (an arrow pointing left or right) for 1.25 s. The word “GO!” is displayed from 3.00 s to 6.00 s, indicating to the participants the movement to execute. Finally, the word “RELAX” is shown with a randomized duration from 1.00 s to 2.00 s to prevent bias between consecutive trials.

The subject was instructed to prepare for movement as the cue appears and to execute the movement at the “GO!” appearance. Each experimental session consists of 3 runs of 30 trials each, randomized between right and left-hand movements. The acquired data are saved for offline analysis along with the paradigm timing information.

B. EEG Signal Analysis

The offline EEG signals analysis was carried out in MATLAB® to evaluate the impact of the measure and delay. Each analysis focused on specific time-locked events and

relevant acquisition channels. In unveiling the neural phenomena contained in the EEG signals, the device-specific measured delays were also taken into account. The aim was to demonstrate that these phenomena appear more evident whenever the delay can be (at least partially) corrected. On the other side, this would suggest that neural phenomena detection is negatively affected by incorrigible delays.

Data pre-processing was carried out according to [27]: signals were pre-filtered by a 4th order zero-phase Butterworth filter with 0.3 Hz to 70.0 Hz band and, by means of EEGLAB [28], artifacts were identified and marked. In details, an artifact was marked if the signal was outside the -200μ V to 200μ V, or if the joint probability or kurtosis was more than five times the standard deviation of the respective statistic of the data. After marking, the whole EEG data were filtered using a band-pass 4th order zero-phase Butterworth filter in the range of interest of the phenomena. At this point, EEG data were segmented trial-by-trial into epochs spanning in a range that allowed visualisation of the phenomena. Finally, epochs with previously marked artifacts were discarded and the remaining epochs were averaged.

The P300 component was assessed in correspondence of the visual cue, namely at 2.00 s. This cue can be regarded as a “go/no-go”, as the subject receives a series of stimuli but only the visual cue triggers the preparation to the action to perform. The signals to consider in this analysis were extracted, for each device, from channels available for the parieto-occipital area. The EEG data were filtered in the 0.5 Hz to 15.0 Hz range [29]. The EEG data were then segmented trial-by-trial into epochs spanning from 200 ms before the visual cue to 1000 ms after it. Finally, all the epochs were averaged.

The MRCPs were assessed in correspondence of the “GO!” indication, namely at 3.00 s. The inherent signals were extracted from EEG channels available at the sensorimotor area as this is mostly involved in motor preparation and execution. The EEG was filtered in 0.5 Hz to 5.0 Hz range for capturing the low-frequency components characteristic of MRCPs [13]. At this point, EEG data were segmented trial-by-trial into epochs spanning from 500 ms before the “GO!” cue to 500 ms after it. This window allows to capture the negative peak occurring around the onset of the movement [12], [13], [27].

For both the P300 and MRCP analyses, the peak amplitude was defined as the maximum (for P300) or minimum (for MRCP) deflection within the selected window. The latency of the neurological phenomenon was retrieved as the time point at which this peak occurred with respect to the respective event. The observed latency was also corrected by taking into account the measured delay of the inherent EEG device

IV. RESULTS

A. Acquisition Delay

The measured delay is reported in Fig. 2 for the three wireless EEG devices. First measurements proved that acquisition delays do not significantly vary from channel to channel. The reported results are relative to the electrodes Fz, Fz, and FCz, for Device 1, Device 2, and Device 3, respectively. In particular, the delay was assessed both at the start and at

