Multimedia **A**uthoring and **M**anagement using your **E**yes and **M**ind

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D2.2

Initial integration and optimization of multi-modal sensors

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Abstract

The deliverable concerns the activities done so far to inspect the integration of the several sensors that are exploited in the two MAMEM platforms (the heavyweight and lightweight configurations). Moreover, the second part of the document analyzes the performance of the EEG filters when applied to devices with different number of channels (i.e. the case of the heavyweight and lightweight EEG sensors).

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Executive Summary

This deliverable takes into consideration the initial integration of the several devices selected for the MAMEM platform, towards producing a final system application. The deliverable is organized into two main parts: the first concerns the activities done so far to inspect the integration of the several sensors that are exploited in the two MAMEM platforms (i.e. the heavyweight and lightweight configurations); the second part analyzes the performance of the EEG filters when applied to devices with different number of channels (i.e. the case of the heavyweight and lightweight EEG sensors).

In the previous deliverable (D2.1), the selected devices were able to stream their data independently to a common software interface based on LabStreamingLayer standards. In this deliverable the synchronization of the independent streams performed by LSL is analyzed. The current results show that LSL align correctly the streams of the heavyweight configuration. For the case of the lightweight one, an irregular sampling rate of the selected EEG headset requires special treatments to produce reliable results.

Finally, the aim of the second part is to find the best EEG filter techniques depending on the exploited hardware.

Abbreviations and Acronyms

API	Application Programming Interface
BCI	Brain Computer Interface
ECG	ElectroCardioGram
EEG	ElectroEncephaloGram
GSR	Galvanic Skin Response
MD	Muscular Disorder
PD	Parkinson Disease
HR	Heart Rate

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1 Introduction

1.1 Description of the current state

This deliverable is organized into three main parts. The first concerns the activities done so far to inspect the integration of the several sensors that are exploited in the two MAMEM platforms (the heavyweight and lightweight configurations). The second part analyzes the performance of the EEG filters when applied to devices with different number of channels (i.e. the case of the heavyweight and lightweight EEG sensors). The third part summarizes a market analysis for off-the-shelf EEG headsets for generic consumers, in order to check if there are other devices that can be alternative to the chosen lightweight EEG headset (Emotiv Epoc).

In particular, for the first part, the communication of the sensors with the LabStreamingLayer (LSL) module is analyzed in terms of synchronization performance among the different streams. The aim of the second part is to find the best EEG filter techniques depending on the exploited hardware. Finally, the third part compares the available solutions based on price and offered functionalities.

1.2 Setup of the heavyweight configuration

The heavyweight configuration is composed by the following three sensors:

- EBNeuro BePlus LTM is exploited as EEG device;
- SMI REDn Scientific is the eye tracker sensor;
- Shimmer3 GSR+ is the device to acquire the Galvanic Skin Response (GSR) and Heart Rate (HR) values.

See deliverable D4.2 [1] for the description of the setup of each device and their software modules; in particular,

- section 3.2 for EBNeuro BePlus LTM
- section 3.1 for SMI REDn Scientific
- section 3.3 Shimmer3 GSR+

Finally, the installation of LSL is already described in D4.2, section 3.4.

1.3 Setup of the lightweight configuration

The lightweight configuration is composed by the following three sensors:

- Emotiv Epoc+ is exploited as EEG device;
- “myGaze Assistive-2” from Visual Interaction is the eye tracker sensor;
- Shimmer3 GSR+ is the device to acquire the Galvanic Skin Response (GSR) and Heart Rate (HR) values.

The setup of Emotiv Epoc have been described in D4.2, section 3.2. The GSR sensor is the same of the heavyweight configuration, and also the LSL software module does not change w.r.t. the heavyweight configuration.

Concerning the eye tracker device, “myGaze Assistive-2” has been released only recently: at the current state of the project it is not available for our experiments. However, since it is based on SMI technology, in terms of synchronization we expect a behaviour similar to the SMI REDn Scientific device.

1.4 Third-party tools

Some external tools will be exploited to check the signal synchronization, namely LabRecorded [2] and EEGLab [3].

Moreover, to verify that each stream is collected in real-time, the MATLAB Viewer included with the full LSL distribution (a MATLAB function called "vis_stream") has been used. It allows to view the signal content of any stream on LSL in real time.

1.4.1 LabRecorded

The LabRecorder is the default recording program that comes with LSL. It allows to record all the LSL streams into a single file, with time synchronization between streams.

The file format used by the LabRecorder is XDF [4]. This is a new open general-purpose format that was designed concurrently with LSL and supports all features of LSL streams. There are importers for MATLAB, and in particular for EEGLAB.

LabRecorder requires that you have installed either Python-2.6 and PySide for Python 2.6 or Python-2.7 and PySide for Python 2.7.

The source code has been compiled with Microsoft Visual Studio 2012, producing the executable file "LabRecorder.exe". A quick overview of its usage is described in the following; see also the official documentation at [5].

With reference to Figure 1, LabRecorder displays a list of currently present device streams under "Record from Streams". If a device has been turned on while LabRecorder is already running, click the "Refresh" button to update the list (this takes ca. 2 seconds).

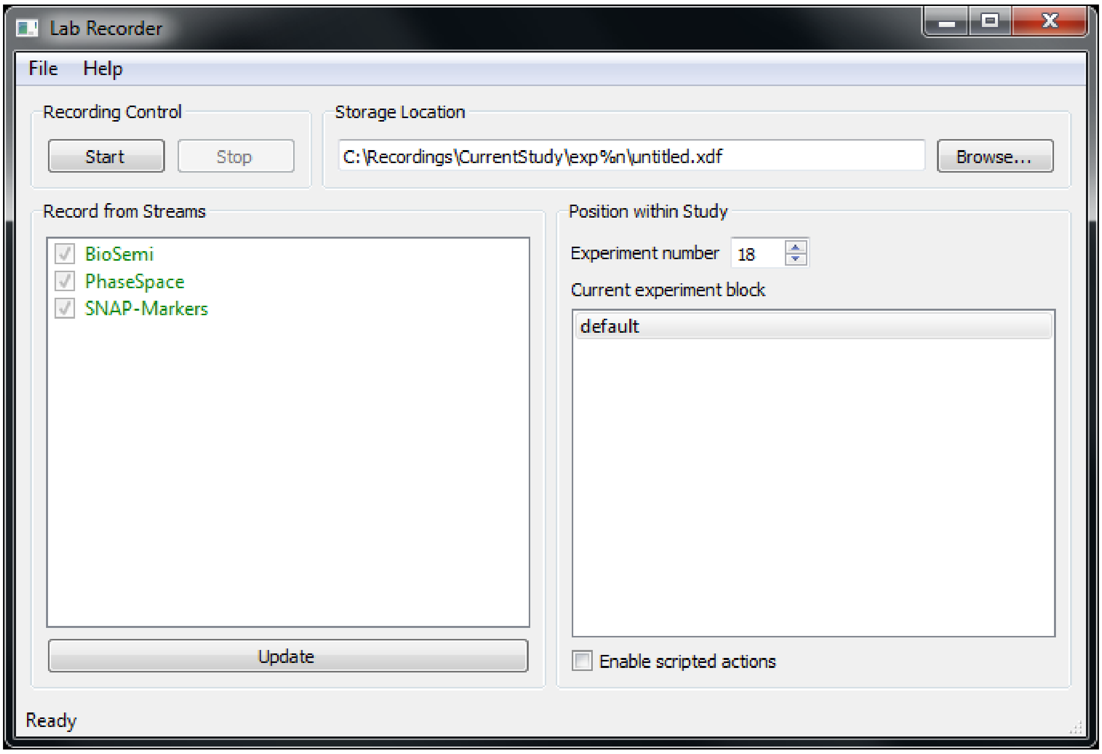


Figure 1: LabRecorder Interface

The entry in "Storage Location" indicates the file name (or file name template) where the recording will be stored.

Click "Start" to start a recording. If everything is successfull, the status bar will now display the time since you started the recording, and more importantly, the current file size (e.g. Recording (00:00:07; 16756kb)...) will grow slowly. This is a way to check whether recording data is active. When recording is completed, click the "Stop" button.

1.4.2 EEGLab

EEGLab is an interactive Matlab toolbox for processing continuous and event-related EEG signals. In the context of this deliverable, it is exploited as importer for XDF files and viewer of the recorded LSL streams.

See the wiki page [6] of EEGLab to see how to install the toolbox into the Matlab environment (in particular the Chapter 1 link). To import XDF files, an extension for EEGLab must be installed: the “xdfimport” package available at [7]. To use it, decompress the downloaded zip file and copy the content into a folder that is in the MATLAB path (or add this folder to the path). Then, in MATLAB type the line "doc load_xdf" to see the documentation.

After the toolbox setup has been completed, Just type "eeglab" at the Matlab command line and hit enter. The blue main EEGLAB window should pop up, with its seven menu headings: File, Edit, Tools, Plot, Study, Datasets, Help arranged in typical (left-to-right) order of use. To load an XDF file click the File menu item, then select “Import data” -> “Using EEGLab functions and plugins” -> “From .XDF or XDFZ file” as shown in Figure 2.

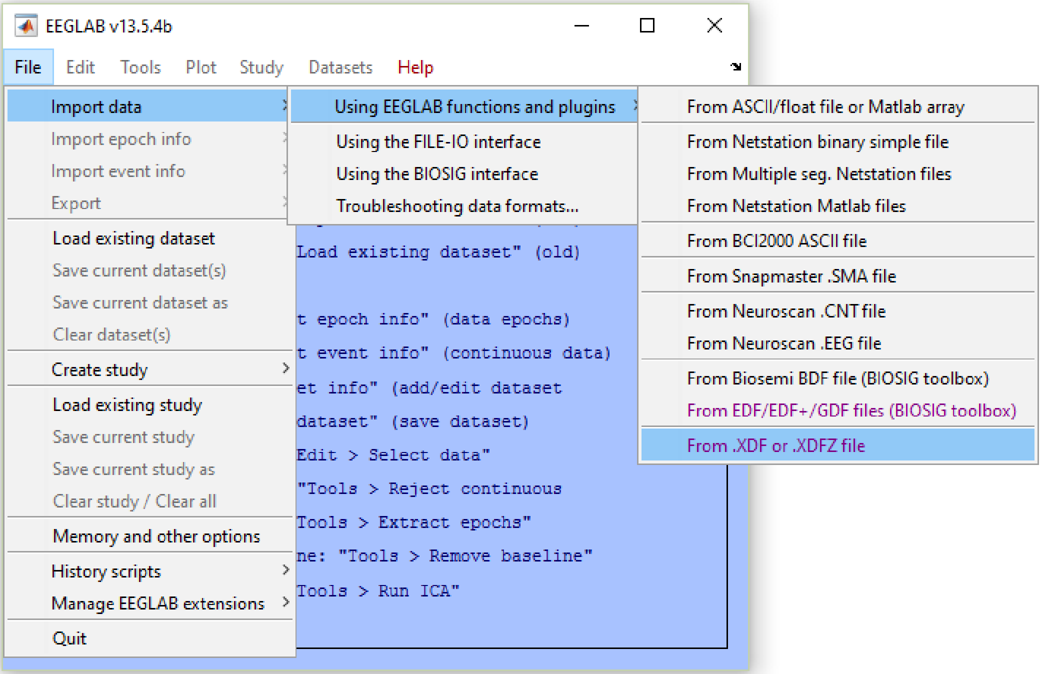


Figure 2: EEGLab interface to load an XDF file

After the selection of the desired file, the window of Figure 3 (on the left) will pop-up: fill-in the name of the stream to be imported (e.g. EBNeuro_BePLusLTM_192.168.1.73) and click "Ok"; then, a second windows appears (Figure 3, on the right) in order to give a name to the loaded dataset (e.g. EBN_test).

