P300 in the park: feasibility of online data acquisition and integration in a Mobile Brain/Body Imaging setting

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Abstract— **In the last years Mobile Brain/Body Imaging (MoBI) has been increasingly used to study cognition in the real world to give more ecological validity to brain imaging studies currently carried only inside the lab. To increase portability of the setup and reduce cabling it is possible to perform a unified and real-time synchronized recording of data from multiple sources. However, delays and jitter may impair the quality of the subsequent ERP analyses. Here we used an online auditory oddball P300 paradigm to compare the quality of P300 ERPs obtained (i) with online synchronization and alignment and (ii) offline with conventional alignment (synchronization channel). We recorded the EEG from one subject in three different conditions: sitting, walking indoors and walking outdoors. We showed that offline and online synchronization strategies provided comparable although slightly different P300 ERP. A decreasing P300 amplitude from sitting to walking indoors and outdoors confirms the dual task effect on P300 amplitude. These results show that integrated real-time P300 protocols are feasible but it is also necessary to test delays and quantify the jitter among different signals when developing real-world MoBI applications.**

Mobile Brain/Body Imaging (MoBI), EEG, Synchronization, Lab Streaming Layer (LSL), P300

I. Introduction

Mobile brain/body imaging (MoBI) is rapidly gaining traction as a novel multimodal imaging technique to study cognitive processes involved during locomotion and other everyday tasks outside lab settings [1]. MoBI applications can be found in different fields such as neuroergonomics, sport performance analysis, spatial cognition and rehabilitation, Within the MoBI framework data coming from different acquisition systems, e.g., electroencephalogram (EEG), electromyogram (EMG) motion capture (MoCAP) are integrated and analyzed together to determine neural correlates of movement while subjects are freely interacting with the environment [2]. Setting up a successful MoBI experiment requires however to overcome several technical challenges to achieve perfect data synchronization, full portability of the setup and minimization of equipment weight. Simplification of the setup can be achieved by minimizing cables, thus reducing movement impairment for the user. For this reason data synchronization strategies also affect the portability of the setup. Offline data synchronization (see PRE-POST strategy described in [3]), consists in the periodic delivery of a train of TTL pulses (or analog pulses in case a TTL port is not available) to all devices involved during the recording. It requires the use of a trigger generator (e.g., a DAQ card) and cables physically-connected to each device. Using a single device (e.g., amplifier) to record every MoBI data type would be optimal to avoid extra synchronization cables. However, while a few devices on the market can simultaneously acquire data from different sources (several EEG manufacturers provide extra bipolar channel acquisition capability e.g., for EMG), the inclusion of every possible data stream, including e.g., full-body kinematics and video capture, is unfeasible given the different nature of the streams (e.g., sampling rates and operation modes). Another possibility to avoid extra synchronization cables is to integrate the different streams by means of a real time server after testing the delay of each recording device, e.g. through Lab Streaming Layer (LSL). LSL is a system for the unified collection of measurement time series providing real-time access, centralized collection and online viewing of data [4]. Real-time access to data streams, however may present drawbacks such as jitter (stream misalignment) caused for instance by non-real-time operating systems (OS) and communication delays, even when every stream is recorded on the same computer [3].

Here we tested the effect, if any, that real-time recording paradigms through LSL have on EEG data and ERPs in particular, using the well-known oddball P300 paradigm [5]. This validation allows to shift from offline to online recording and analysis paradigms. We compared the P300 evoked potential obtained with conventional offline synchronization against the one obtained with the online paradigm in the sitting condition. We then replicated the experiment during free walking conditions, both indoors and outdoors to determine whether the P300 ERP peak could still be identified. P300 Oddball tasks have been widely studied and used in various fields (e.g., BCI [6]) and therefore constituted a good test of our online setup in a real-life environment.