¹<https://unity.com/>

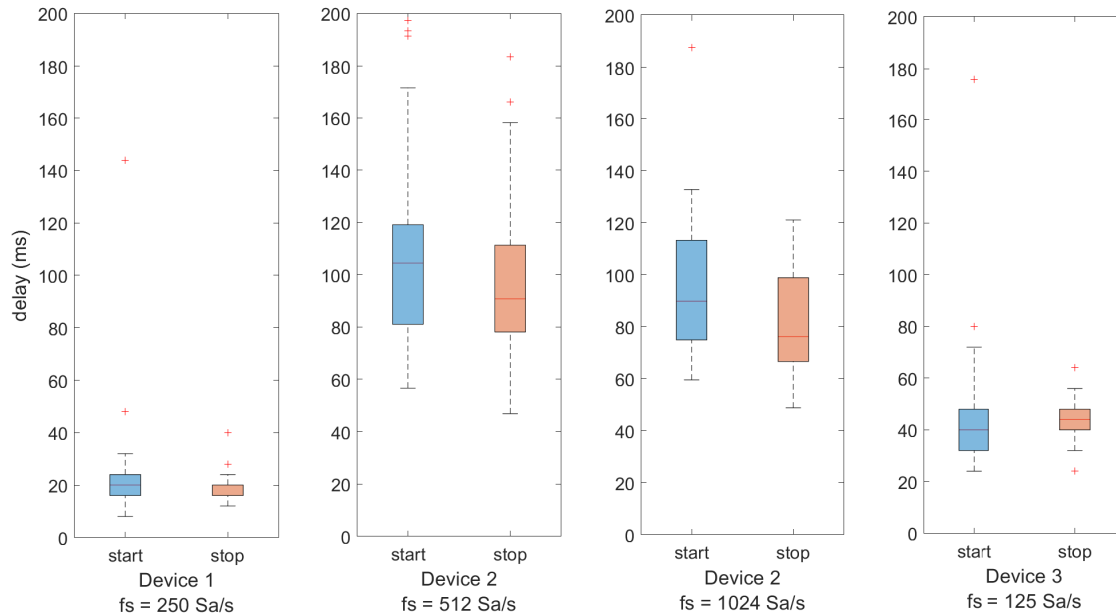


Fig. 2. Acquisition delay in the data processing software for each of the three wireless EEG devices under test. The delay was measured at both start and stop of the signal generator.

the stop of the signal generator. Each box plot represents the distribution of repeated delay measures for each device. In the case of “Device 2”, two different settings were considered for the sampling frequencies.

Device 1 exhibited the lowest delay. Specifically, the mean delay was 20 ms. Notably, the delay was about 6 samples at the start of the signal generator, while at the stop it was about 5 samples. This makes it suitable for real-time EEG applications.

Device 2 performed noticeably worse, especially at a sample rate of 512 Sa/s. In this configuration, the mean delay was 102 ms, corresponding to about 54 samples (again with more delay at the start than the stop). When the sampling rate was increased to 1024 Sa/s, there was a mean delay reduced to the 88 ms. Nevertheless, Device 2 continued to exhibit the poorest performance if compared to the other DUTs.

A noteworthy aspect is that Device 2 lacks a direct API for communication with the control unit. Instead, the EEG data are first sent to its proprietary software that in turn forwards them to the acquisition and processing software (Simulink in the present case). This additional step likely contributes to the measured delays. While the contribution of LSL is expected to be below 1 ms [30], it was not possible to disentangle all the contributions to the acquisition delay because of the proprietary software.

Device 3 exhibited a moderate performance, with a 47 ms mean delay. Despite the mean delay in ms is higher, it is worth noting that this correspond to about 6 samples at the generator start, while the mean delay at the generator stop was about 5 samples. This behavior is comparable with Device 1, and hence the greater absolute delay would be explained by the lower sample rate.

As expected, the delays measured at start and stop of each generated wave are compatible (i.e., the intervals associated

with different measures overlap) for a fixed device. Significant differences would have suggested samples loss, which instead can be excluded. This was confirmed by measuring the half-period of the square waves acquired by the EEG devices. For all the devices, the mean half-period consistently resulted equal to 50 ms. Moreover, the mean duration of start-stop cycles was 120 s, thus excluding that data packets were lost during the tests.

It is ultimately interesting to note that the highest delay values were observed in correspondence of the first wave for all the devices. This was found to be linked to the initialization of Simulink. Indeed, once the system reached a stable state, delays were shorter and more consistent.