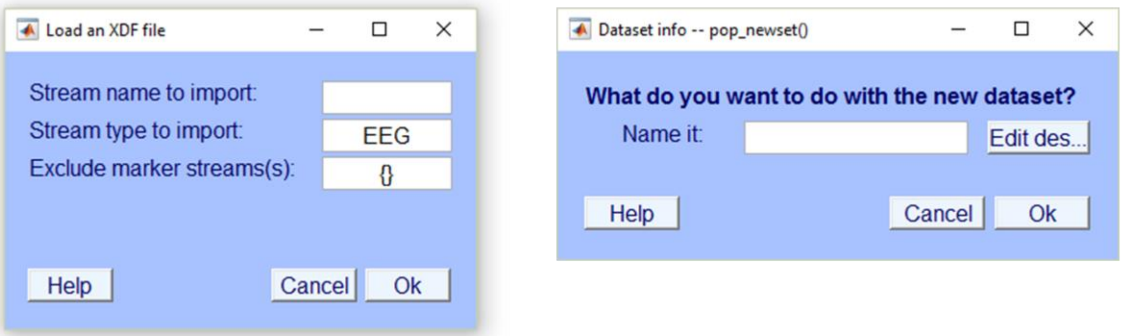


Figure 3: Remaining steps to load an XDF file

Now the EEGLab interface shows some info about the loaded stream (Figure 4, on the left); to display the stream click "Plot" -> "Channel data (scroll)" (Figure 4, on the right). Although only one stream at time can be viewed, the marker channel is always visible: this feature will be exploited during the synchronization experiments.

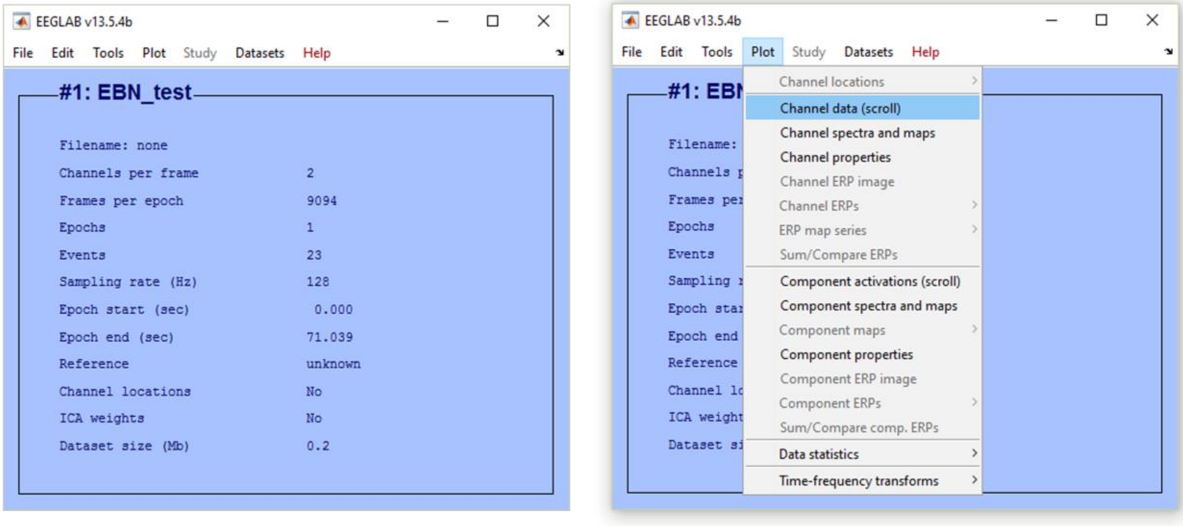


Figure 4: On the left, EEGLab shows a summary of the loaded XDF file. On the right, the menu item to plot the data is displayed.

2 Synchronization analysis

LSL can be configured to use different synchronization techniques: packet timestamps may be taken unchanged from one acquisition device or they may be synchronized using local time. Local wall-clock may be used as-is or periodically adjusted to compensate drift and jitter.

There are different cases here:

- Clock is periodically adjusted (each 50 samples of the fastest input) to compensate drift. Exact amount of drift depends on many factors (see later), this technique is the simplest one and do not guarantee that clock is monotonically increasing.
- Clock is periodically adjusted to compensate jitter. Algorithm is complex but it has better results than previous one however, it has the disadvantage to be slow to react to changes. Optionally this clock can be configured to be monotonically increasing.

Regardless which compensation algorithm has been chosen the underlying implementation represents time in nanoseconds, storing value in a double precision floating-points the resolution is one nanosecond with an error of 2^{-53} nanoseconds.

Note that multiple floating-point operations are performed on raw time then error will sum in an unpredictable way (because some expressions may be calculated completely on 80 bit FPU registers but this is compiler-optimizations dependent). Without a more formal analysis, it is reasonable to assume a resolution of one nanosecond; this is our first hard-limit in synchronization.

However, time resolution and timer granularity are different. Current LSL implementation relies on Boost `high_resolution_timer` implementation. Default implementation uses underlying compiler support.

Boost compiled on Microsoft Visual C++ before version 2015 used `system_timer`. This timer relies on Windows system timer but its resolution is not fixed, application and power management options may change this value from a minimum of one millisecond to virtually tens of milliseconds. This value is shared across all the applications and if the fastest request is honored then its value also varies over time. Practically value is set to a maximum of 15,6 ms by default and other application will change it to one millisecond (at best). In this case we then have a hard-limit for our timer granularity of one millisecond (for simplicity we can consider this value as constant), eventually LSL application may explicitly call `timeBeginPeriod(1).`

Boost compiled with Microsoft Visual C++ 2015 or with MinGW will instead use `steady_timer` which is implemented with performance counters.

Starting from Windows 7 and Windows Server 2008 R2, when CPU supports constant-rate Time Stamp Counter (TSC) and system is not a huge multiprocessor system, Windows internally always uses TSC to implement the Performance Counters. TSC introduce a latency (depending on CPU speed) in the order of hundreds of nanoseconds, plus a small error due to multiprocessor/multicore synchronization.

The behaviour of constant TSC (supported by most of the recent CPUs[1]) ensures that the duration of each clock tick is uniform and makes it possible to use of the TSC as a wall clock timer even if the processor core changes frequency. By exploiting the performance counters, the results are the same for all systems with timer granularity of one microsecond (or better).

To summarize: resolution is 1 nanosecond but typical timer granularity is 1 millisecond with best case of 1 microsecond (when performance counter are exploited), and worst case of 16 milliseconds (without performance counters); error is typically in the order of hundreds of nanoseconds but less than 1 millisecond.

2.1 General description

In this section the guidelines are roughly described for a proper understanding of the synchronization test procedure. With reference to Figure 5, three data stream flows through the standards peripherals interfacing to specific application, through the proprietary SDK. Data is simultaneously recorded through the Lab Recorder and later visualized with the EEGLab applicative. In order to prove the synchronization the Be Plus LTM amplifier is adopted as reference system due to the full controls on the data flow and the internal HW architecture. A general description of the BE Plus LTM data management is detailed in section 2.2.1 .

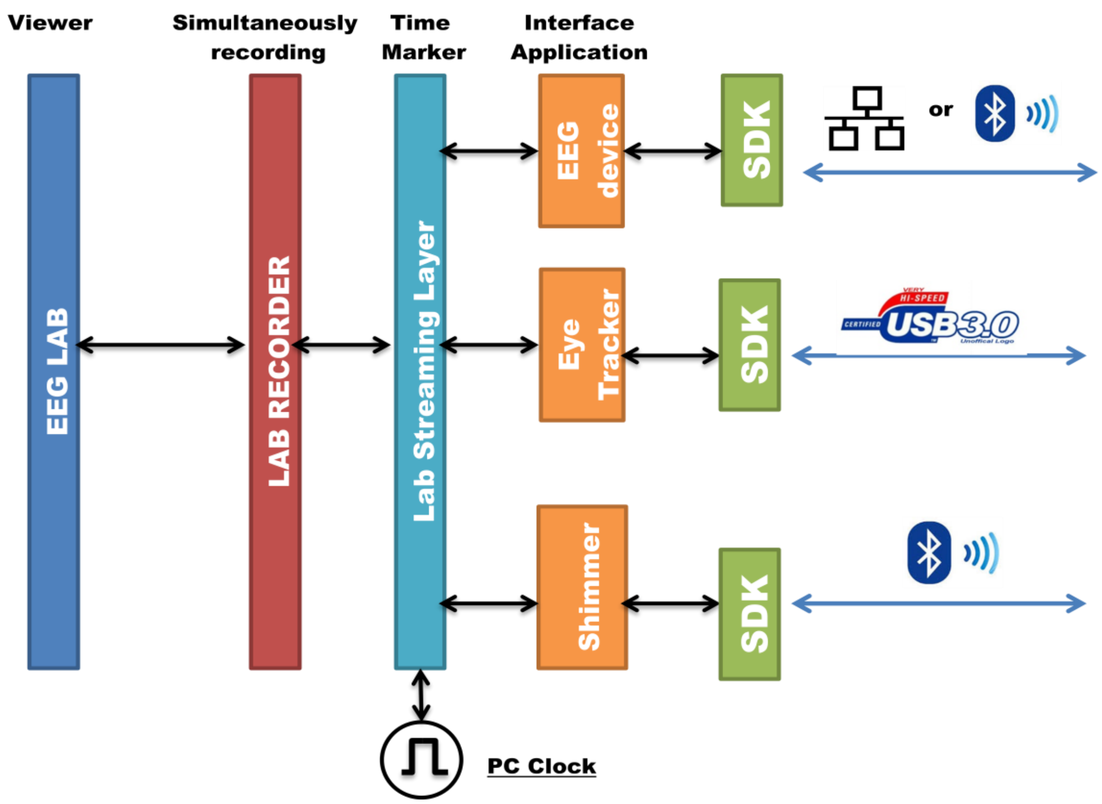


Figure 5: General overview of the pipeline used in the synchronization experiments.

[1] See [14] for a list of CPUs that support or not constant TSC.

2.2 Method and constraints

The synchronization will be checked in three steps using the Be Plus LTM device as reference device. The data timings of the devices are compared among them based on the time stamp recorded by LSL and common reference analog signal such as TTL trigger input or Eye Blink physiological signal.

2.2.1 BE Plus LTM Reference system

Thread Management

The device guarantees synchronization between sampled data and trigger input events. This feature is implemented by firmware, which takes advantage of the fact that the delay between data and events is constant for any given collection rate, and internally compensated.

The analog data are sampled at a fixed rate of 8192 Hz. The sample frequency is derived from an on-board clock that yields a 49.152 MHz frequency.

A Digital Signal Processor (DSP) executes a hardware interrupt at 16 kHz rate: this thread polls the trigger input line. When the line voltage is 0 (low level), a semaphore is posted in order to signal the trigger event to the acquisition thread. Sampled data are collected at sampling date by the DSP, which triggers a hardware interrupt any time a complete set of samples from all channels is received.

This acquisition thread has the highest priority possible among the DSP threads, so it guarantees an immediate execution. This thread polls for the trigger event semaphore and possibly inserts a flag in a special channel (called "service" channel), that is stored alongside the sampled data channels.

A software interrupt takes care of calibration and digital filtering of sampled data. This routine forwards the service channel without any modification, and compensates for the delay between data and trigger events, by delaying the service channel of a fixed amount of samples that depends on the filter applied, in order to align it to the corresponding sampled data channels.

Computation delay

The delay is given by two components:

A small delay is introduced by hardware filters present in the acquisition chain; this delay component is constant.