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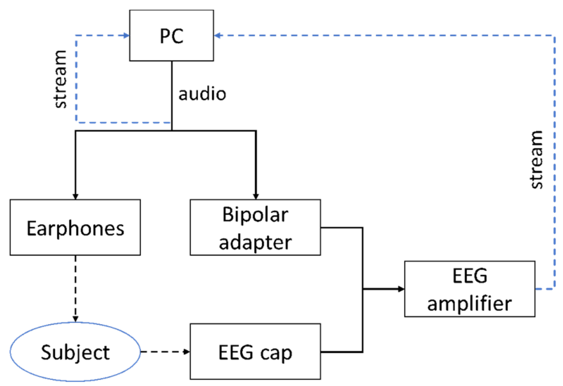

Figure 1. Schematic of the experimental setup. The auditory stimuli generated by the PC are sent to the subject through earphones and to the EEG amplifier by means of a bipolar adapter. Generated events are streamed to the PC through the LSL interface and merged online with the data stream sent by the EEG amplifier. Preliminary measurements allowed to compesate for delays.

II. Methods

The experiment was performed on one healthy subject (female, age 24). It consisted in a P300 auditory oddball experiment delivered in three different conditions i.e., “sitting”, “indoors”, and “outdoors”. In the “sitting” condition the subject sat in a comfortable armchair inside a specifically designed insulated room (faraday cage), in the “indoors” and “outdoors” condition the subject walked around in a spacious room at Campus Biotech, Geneva (10 by 8 m rectangle) and outdoors (Barton Park, Geneva Lake coast). During each session a total of 538 100ms-long auditory stimuli (beeps, 88% standard 600Hz tones, 12% 1200Hz deviant tones [7]) were generated by a custom Python script every 1s and delivered to the subject through commercial earphones (Jays a-JAYS Four). The subject was instructed to mentally count the occurrences of infrequent tones. High density 64ch EEG (Ant Neuro eego sports amplifier) was recorded during each session with a sampling rate of 2000Hz. The electrodes were positioned following the 5% 10/20 system and the electrode impedance was kept below 10 kΩ [8]. Surface EMG and kinematics were also recorded.

Fig. 1 shows a schematic of the experimental setup. During the experiment (“sitting” condition) the auditory stimuli were sent from the PC to both earphones and to a bipolar adapter, connected to the EEG acquisition system. The volume was regulated so as to ensure detection as a signal by the dipolar device and hearing comfort for the subject. At the same time, events corresponding to the beginning of each beep as well as real time EEG data were streamed through the local LSL pipeline and recorded. This setup allowed to compare the timing of events obtained during online and offline streaming.

Collected data were analyzed using Matlab scripts based on the EEGLAB toolbox [9]. Continuous data were high-pass and low-pass zero-phase filtered (1 – 45 Hz, Chebyshev type II filter). Channels with prolonged prominent artifacts (identified by visual inspection) were removed [10, 11] and remaining channels were considered for further analysis. Careful visual inspection allowed to identify and remove epochs containing high-amplitude artifactual potentials, high-frequency muscle noise and other irregular artifacts. Remaining data were