Tab. II summarizes these measurement results by considering mean values and associated standard deviations obtained across generated waves. ThreeA statistical analysis was carried out to prove the statistical significance of the highlighted difference (Tab. III). The Shapiro-Wilk test was used to test whether the data were distributed normally. TwoThe tests significance was fixed at $\alpha = 5\%$. However, Bonferroni correction was applied to compensate the increase in false negatives probability due to the multiple comparisons. TwoThe data resulted as not normally distributed at either the start or stop events. W-values for the Shapiro-Wilk test equaled 0.36, 0.91, 0.88, 0.59 at start, 0.83, 0.94, 0.94, 0.92 at stop, with $p < 0.05$ for all devices. Consequently, Bonferroni-corrected Kruskal-Wallis tests were performed. Kruskal-Wallis statistics were $H = 151.9$ and $H = 163.9$, with 197 and 196 degrees of freedom used for the error evaluation, respectively at the start and at the stop of the signal generatorThree, with p-values $\ll 10^{-31}$ in both cases. Two Tab. III highlights the cases where no significant difference was found by considering pairs of devices under both start and stop conditions.

TABLE II

MEASURED DELAYS, HALF-PERIOD OF THE SQUARE WAVES, AND START-STOP PERIOD DURATION FOR EACH OF THE THREE WIRELESS EEG DEVICES UNDER TEST. THE MEAN AND STANDARD DEVIATION OF THE MEAN (RESOLUTION FOR THE "HALF-PERIOD") OF EACH QUANTITY ARE REPORTED

DUT	fs (Sa/s)	delay at start (ms)	delay at stop (ms)	half-period (ms)	start-stop (s)
Device 1	250	22 ± 2	18 ± 1	50 ± 4	120.09 ± 0.02
Device 2	512	106 ± 4	98 ± 4	50 ± 2	120.03 ± 0.02
	1024	94 ± 5	81 ± 4	50 ± 1	120.03 ± 0.02
Device 3	125	50 ± 6	43 ± 2	50 ± 4	120.07 ± 0.03

TABLE III

COMPARISON OF START/STOP DELAYS BETWEEN DIFFERENT DEVICES. TWO BONFERRONI CORRECTION WAS APPLIED TO THE P-VALUES

Devices		Start	Stop
Device 1	Device 2 - 512 Sa/s	$p < 0.01$	$p < 0.01$
Device 1	Device 2 - 1024 Sa/s	$p < 0.01$	$p < 0.01$
Device 1	Device 3	$p < 0.01$	$p < 0.01$
Device 2 - 512 Sa/s	Device 2 - 1024 Sa/s	$p > 0.05$	$p > 0.05$
Device 2 - 512 Sa/s	Device 3	$p < 0.01$	$p < 0.01$
Device 2 - 1024 Sa/s	Device 3	$p < 0.01$	$p < 0.01$

Overall, the tests proved statistically significant differences in delays between Device 1 and Device 2 (for both sample rate configurations), between Device 1 and Device 3, and between Device 2 with 512 Sa/s sample rate and Device 3. Instead, the tests failed to reject the hypothesis of different delays when changing the sample rate for Device 2. This supports the observation that the main contribution to the delay of this device comes from the lack of a direct communication with the control unit.

B. Delay Impact on Neural Phenomena Detection

The experiments were done on the same day with the different EEG devices. Each session lasted approximately 30 min per device. During the experiments, the participant was instructed to perform repeated squeezing motions with either the right or left hand, using a soft ball provided for the task. This motor task was specifically chosen to ensure consistent muscle activation and to facilitate the reliable detection of motor-related EEG signals. An operator continuously monitored EEG signals on a second monitor to check for any electrode pop or other artifacts.

To demonstrate the impact of delay on the detection of EEG phenomena, the exploited EEG devices were the previously identified best- and worst-performing ones, namely Devices 1 and Device 2 with a sample rate of 512 Sa/s. Notably, Device 2 was used before Device 1.

Electrodes could not be placed in the same positions because of the manufacturing differences between devices. Therefore, the EEG channels for P300 analysis were carefully chosen to be the closest ones among the available electrodes, while also considering that the different placements imply different effects of signal propagation along the scalp [10]. PO7, Oz, and PO8 were used for Device 1, whereas O1 and O2 were

TABLE IV

P300 PEAK LATENCIES BEFORE AND AFTER DELAY CORRECTION

	channel	peak latency (ms)	corrected peak latency (ms)
Device 1 (fs = 250 Sa/s)	PO7	384	364
	Oz	376	356
	PO8	376	356
Device 2 (fs = 512 Sa/s)	O1	462	360
	O2	454	352

used for Device 2. Fig. 3 reports the 90 aligned and filtered epochs in the time domain (top) and the ERP obtained by averaging (bottom) for each selected electrode of the respective device in these plots, the dashed vertical black line marks the cue event, while the red line was put 300 ms later.