A bigger delay is introduced by the digital filtering implemented by the DSP. FIR filters introduce a delay that depend on their length:

$$\text{Delay} = \text{N° of Coeff}/2$$

The delay has been computed and tested in the firmware development process, in order to compensate for both the hardware and the firmware components. Evidence of this is also described in section 2.2.2 .

2.2.2 LSL synchronization test with Be Plus LTM

This first test aims to verify the alignment performed by LSL on the received streams.

Two BePlus LTM amplifiers are exploited (Figure 6): a signal generator is used to feed the bipolar channel A (CH A) of both the amplifiers with a square wave; on one of the devices also the trigger input signal is fed by signal generator.

Besides the standard data streams (stream#1 and stream#2) collected by the LSL wrapper application for EBN Be Plus LTM, a new LSL stream is introduced here to accomplish the synchronization tests: the “BePlusLTM Time Marker” stream, obtained from an ad hoc LSL interface that analyzes the service channel of a Be Plus LTM in order to send to LSL an event each time there is a marker into the service channel.

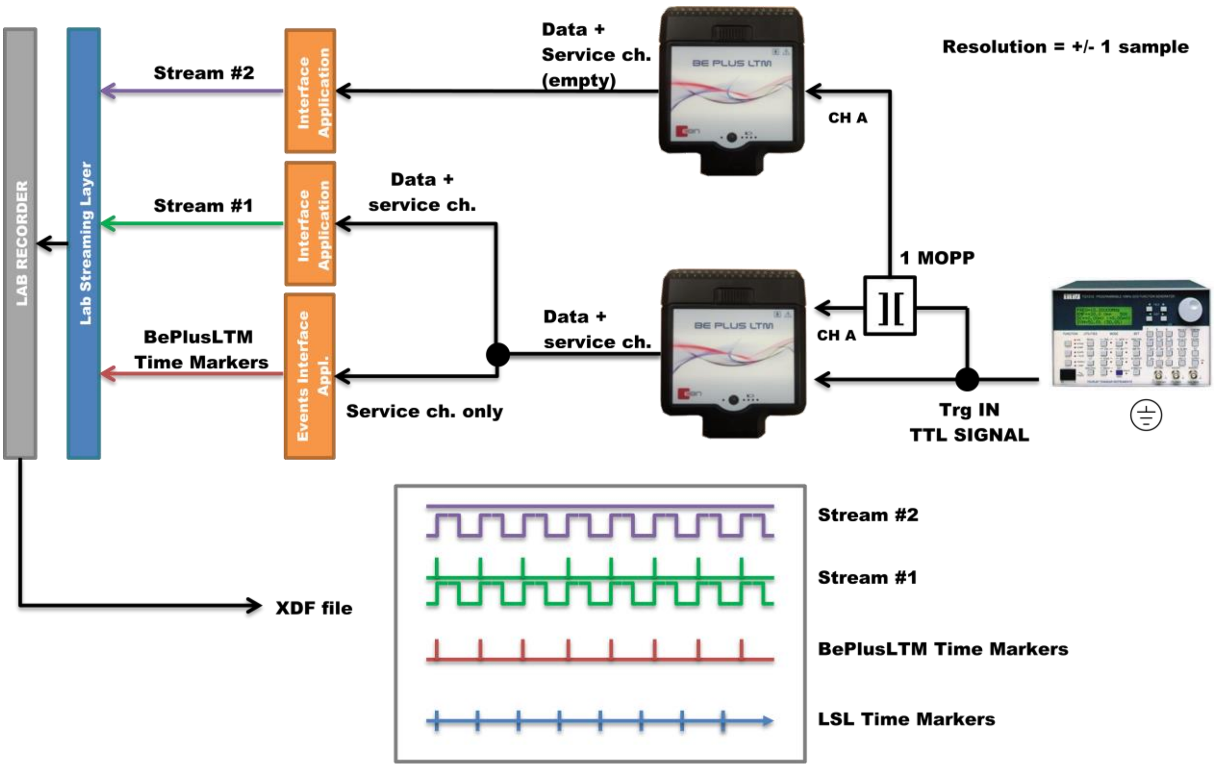


Figure 6: Hardware and software layout to analyze the synchronization performed by LSL.

As described in section 2.2.1 all the input channels are sampled simultaneously and the TTL trigger input is collected and aligned with the sampled data; the TTL signal is isolated before feeding CH A, so the on board protection mean is not compromised.

The amplifier recognize and samples each negative edge of the TTL signal as Trigger IN events.

The synchronization among the edges of the analogic collected signals and the Service channel (recording the events) can be later investigated on a sample by sample basis visually checking the alignment of the signal edge and the events of the “Be Plus LTM time marker” stream.

As detailed in section 2.2.1 a resolution of +/- 1 sample is achieved by the Be Plus LTM HW platform. Let’s consider a sampling rate of 256 Hz, suitable for the MAMEM project: this mean a resolution of +/- 4 ms; if a higher resolution is needed a maximum sampling rate of 8192 Hz increases the resolution up to +/-122 ns.

Since the reference clock is the amplifier on board crystal oscillator and the timing is based on the sampling frequency a drift is expected for long time acquisition. The Be Plus LTM amplifier uses high precision clock oscillator 49.152 MHz (see also section 2.2.1), with +/-25 ppm in the range [-10/+70 °C], phase shift max= 1ps, aging (@25 °C) = +/-3 ppm. To summarize, we have a maximum drift of 6 sample/day at the highest sampling rate, and only 2 samples/year @ 256 Hz, suitable for the MAMEM project.

2.2.3 LSL synchronization test with Shimmer3 GSR+

In the second test, the synchronization of the Shimmer3 GRS+ device with the Be Plus LTM amplifier is verified. With a hardware layout similar to the previous one (section 2.2.2), the same square wave signal is acquired simultaneously by both the devices and the time stamp are evaluated along with the edge of the signal; see also Figure 7.

The Shimmer device handles signal slower than EEG but in order to prove the synchronization we will run the device at the same frequency of the EEG devices.

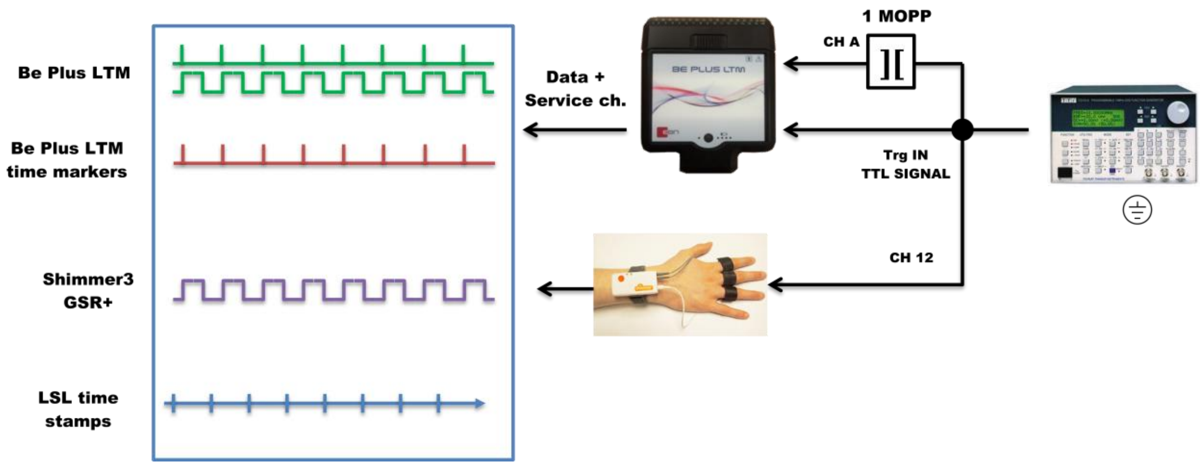


Figure 7: Hardware and software layout to analyze the synchronization of the Shimmer3 GSR+ data stream w.r.t. the Be Plus LTM stream.

2.2.4 LSL synchronization test with SMI REDn Scientific

The SMI REDn Scientific eye tracker doesn't allow, in the configuration provided for the MAMEM project, the acquisition of any Trigger IN signal; for this reason we are obliged to check the synchronization between the EEG signal and the eye tracker in a qualitative way that anyway is suitable for the MAMEM project.

In the adopted strategy, the EEG signals of the user are collected by mean of the Be Plus LTM amplifier while the person performs some eye blinks at several predefined instants (Figure 8). A marker is also added in correspondence of the eye blinks onto the Be Plus LTM stream by manually pressing each time the "Multifunction control button" of the device (see deliverable D4.2, section 3.2). These manual markers are exploited to identify the voluntary eye blinks w.r.t. the spontaneous ones.

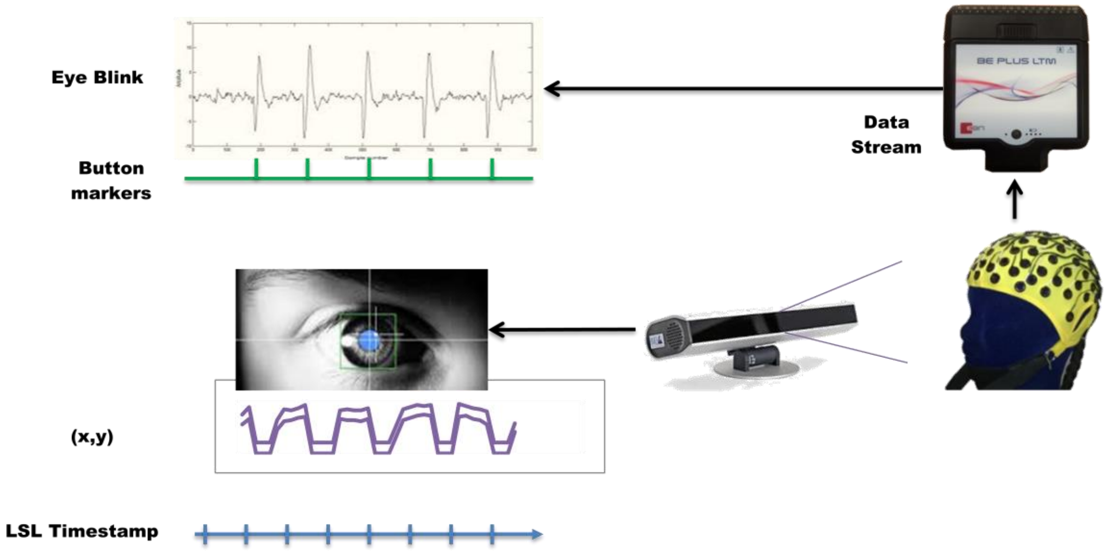


Figure 8: Hardware and software layout to analyze the synchronization of the SMI REDn Scientific data stream w.r.t. the Be Plus LTM stream.

The Eye Tracker provides data @ 30/60 Hz, streaming out several measurements about the position and gaze onto the screen for each eye; in particular, the (x,y) values of such measurements are set to (0,0) when a blink is detected. The blink event is easily recognizable also in the EEG signal shaping a rapid change of amplitude. The event is easily recordable on the frontal electrodes (Fp1-Fp2) and last roughly 300 ms (Figure 9). The peak point, shows the inversion of the eyelid, can be used as references point for both the devices. The synchronization can be evaluated comparing the alignment of the analogic signal and the consistency of the time marker computed by the LSL.