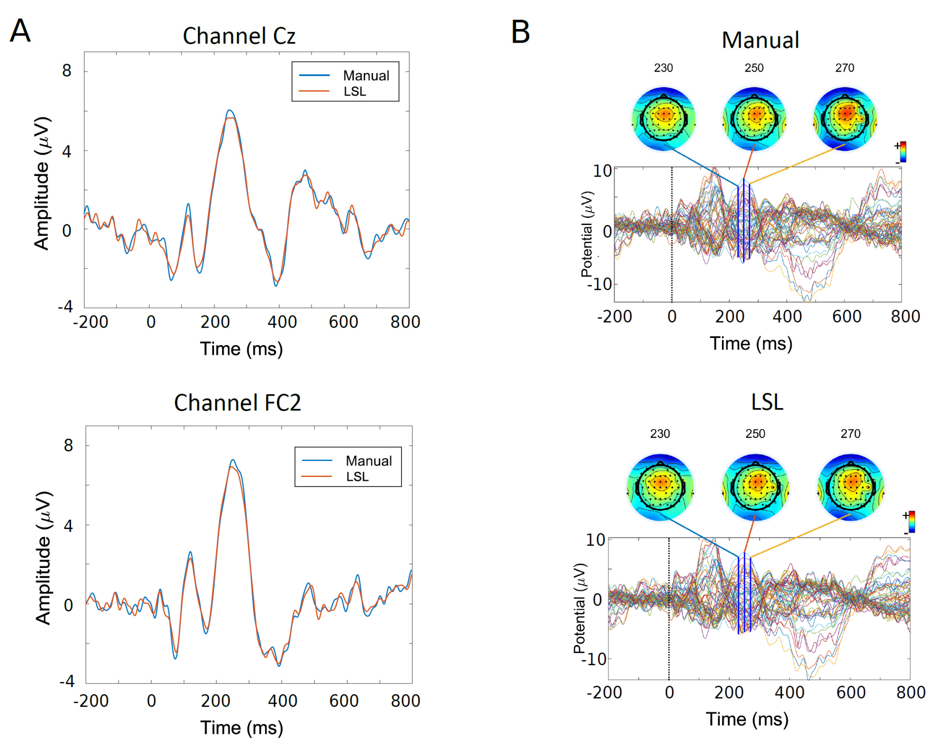

Figure 2. A. Comparison of the averaged ERP across all trials between the offline (manual) and online (LSL) transmission modality on two different EEG channels (Cz and FC2). B. Scalp maps across the P300 peak in the two transmission modalities.

processed via Independent Component Analysis (ICA) filtering to remove non-neural sources and artifacts [12].

Epochs ranging from −200 ms to 800 ms time-locked to the onset of the stimulation (i.e., trials) were then extracted and visually inspected for residual artifacts. The baseline value (i.e., mean in [−200 0] ms) was subtracted from each trial [13]. Time-locked normalized trials were averaged across trials to obtain the grand average ERP (Figure 2, panels A) and ERP topography (Figure 2, panels B). For the "still" condition ERPs and scalp maps sampled at relevant latencies (i.e., corresponding to the P300 peak) were compared across the two data synchronization modalities (i.e., offline and online); to compare the ERP scalp maps we calculated the difference at a specific timestamp (latency), indicated by $d_{LAT} = \frac{|a-b|}{\sqrt{|a|*|b|}}$, a and b being vectors containing the mean value computed across all trials of the P300 amplitude respectively in the offline and online modality and |.| indicating the l_2 norm. We computed such difference at three latencies across the P300 peak, respectively at 230 ms, 250 ms, and 270 ms after the stimulus onset. Comparisons across the three conditions ("still", "indoors", "outdoors") were performed in the online modality.

III. Results

Fig. 2 shows the P300 ERP obtained in the still condition for the deviant stimuli. Streaming timestamps were corrected by adding the mean value of the delays computed between the online and offline transmissions, prior to the experiment. It is possible to note the effect of the jitter on the P300 peak, which resulted in a smoother signal with a smaller amplitude. These measures are noticeable but not prominent enough to be statistically significant, considering only one subject. Fig. 2, panels B show qualitatively comparable P300 scalp maps, but quantitative differences in norm were noticeable i.e., $d_{LAT} =$ $12.1\%, 12.8\%, 15.9\%$ respectively at 230ms, 250ms and 270ms after the stimulus onset. We also computed the same measure by comparing the grand average scalp maps in the interval corresponding to the peak, i.e., in the interval [230 - 270] ms and obtained $d_{LAT} = 4.2\%$. This result shows that, while single scalp maps at a single latency might differ, the difference is reduced considering the whole peak.

Next, we compared the P300 peaks in three different conditions using the online modality: still, walking indoors and walking outdoors. A significant P300 peak could be observed in all three conditions, with a consistent decreasing amplitude comparing still, walking indoor and walking outdoor conditions respectively. The constant amplitude of earlier peaks also demonstrates that this decrease is not a result of artifacts or other issues with the data analysis.