Both the aligned trials and ERPs point out a positive peak amplitude occurring approximately 300 ms after the cue. Notably, Device 1 shows greater alignment of the peaks in single trials than Device 2. This can be attributed to the measured uncertainty of the delay, which was found to be lower in Device 1 than Device 2. Moreover, although detected with both devices, the P300 latency for Device 2 is greater than that of Device 1. To investigate the cause, the observed latencies were corrected by subtracting the respectively measured delay. Notably, the mean delay values of Tab. II were exploited.

The numerical results are reported in Tab. IV. The column with corrected latencies illustrates that, at less than a few milliseconds deviation, the latency values are now compatible across both devices. These results also suggests that the subject's fatigue throughout the experiment did not affect the P300 significantly.

For the MRCPs analysis, the channels in the sensorimotor area C3, Cz, and C4 were selected for both devices. Fig. 4 reports again a color-scaled plot with the 90 aligned epochs but filtered in a different band (top) and the MRCP obtained by averaging per channel (bottom). In these plots, the dashed vertical purple line indicates the movement (nominal) onset. The amplitude of the MRCPs is less pronounced than P300, so that a greater impact of the acquisition delay and its associated uncertainty was expected. In the case of Device 1 (Fig. 4a), a negative peak at the onset of movement is particularly evident at Cz and, consistently, on the other two channels. In contrast, the data of Device 2 do not point out clear MRCPs while a lack of consistent patterns hold across the three channels. Tab. V reports the numerical results for

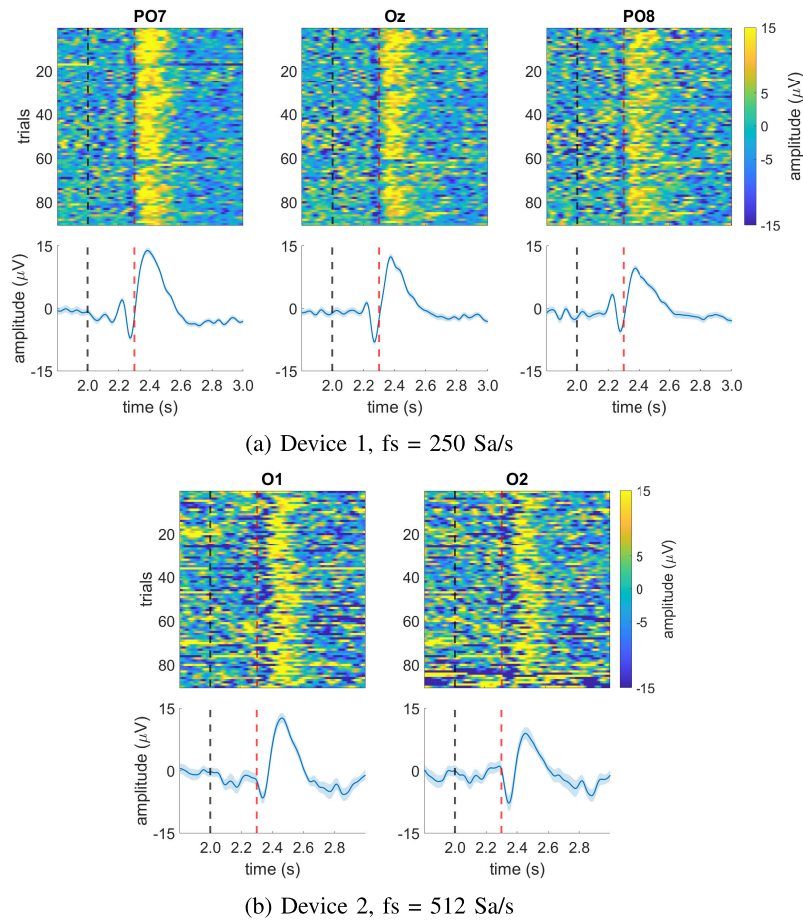


Fig. 3. P300 analysis results: (a) focus on PO7, PO8, and Oz channel of Device 1, (b) focus on O1, and O2 channels of Device 2. The top part shows the 90 filtered epochs in a color-scaled plot, the bottom part reports their grand average and the associated standard deviation of the mean. The black dashed lines correspond to the cue, and the red lines are 300 ms after.