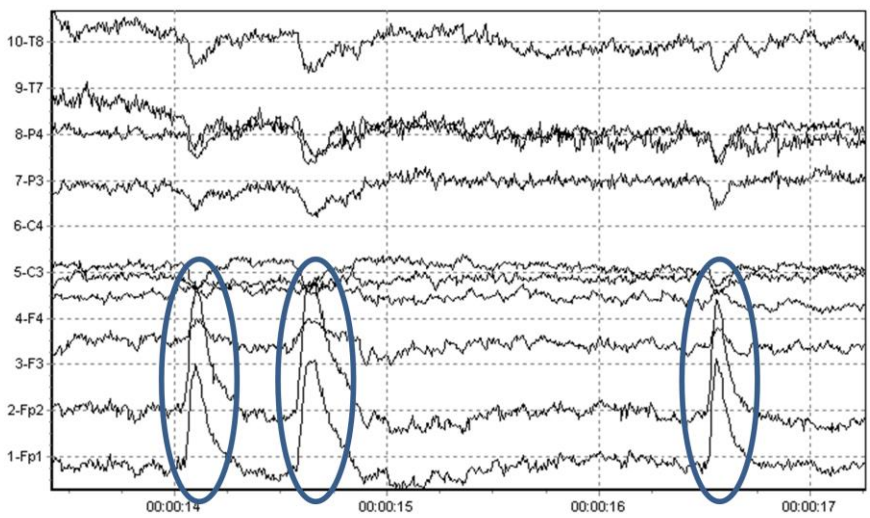


Figure 9: Eye blink effect on EEG signal

We expect a latency of +/- 1 sample.(33 ms @ 30 Hz).

As a consequence of this solution, it will be not possible to test the synchronization of all the three devices (Be Plus LTM, REDn Scientific and Shimmer3 GSR+) simultaneously, since for the eye tracker we must exploit a biological signal, while for the shimmer the comparison must be evaluated on the basis of an artificial signal (i.e. a square wave).

2.2.5 LSL synchronization test with Shimmer3 GSR+ and Emotiv Epoc

The aim of this test is to check the synchronization of the Shimmer3 GSR+ and Emotiv Epoc together, being the Be Plus LTM the reference hardware for the timestamps (Figure 10), similarly to what already done in section 2.2.1.

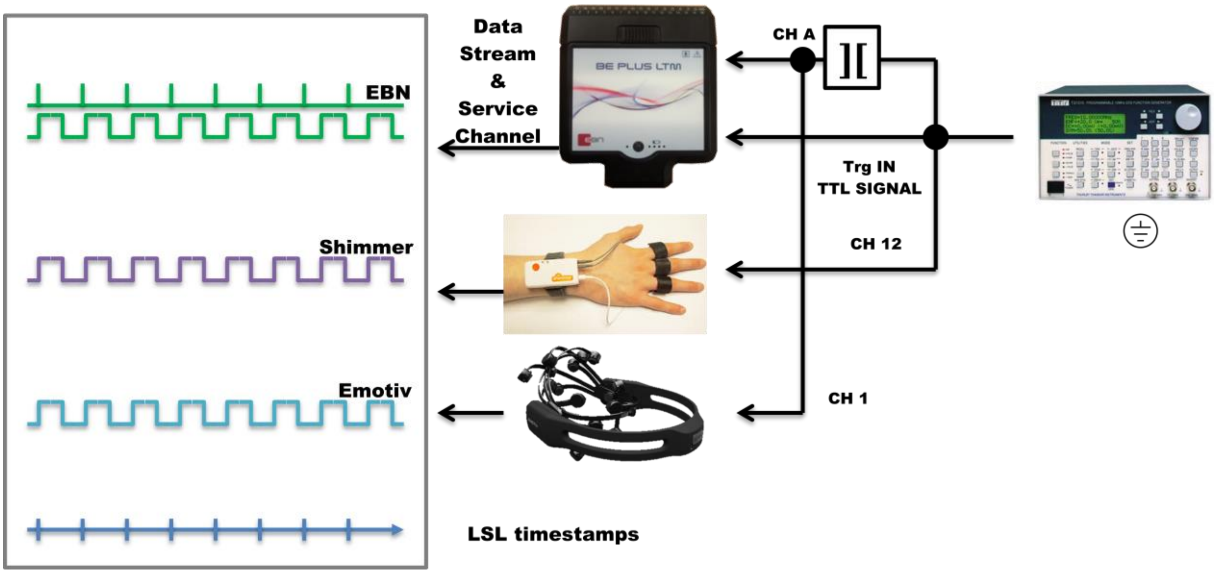


Figure 10: Hardware and software layout to analyze the synchronization of the Shimmer3 GSR+ unit and Emotiv Epoc headset.

Unfortunately, after the first experiments with the Emotiv Epoc headset, we have noticed that the stream of the device does not guarantee a stable sampling rate; see section 3.2 for a detailed discussion about this shortcoming. At the current state, this fact represents a problem to be solved if signal synchronization must be ensured.

3 Experimental results about synchronization

Based on the methodologies detailed in section 2, the gained experimental results about synchronization are reported as following. All the streams shown in the following figures have been displayed by opening the XDF file with the EEGLab viewer.

3.1 Heavyweight configuration

The following subsections cover the experimental results related to the methodologies described in sections 2.2.2 , 2.2.3 , 2.2.4 . In all the experiments a recording session of 20 minutes have been performed.

3.1.1 Experimental results with Be Plus LTM

Figure 11 shows the stream of the first Be Plus LTM with the TTL trigger input (on top) and the stream of the second Be Plus LTM (on bottom). In correspondence of each trigger event, the red line of the “BePlusLTM time maker” stream is displayed, showing that also the square wave of the second stream is perfectly aligned with the stream of the first device, also after 20 minutes. This result proves that the two streams are synchronous.

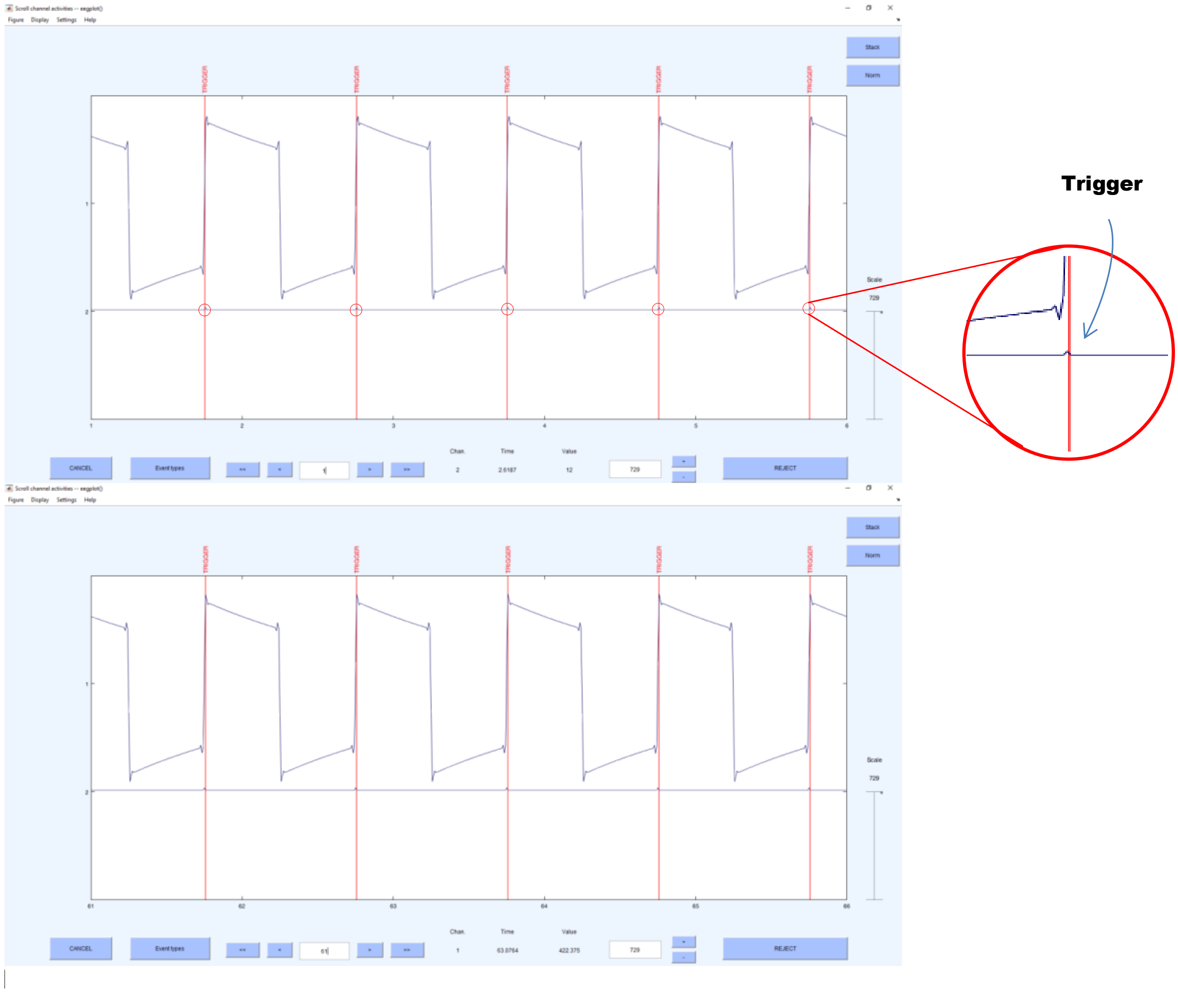


Figure 11: Experimental results showing the synchronization of two independent Be Plus LTM streams.

3.1.2 Experimental results with Shimmer3 GSR+

Figure 12 shows the perfect alignment of the square wave in input to the Shimmer3 GSR+ device w.r.t. to the “BePlusLTM time maker” stream. Also in this case, the streams of the two devices (Be Plus LTM and Shimmer3 GRS+) are synchronous.

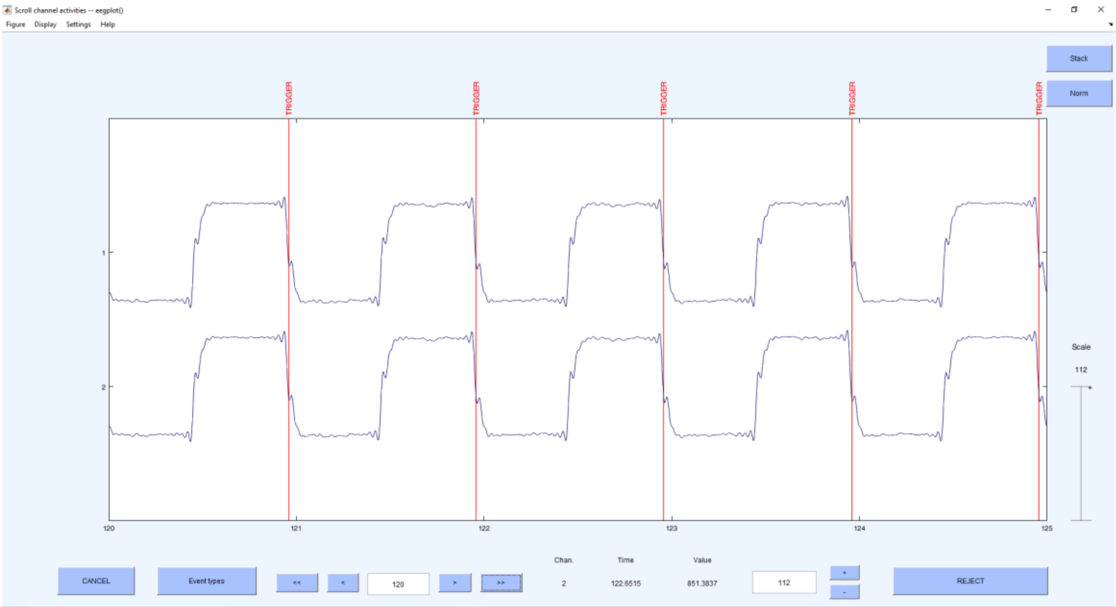


Figure 12: Experimental results showing the synchronization of the Shimmer3 GSR+ stream w.r.t. the Be Plus LTM stream.