IV. Discussion

Online and offline modalities of data collection for a P300 auditory oddball paradigm resulted in similar ERPs but with noticeable differences. A preliminary comparison of the

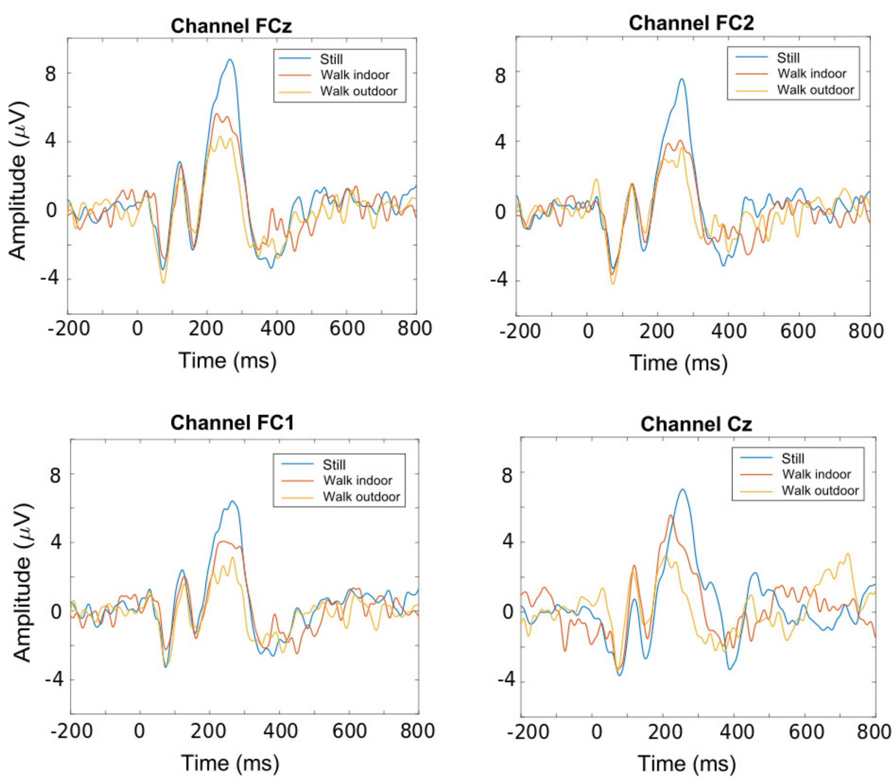

Figure 3. P300 ERP averaged across all epochs in four different EEG channels. For each channel the different colors correspond to the signal obtained in three different conditions, namely "still" (blue), "walk indoors" (red) and "walk outdoors" (yellow).

delays between each set of timestamps in the "online" modality (event time stamps retrieved through LSL) and "offline" modality (i.e., received through the bipolar adapter directly by the EEG amplifier) highlighted the most likely cause. While the delay in the online transmission of the auditory stimuli, (generation, streaming and receiving beep events through LSL with respect to the EEG data stream) constitutes a systematic error that can be compensated, the jitter in the real-time transmission is random and the most likely to affect the ERP.

In fact, jitter causes slight misalignments across trials and has the effect of spreading the peaks. This is also confirmed by the distance between scalp maps of the online and offline modalities. In fact when considering point-by-point maps the distance was considerably higher with respect to maps calculated over the peak average. This demonstrates that the point-by-point scalp distribution is less consistent in the online case. Anyway the differences highlighted in this work were subtle, demonstrating that the increasingly popular P300 MoBI paradigm [5-7, 14] can indeed be integrated into multimodal acquisitions through LSL without particular equipment (e.g., external precise clock). However these differences might have an adverse impact on other experiments and paradigms where peaks are not as wide or strong as the P300 (e.g., small somatosensory evoked potentials - SEPs - such as N20 or P27 [15, 16]).

Noticeably, the jitter might not only depend on the setup but also on other factors, namely the actual workload of the device (e.g., laptop) during the acquisition, CPU speed (e.g., power saving mode of the laptop) or network load (if streaming over a network). Therefore, if an accurate comparison between sessions is needed, it is important to determine that changes due to the different conditions of the experiment or to the equipment (e.g., temperature, load etc.) are accounted for.

As a further result we confirm the P300 amplitude decrease in dual task experiments as already reported in literature [5-7, 14]. We further report a more prominent decrease of the P300 amplitude in the outdoor walking condition with respect to indoor walking, probably due to the more demanding attentional stimuli and distractions when moving outside in the real world [6, 14].

Although the analyses were performed on just one subject it is possible to conclude that auditory MoBI P300 paradigms can be successfully integrated within LSL but it is advisable to quantify or at least take into account the effect of delays and jitter on ERPs in online recording protocols.

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