TABLE V
MRCPS NEGATIVE PEAK LATENCIES OF DEVICE 1 BEFORE AND AFTER DELAY CORRECTION

	channel	peak latency (ms)	corrected peak latency (ms)
Device 1 (fs = 250 Sa/s)	C3	-12	-34
	Cz	-8	-30
	C4	-12	-34

the Device 1, while the same analysis for Device 2 was not possible due to the negative peaks being undetectable.

V. DISCUSSION

The results of this study suggest the importance of accurately characterizing the acquisition delay in wireless EEG devices, especially when performing time-sensitive analyses of EEG phenomena. Indeed, the delay assessment pointed out significant differences between the EEG devices under test, with Device 1 exhibiting a lower and more stable delay than the other two. It should be remarked that the investigated devices were treated as “black boxes”, i.e. hardware characteristics and adopted transmission protocols were unknown.

The issue of delay in wireless EEG systems is well-documented in literature. However, it is typically addressed through new hardware designs [3], by focusing on the synchronization between multiple devices [31], [32], or by means of an external trigger [6], [23]. While these approaches mitigate delay variability, they cannot cancel the inherent uncertainty of real-time acquisition. Hence, a delay characterization appears particularly necessary for consumer-grade wireless devices.

The presented work showed that, once measured, mean delay can and should be corrected in post-processing. Meanwhile, its uncertainty introduces a noise that, as such, cannot be corrected. This contributes to the challenge of accurately detecting neural phenomena, like in the case of the time-locked ERPs and MRCPS. Indeed, the larger the delay uncertainty, the harder it is to investigate such neural phenomena. Hence, the delay variability is a critical parameter for assessing the device performance.

The impact of delay on P300 detection appears indeed relevant because of the large usage of this ERP in cognitive and clinical assessments. According to literature, a healthy individuals has a P300 latency in the 300 ms to 600 ms range [11]. This range is considered physiological and it can vary due to factors such like age and task complexity. Nonetheless, the 100 ms delays of devices like Device 2 could