3.1.3 Experimental results with SMI REDn Scientific

Figure 13 shows the stream of the SMI REDn Scientific (top stream) compared to the EEG signal (bottom stream) in correspondence of a voluntary eye-blink. We have observed a constant alignment of the two signals, even after 20 minutes of data recorded.

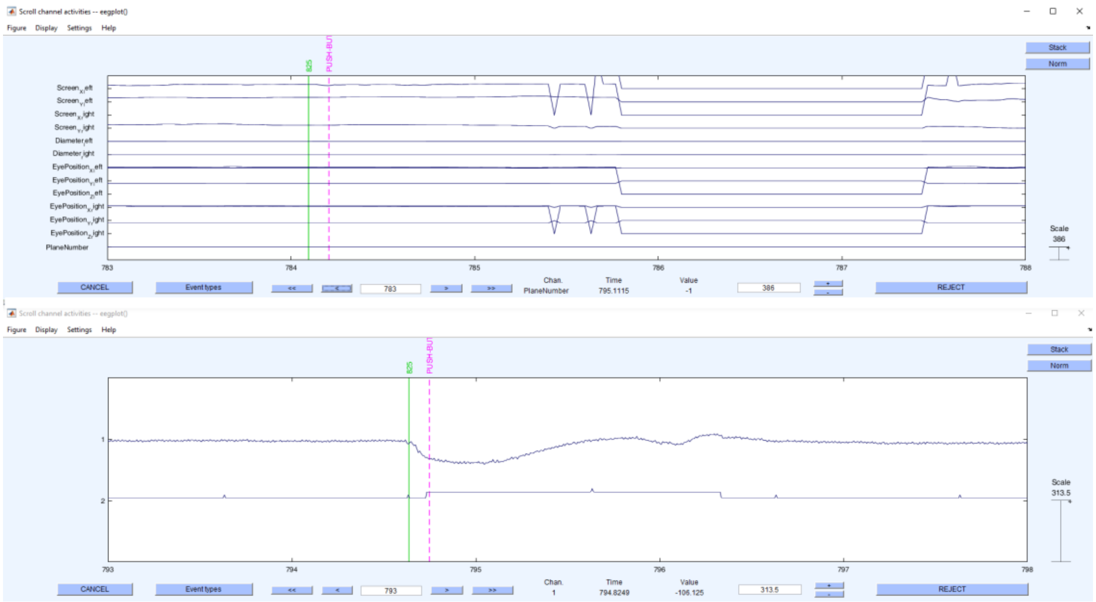


Figure 13: Experimental results showing the synchronization of the SMI REDn Scientific stream w.r.t. the Be Plus LTM stream.

3.2 Lightweight configuration

The tests about synchronization in the case of the lightweight configuration could not be performed, due to the shortcoming of the irregular sampling rate of the Emotiv Epoc.

In our tests, a square wave signal with period of 1 Hz was the input for channel #1 of the Epoc headset, and then the recorded stream was analyzed. In particular, by overlapping windows of the same length (e.g. 3 seconds) taken at multiple of the signal period the shape of the signal into the window must be exactly the same. This is the case of the BE Plus LTM stream (Figure 14), while for the Epoc headset this is not true (Figure 15).

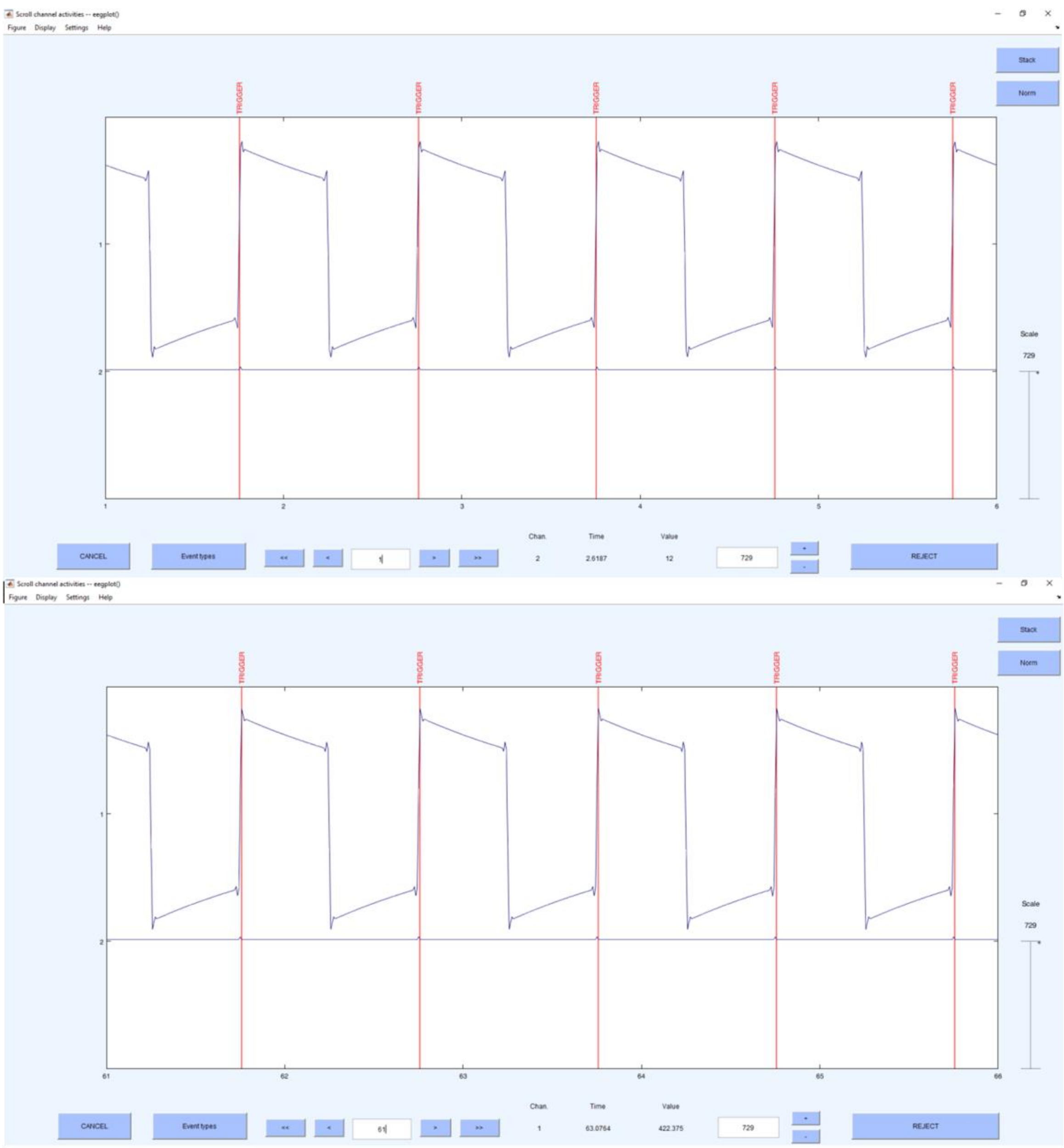


Figure 14: Good alignment of the square wave sampled by the Be Plus LTM after 60 seconds.

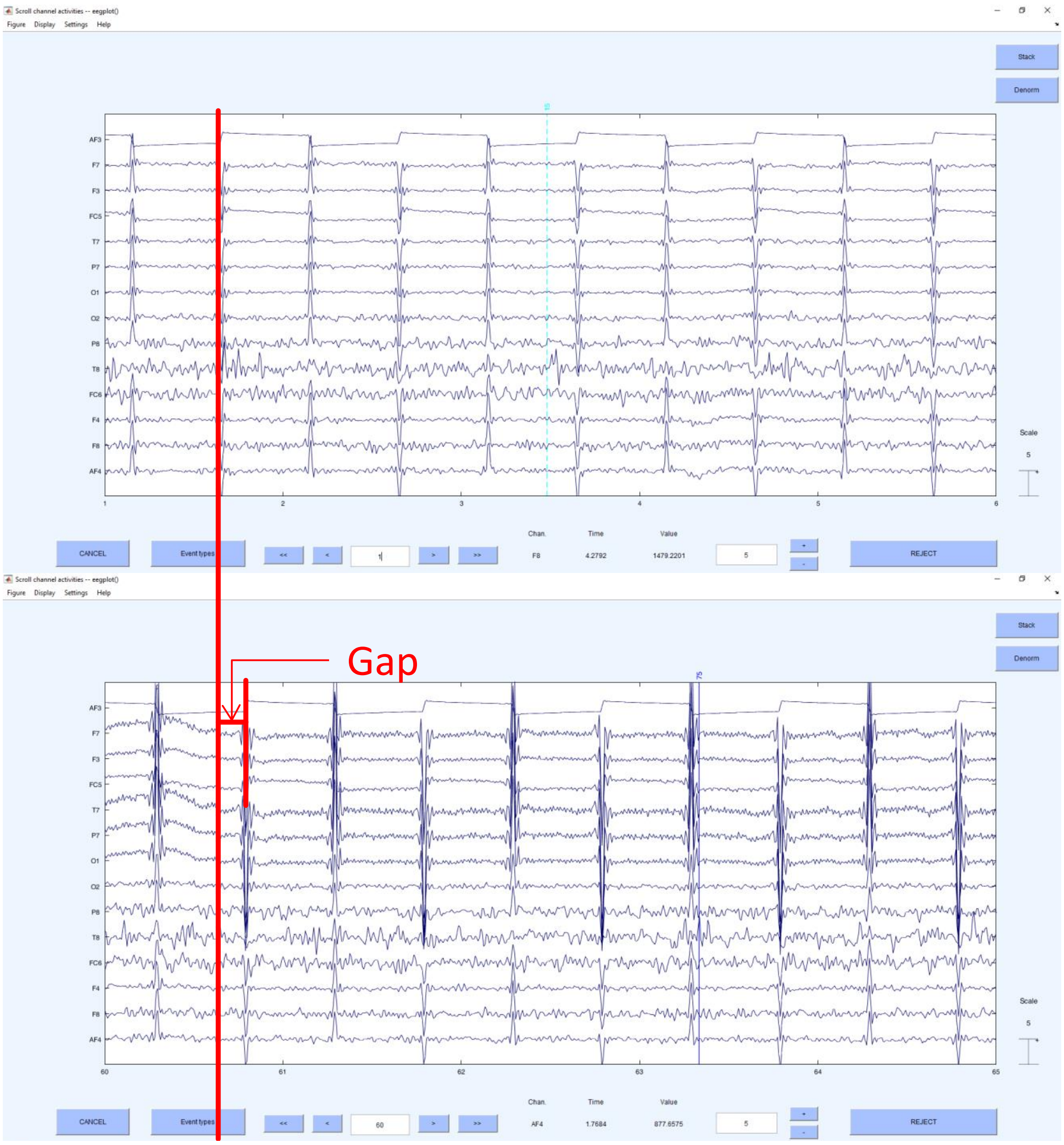


Figure 15: Bad alignment of the square wave sampled by the Emotiv Epoc after 60 seconds.

Similar results have been measured also by recording for 30 minutes the Epoc data stream with its native "Emotiv Xavier TestBench" application and inspecting the EDF file saved by the application at 128 Hz. The analysis of the native recorded data has shown that in average there is a loss of a sample every 7.5 seconds, measuring a delay of 1 second every 16 minutes.

This issue was already discussed among the Epoc users (see [15]), and a solution was made available in [16]; thus, we tested it for our purposes. Unfortunately we continued to observe the drift together with some strange discontinuities (Figure 16). Hence that implementation was discarded, and it was decided to find a new strategy to cope with the irregular sampling rate of the Epoc headset.

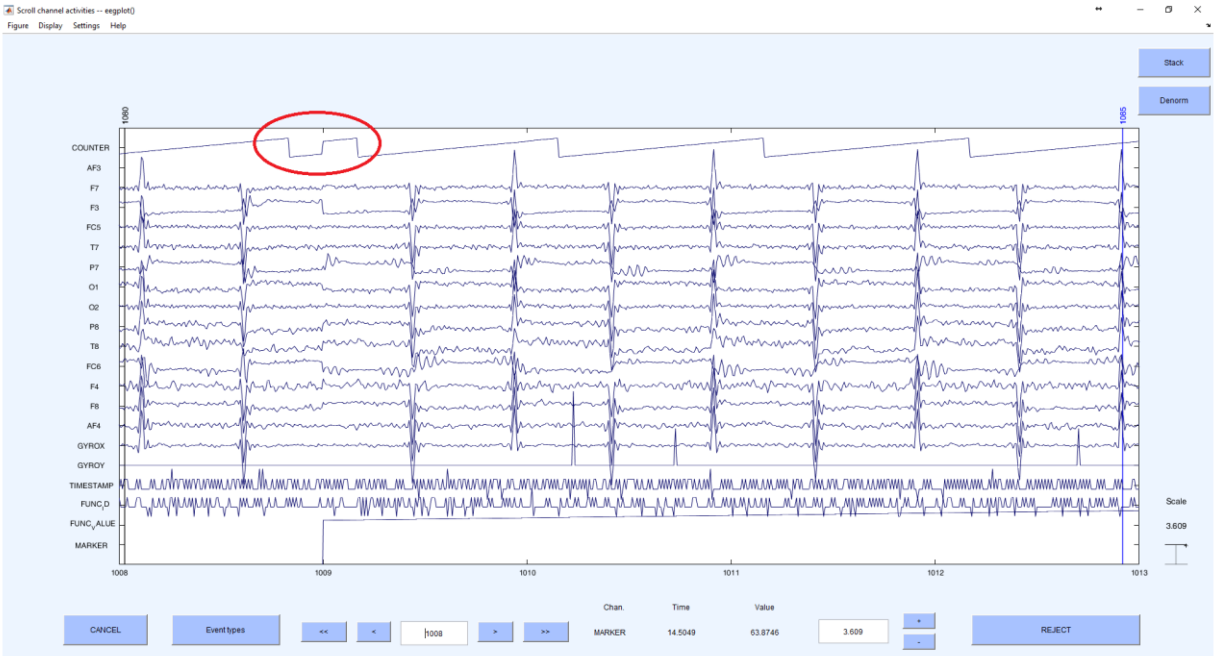


Figure 16: Synchronization test for the Epoc headset using the implementation proposed in [16]. Strange discontinuities have been recorded.

3.2.1 Strategy to compensate the irregular sampling rate of Epoc headset

The basic concept of the solution proposed by EB Neuro is to count in each second the number N of samples arrived from the device, and to add or remove some samples if N differs from the expected nominal value (i.e. the sampling rate).

A timer indicates every second when the correction must be carried out. All the data chunks **c** arrived from the Epoc when the timer is running are simply copied and delivered as data chunks **s** to LSL. When the timer rings, the chunk **s** sent to LSL may differ from the chunk **c** arrived from Epoc.

More precisely (see Figure 17),

1. At each chunk of m items arrived from the Epoc headset between two timer rings, corresponds a chunk of m items to LSL, i.e.
    - $k = m$
    - $s_i = c_i$, i=0…k-1
2. Only when the timer rings (let N the counted samples in the last second, and d=r-N):
    - $k = m + d$
    - if $N < r$, d samples must be added
        i. $s_i = c_i$, i=0…m-1
        ii. $s_m = s_{m+1} = \ldots s_{m+d} = c_{m-1}$; (the latest sample is replicated d times)
    - if $N > r$, $|d|$ samples must be removed
        i. $s_0 = (b + c_d)/2$ (interpolation is required in order to avoid discontinuities)
        ii. $s_i = c_{d+i}$, i=1…k-1

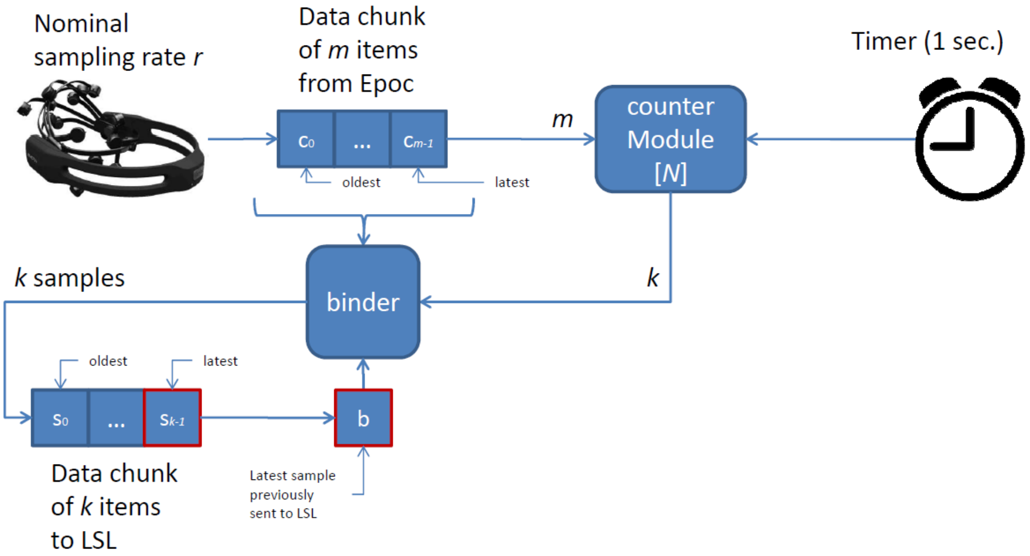


Figure 17: Compensation technique to cope with the irregular sampling rate of the Epoc headset. For simplicity, the special case of 1 channel is here discussed; the generalization to *n* channels is straightforward.

The implementation of this solution was tested with the usual approach, obtaining a remarkable improvement in terms of synchronization. The drift has disappeared in practise, and only some residual jitter remains. After an acquisition of 20 minutes, we have found that the temporal distance between the timestamp markers recorded by the Be Plus LTM amplifier and the rising edge of the square wave recorded by the Epoc headset are constant in average (few milliseconds). The performed tests have also shown that the real sampling rate is always lower than the nominal value (128 Hz). Using the compensation approach the gained average sampling rate is 127.9247 against 126.8873 (i.e. the value measured in the original implementation). As shown in Figure 18 and Figure 19, the offset at the beginning of the recording session (Figure 18) between the Be Plus LTM time markers (the redline) and the peaks corresponding to the edge of the square wave is the same of the offset at the end of the recording session Figure 19).

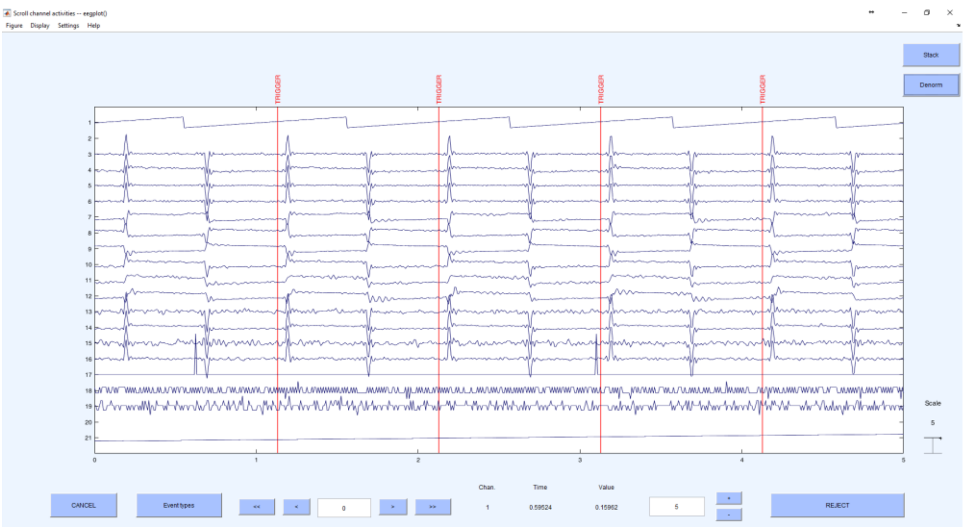


Figure 18: starting point of the recording session using the compensated strategy

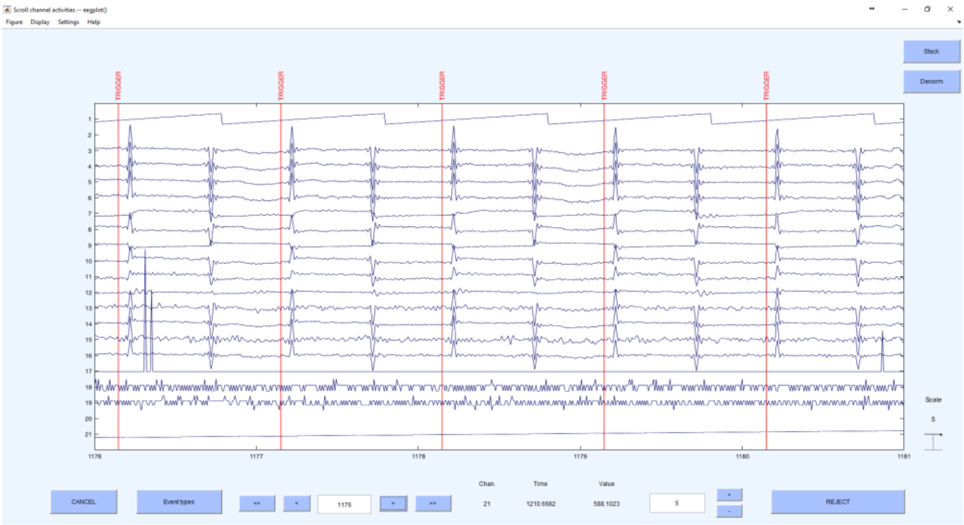


Figure 19: ending point of the recording session using the compensated strategy

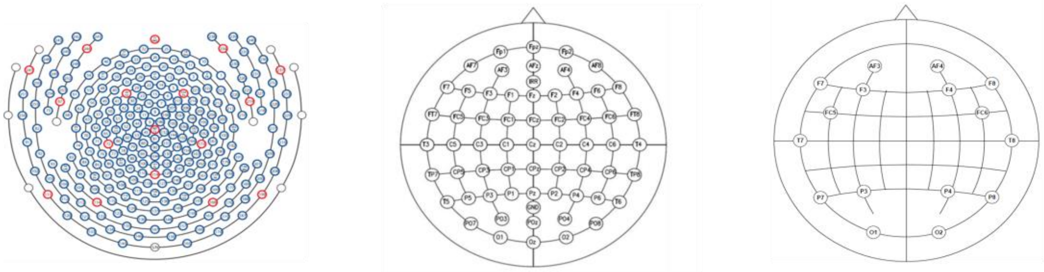
3.3 Conclusions

The synchronization experiments have shown that LSL works properly, since it has been able to align the streams of different devices. After an initial drawback about the irregular sampling rate of the Emotiv Epoc headset, the proposed compensation technique allows the devices to be sufficiently synchronized.

4 EEG filters vs channel configurations

The two EEG datasets exploited in deliverable D3.1 [8], have also been used to analyze the performance of artifact reduction when dealing with different number of channels. The datasets are available in [9] and contain several EEG sessions with SS-VEP stimulation applied to a set of 11 persons. In dataset #1 the SS-VEP stimulation is isolated (SSVEP-SINGLE dataset); in dataset #2 (SSVEP-MULTI dataset) the stimuli are shown simultaneously.