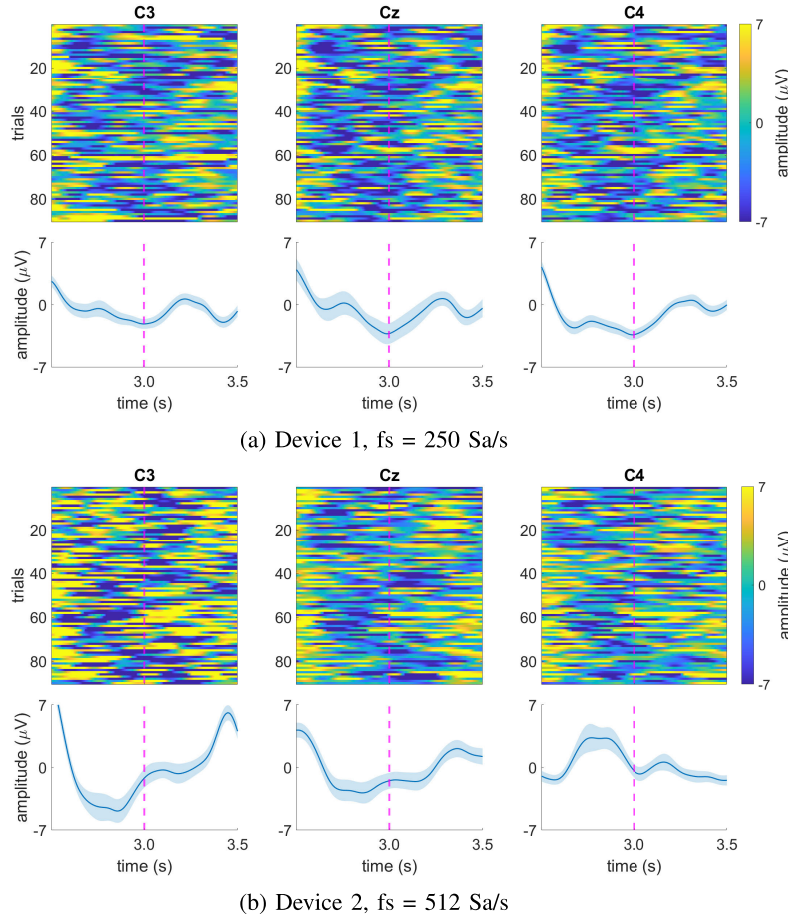


Fig. 4. MRCP analysis results with a focus on the C3, Cz, and C4 channels covering the sensorimotor area: (a) Device 1, (b) Device 2. The top part shows the 90 filtered epochs in a color-scaled plot, the bottom part reports their grand average and the associated standard deviation of the mean. The purple dashed lines correspond to the appearing of GO! at 3.00 s.

lead to misleading conclusions, with clinical implications like the misdiagnosis of disease in individuals who actually have normal cognitive function [33]. Instead, after correcting the delay, even a device like Device 2 could be used for the P300 analysis. In addition to the differences in electrode placement between the two devices, the slight discrepancy in the latency and amplitude of the P300 between the two devices can also be attributed to the differing conditions of the participants during the experiments. As the experiments were conducted in a consecutive rather than simultaneous manner, it is possible that the subject's state may have exhibited slight variations between trials [32].

With respect to MRCP detection, a more pronounced difference was observed when the same experimental setup, the same participant, the same signal processing but different devices were used. While Device 1 consistently captured the negative deflection associated with the neural phenomenon, Device 2 struggled to detect any clear MRCP pattern. This can be attributed to factors like the higher delay uncertainty and the inherently low amplitude of MRCP, making it more susceptible to distortion due to temporal inaccuracies.

It is also important to note that, in many MRCP studies, trials were aligned with an external trigger marking the actual onset of movement in spite of the nominal one, thereby

enhancing MRCPs detection. For instance, this synchronization was obtained through exoskeletons, motion sensors and/or cameras [13], [27]. In the current study, however, no external reference was used, so that slight variations in the actual movement start could affect the MRCP detection. As representative cases, this happened with Device 2, while the detection of MRCP with Device 1 was still possible.

Ultimately, it is worth noting that experimental protocols for MRCPs typically make the cue and the “GO!” indication coincide. However, in the adopted protocol they were separated to prevent the overlap between post-P300 components with pre-MRCP components. This allowed for a clearer distinction between the cognitive and motor-related potential. Rather, future studies could consider even more temporal distance between the two indications as well as the external marking of actual movement onset.

VI. CONCLUSION

The objective of this study was to propose a measurement station for the characterization of acquisition delays in wireless EEG devices. Moreover, the influence of the delay on the identification of time-locked EEG phenomena was investigated with specific regards to the P300 and MRCP. The findings

indicated that the delay, and even more the associated uncertainty, can negatively impact EEG-based measurements. While the mean delay could be corrected in post-processing once the device is characterized, the inherent variability of acquisition systems presents a significant challenge. This particularly affects the detection for a phenomenon with poor signal-to-noise ratio like the MRCP.

The findings highlight the importance of reducing both the magnitude and uncertainty of delays in wireless EEG devices to ensure accurate measurements. Device 1, which had lower delay variability, demonstrated more reliable detection of both EEG phenomena, underscoring the need for improved hardware solutions that minimize temporal uncertainty.

Future developments could involve a sensitivity analysis to investigate the contribution to the measured acquisition delays. However, this would require a joint effort with manufacturers, especially in the case of the Device 2. By implementing appropriate corrections based on these characterizations, these wireless EEG systems could potentially be used in clinical settings and for diagnostic purposes, provided they meet the necessary reliability standards.

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