Besides the original configuration (EGI 300 Geodesic System, with 256 channels), the datasets have been spatially subsampled in order to reproduce the channel configurations of EBN BePlus headcap (64 channels) and Emotiv Epoc headset (14 channels), by selecting the related EEG channels. The different channel configurations are summarized in Figure 20.



EGI configuration **BePlus configuration** **Epoc configuration**

Figure 20: On the left, the original EGI channel layout of the datasets; in the middle, the Be Plus LTM configuration with 64 channels; on the right, the Emotiv Epoc configuration with 14 channels.

4.1 EEG filter analysis

These datasets have been used to analyze the efficacy of the artifact reduction technique based on the Amuse algorithm and CAR (Common Average Removal) filter (see deliverable D2.1 [10]), trying to increase the classification results of the overall processing pipeline performed by the ssvep-eeg-processing-toolbox [9] (standard frequency filters are already exploited in the existing toolbox pipeline of this toolbox).

AMUSE decomposes the raw EEG data into independent components (ICs), usually representing i) external noise and ii) real EEG activity. Different approaches to handle the noisy components have been tested (see Table 1), besides the “Fixed rej.” approach implemented in D3.1.

Type	Description
NR	No rejection (i.e. artifact removal not performed)
Fixed rej.	Rejection of the first N and last M ICs (toolbox approach) [11]
Energy rej.	Rejection of ICs based on the energy estimator defined in [12] (the approach suggested in deliverable D2.1)
WT cor.	Correction of noisy ICs based on wavelet analysis [13]

Table 1: Adopted strategies to handle the noisy independ components produced by AMUSE.

The "WT cor." strategy is a new approach that has been investigated after some preliminary results on the reduced datasets obtained with "Fixed rej." and "Energy rej." strategies. This approach calculates the WT (Wavelet Transformation) of the ICs, and the WT coefficients resembling undesirable properties in the signal are suppressed by thresholding. Thus WT permits to filter the ICs without the need to reject them completely (Figure 21).

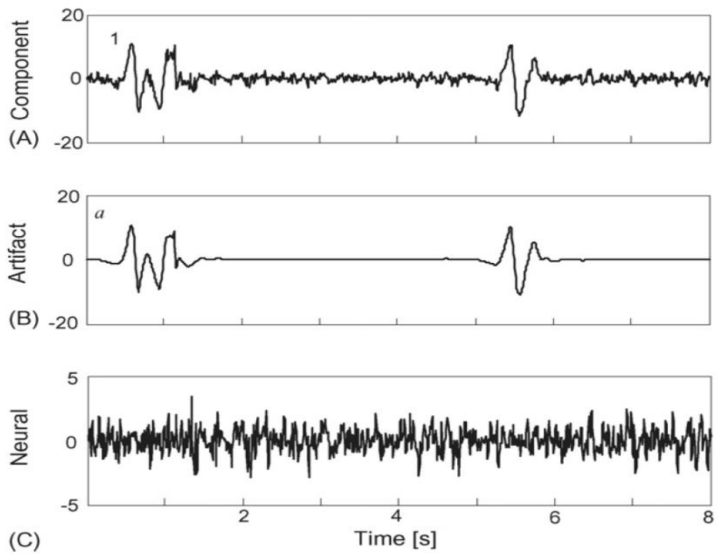


Figure 21: (A) The IC has two episodes of eye blinking. (B) Artifactual source in the IC. (C) Underlying neural signal into the IC.

Table 2 and Table 3 summarize the average final results of the tests. The analysis of the several approaches tested are reported for completeness.

Set	# Ch	NR			Fixed rej.			Energy rej.			WT cor.		
		No CAR	CAR	Δ	No CAR	CAR	Δ	No CAR	CAR	Δ	No CAR	CAR	Δ
Dataset 1	256	74,66	77,12	2,46	81,23	81,07	-0,16	76,20	77,26	1,06	77,80	79,12	1,32
	64	72,83	73,90	1,07	74,17	75,41	1,24	74,41	74,78	0,37	75,73	75,75	0,02
	14	72,83	73,58	0,75	72,29	75,28	2,99	73,38	72,74	-0,64	76,35	73,56	-2,79
Dataset 2	256	68,29	70,47	2,18	71,71	71,93	0,22	68,95	70,55	1,60	68,73	70,69	1,96
	64	66,40	67,27	0,87	63,78	65,09	1,31	64,22	65,82	1,60	68,29	69,16	0,87
	14	66,40	66,47	0,07	61,96	64,95	2,98	63,13	64,07	0,95	65,96	66,98	1,02

Table 2: Results obtained by averaging the score of the 11 subjects for both the datasets. Green cells shows the two best approaches for the different configurations per dataset.

Set	# Ch	NR			Fixed rej.			Energy rej.			WT cor.		
		No CAR	CAR	Δ	No CAR	CAR	Δ	No CAR	CAR	Δ	No CAR	CAR	Δ
Dataset 1	256	90,70	95,35	4,66	96,77	96,90	0,14	94,30	96,23	1,93	93,35	96,39	3,04
	64	86,73	89,15	2,42	89,45	91,40	1,96	90,35	90,64	0,29	90,40	91,19	0,79
	14	86,73	88,56	1,83	87,23	90,47	3,24	88,65	89,04	0,39	89,76	88,17	-1,59
Dataset 2	256	79,60	82,80	3,20	81,70	81,50	-0,20	79,30	81,60	2,30	79,90	82,70	2,80
	64	77,20	79,00	1,80	73,80	75,90	2,10	75,60	77,90	2,30	77,90	79,50	1,60
	14	77,20	78,40	1,20	71,20	75,40	4,20	74,60	76,40	1,80	75,80	78,60	2,80

Table 3: Results obtained by averaging the score without subjects # 3, 5, 8 for both the datasets. Green cells shows the two best approaches for the different configurations per dataset.

Table 2 collects the results obtained by averaging the score of the 11 subjects, while Table 3 shows the corresponding averages obtained excluding the 3 "poorly accurate" subjects already identified in deliverable D3.1 (i.e. subjects # 3, 5, 8). This is because it can be argued that the significance of the application of the different approaches on those data should be very poor and this could affect the evaluation of the approaches themselves.

One further confirmation of this hypothesis can be found in the appendix A where the detailed data of the 11 subjects are listed. In the detailed tables it can be seen that the application of the CAR to NR case reduces the score for the 3 "poorly accurate" subjects while increases it for the other subjects. The green cells shows the two best approaches for the different configurations per dataset.

4.2 General observations

Some observations can be done taking into account the results of Table 2 and Table 3, as it follows.

4.2.1 Comparison between the 3 configuration

It can be seen clearly that the performances with the 256 channel are the best, while the 14 channel configuration offer the poorest performances.

4.2.2 Comparison between the 2 datasets

On average, the results on the 2 datasets are quite different. Considering the full set of subjects, the scores on the first dataset are much better, with a difference between around 7 and 10 %. Considering the reduced set of subjects, the difference are higher, between around 10 and 15%. It is noticeable that in all cases, with few exceptions, the best approach for the first dataset is not the same as for the second one.

4.2.3 Comparison between the 4 approaches

Considering first the case NO CAR, the 4 approaches shows different effectiveness depending on the number of channels. On average, the "Fixed rej." approach is the best for the 256 channel configuration. In the configuration with 64 channels the wavelet approach seems to give always the best results. Finally, in the 14 channel case the two datasets give different result: in dataset 1 the wavelet approach wins, while in the dataset 2 the unprocessed data seem to work better.

The evaluation of Table 3 confirms this results, but it seems to be clearer that the unprocessed data are still better for the 14 channel configuration.

4.2.4 Evaluation of the CAR processing

With very few exception (2 in both the 2 tables) the CAR processing improves always the score of all the configurations and approaches, but differently approach by approach.

In order to evaluate the real effectiveness of the CAR on the different approaches and configuration, Table 4 shows the variation of the percentage score after the application of the CAR filter in all the configuration separately for the full set of subjects and the reduced set (without the 3 "poorly accurate" subjects). An additional column shows the difference between the CAR improvement in the two sets for all configuration, so highlighting the effect of the use of the reduced set.

The green cells shows the overall best CAR improvements.

Set	# Ch	NR			FIXED			ENERGY			WAVELET		
		Full	Red.	Δ	Full	Red.	Δ	Full	Red.	Δ	Full	Red.	Δ
Dataset 1	256	2,46	4,66	2,19	-0,16	0,14	0,30	1,06	1,93	0,87	1,32	3,04	1,73
	64	1,07	2,42	1,34	1,24	1,96	0,72	0,37	0,29	-0,08	0,02	0,79	0,77
	14	0,75	1,83	1,08	2,99	3,24	0,25	-0,64	0,39	1,03	-2,79	-1,59	1,20
Dataset 2	256	2,18	3,20	1,02	0,22	-0,20	-0,42	1,60	2,30	0,70	1,96	2,80	0,84
	64	0,87	1,80	0,93	1,31	2,10	0,79	1,60	2,30	0,70	0,87	1,60	0,73
	14	0,07	1,20	1,13	2,98	4,20	1,22	0,95	1,80	0,85	1,02	2,80	1,78

Table 4: Variation of the percentage score after the application of the CAR filter in all the configuration, for the full set of subjects and the reduced set; green cells shows the overall best CAR improvements.

At a first look, the approaches that seem to be the more affected by the CAR are 256 ch. with NR and 14 ch. with "Fixed rej." strategy. Moreover, it can be observed that the use of the reduced set of subjects has a greater effect in the "NR" and "WT cor." approaches on average. In the other cases the improvement seems to be quite low, around 1%. In other words, if we consider the reduced set, the actual effectiveness of the CAR is quite higher, and in the “NR” case the improvement is very high, so that the “NR” + CAR approach reaches similar performance than the other approaches.

The three following sections (4.3 , 4.4 , 4.5) will show the best approaches for the different configuration, taking into account both the full and the reduced set of subjects. In particular, Table 5 shows the average score of the two datasets.

Set	# Ch	NR		Fixed rej.		Energy rej.		WT cor.	
		No CAR	CAR	No CAR	CAR	No CAR	CAR	No CAR	CAR
Full	256	71,47	73,80	76,47	76,50	72,57	73,90	73,26	74,90
	64	69,61	70,59	68,98	70,25	69,31	70,30	72,01	72,46
	14	69,61	70,02	67,13	70,11	68,25	68,41	71,16	70,27
Reduced	256	85,15	89,08	89,23	89,20	86,80	88,92	86,63	89,55
	64	81,97	84,07	81,62	83,65	82,98	84,27	84,15	85,34
	14	81,97	83,48	79,21	82,94	81,63	82,72	82,78	83,39

Table 5: Average percentage score of the best approaches for the different configurations, taking into account both the full and the reduced set of subjects. The green cells point the best score, while the yellow ones good second choice approaches, often with differences statistically non significant (best viewed in colour).

4.3 Results for the EGI configuration

As concerns the EGI configuration, with the first dataset, the best approach is the “Fixed rej.” one, with differences statistically non significant between CAR and NO CAR, both with the full and reduced set.

If we consider the second dataset, the situation is more confusing, as the full and reduced set do not share the best approach. However, the fixed approach seems to give good performance anyway, slightly lower than the “WT cor.” strategy.

4.4 Results for the Be Plus LTM configuration

As concerns the 64 channel configuration, the best approach seems to be the “WT cor.”one, with both dataset and both with the full and reduced set. The differences between CAR and Not CAR seems to be statistically non significant in the full set of subjects, while with the reduced set the “WT cor.” + CAR seems to be the best.

4.5 Results for the Emotiv Epoc configuration

As concerns the 14 channel configuration, with the full set, the best approach is the “WT cor.” without CAR in the first dataset and the “WT cor.” + CAR in the second dataset. In this last case “WT cor.” without CAR offers similar performances as well.

Anyway, also the “NR” + CAR approach has good performances, especially in the second dataset.

On the contrary, if we consider the reduced set of subjects, in the first dataset the best approach is the “Fixed rej.” + CAR, but also “WT cor.” + CAR has good performances, statistically equivalent. If we consider the second dataset, the “WT cor.” + CAR has the best score, together with “NR” + CAR that offer a similar score.

In conclusion, the “WT cor.” + CAR seem to be the best approach for the 14 channel configuration, but the “NR” + CAR can be a good choice as well, especially considering the computational cost.

4.6 Conclusions

In conclusion we can state that configurations with a medium-low number of channels don't get much advantage from the simple AMUSE approaches. With 64 channels the best approach is surely the “WT cor.” + CAR, while with 14 channels both “WT cor.”+CAR and “NR” + CAR are good choices.

A low spatial resolution in terms of channels decreases the performance of AMUSE algorithm: the number of ICs is limited by the number of available channels; thus, with few ICs the separation between noise and EEG activity becomes difficult. As a consequence, a ICs can contain both noise and part of the real EEG activity. For this reason, the “WT cor.” approach gives better results than “Fixed rej.” or “Energy rej.” strategies when applied to the datasets of the subsampled configurations: the complete rejection of an ICs can remove also part of the EEG signal, while removing only the noisy wavelet coefficients preserves the EEG activity. To better understand this, compare the filtered channels (in red) of Figure 22, obtained with the “Energy rej.” strategy, w.r.t. the filtered data of Figure 23 obtained with the “WT cor.” approach. The recovered EEG data inside the marked ellipses, in correspondence of some artifact, are much richer in the latter case w.r.t. the first one, where some part of the real EEG activity has been removed by the suppression of some (entire) ICs.

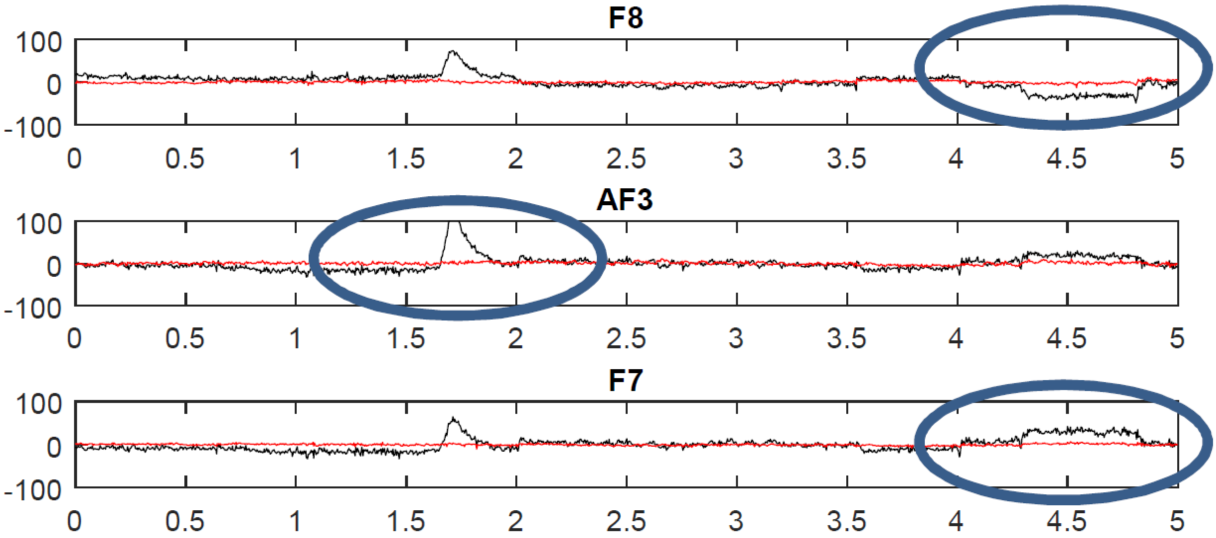


Figure 22: Artefact reduction by exploiting the "Energy rej." approach on a 14-channel EEG data stream.The recovered (red) signal is almost flat (best viewed in colour).

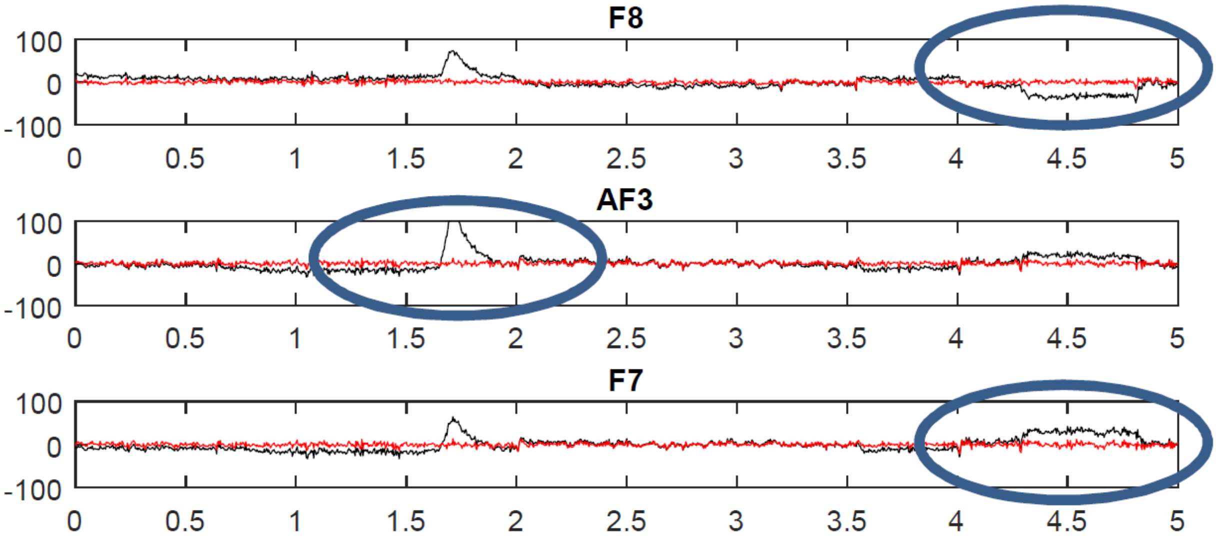


Figure 23: Artefact reduction by exploiting the "WT cor." approach on a 14-channel EEG data stream. The recovered (red) signal still contains the EEG activity (best viewed in colour).

5 EEG Device for lightweight configuration

5.1 Intro

As per chapter 5 of D2.1 MAMEM project EEG subsection is based on two main configurations, so called Heavyweight and Lightweight, where many technical parameters have been taken in account, like HW tech specs, availability of a Lab Streaming Layer interface, availability of a C/C++ SDK.

Beside the previous specs, both configurations have been defined taking in account one essential common point, the user. MAMEM project users are not common people, but special persons who cannot have full control of their body or movements and that in most cases are forced on a wheelchair.

In order to better cope with so special persons the consortium had clear the following features were basic milestones for both the configurations:

a) Easy to setup on a wheelchair or close to
b) Causing the minimum discomfort to the user when worn
c) Compact dimension

While the "Heavyweight" solution has been found from within the expertise of the consortium, the Lightweight solution required a thorough analysis of the market where also the following extra parameters have been taken in account

d) Wireless capability
e) Time to Market
f) End user price
g) Design

Wireless capability avoids the need of wires and makes it easier to the end user to wear it. Time to market is essential to grant the capability that any solution developed in the consortium can be deployed in the market in the shortest time, so certifications and intended use have been essential in the decision of the consortium. In addition, the end user price of the device need to be as lower as possible, so as to maximize the chances of its adoption even to people with lower income. Finally, the device design is essential for allowing the end user to feel comfortable in wearing it. This point is quite essential in persons who need to cope day by day with their personal issues, so no need to add extra reason of concern.

Table 6 summarizes the results of our market study for lightweight EEG devices. More specifically, the table lists the name of the company, the model, the indicative price, the number of EEG sensors, the sensor type (wet or dry), the sample rate and the duration of portable use. From the market survey we found Epoc+ from EMOTIV to be actually the most suitable for MAMEM project needs: successfully used in countless BCI projects, in a reasonable price, available for online purchase and sold as consumer device. We didn't take in consideration in our survey any "do it yourself" product, since the time to market would have been definitely too high.

Company	Model	Indicative Price	N° EEG sensors + ref/gnds	Sensor type	Additional sensors	Sample rate (kHz)	Duration of portable use
Advanced Brain Monitoring	B-Alert X10	USD 9,950	9 (head cap)	wet	ECG, EMG, EOG (4 channels)	0.256	8+ hr (bluetooth)
Biosemi	Active Two	€13,500	8+2 (Head cap)	wet	7 input channels available	N/A	5-72 hr for 256-16 channels (USB connection)
Emotiv	EPOC+	USD 799	14+2 (head set)	wet	Gyro(3 axis) accelerometer (3 axis) magnetometer (3 axis)	0.128	12 hr (RF) Or 6hr (Bluetooth)
InteraXon	Muse	USD 299	5+2 (head set)	dry	accelerometer (3 axis)	0.22	5hr (Bluetooth)
Macrotellect	BrainLink	USD 370	1+2	dry	N/A	N/A	4hr (Bluetooth)
Melon	Melon EEG Head Band	USD 149	1+2 (head set)	dry	N/A	0.25	8hr (Bluetooth)
NeuroSky	Mind Wave Mobile	USD 130	1 (Headset)	Dry	accelerometer (3 axis)	0.25	8hr (RF)
NeuroElectrics	Enobio	USD 4,995	8+2 (head cap)	Wet/dry	Accelerometer (3 axis) ECG–EMG–EOG-GSR	0.25	8hr (Bluetooth)

Table 6: Market survey for lightweight EEG device

5.2 EMOTIV EPOC+ 14 Channels Mobile EEG

Figure 24: Emotiv Epoc EEG Headset

EMOTIV EPOC+ headset (**Figure 24**) is probably the best Performance/Price/Design ratio in the consumer segment. While this device has some week points, it has some strong points too which make it the best option for the consortium need.

The price per channel ratio of about 57 USD per channel is by far one of the best in the market, and the ADC specs still grant enough power to perform ERP acquisition.

The overall headset design has been well accepted in our survey, judging the headset look as modern and appealing. Weight and shape of EPOC+ made it very comfortable to wear, again a very essential point in MAMEM project where the end users are impaired persons.

The EMOTIV SDK Package provides all necessary software to interface EPOC with MAMEM infrastructure, and many other code sample can be found in the Open Source community.

Last but not least this is a consumer device, available almost anywhere in the world, resulting in a time to market almost instantaneous. Many of the other devices available in the market for BCI applications have medical certification or no certification at all and can be used only for research projects, meaning a lot of work and costs to try to get this product available as consumer product.

Below a summary table of EPOC+ Headset specifications

Specification	Value
Number of channels	14 channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF42
References	References: In the CMS/DRL noise cancellation configuration P3/P4 locations

Sampling method	Sequential sampling. Single ADC
Sampling Rate	128 SPS (2048 Hz internal)
Resolution	14 bits 1 LSB = 0.51µV (16 bit ADC, 2 bits instrumental noise floor discarded)
Bandwidth	0.2 – 43Hz, digital notch filters at 50Hz and 60Hz
Filtering	Built in digital 5th order Sinc filter
Dinamic Range (input referred)	8400µV(pp)
Coupling Mode	AC Coupled
Connectivity	Bluetooth® Smart
Communication Protocol	Proprietary wireless: 2.4GHz band
Battery	Internal Lithium Polymer battery 640mAh
Battery Life	up to 12 hours using proprietary wirelss, up to 6 hours using
EMC and Telecom	Class B; ETSI EN 300 440-2 V1.4.1; EN 301 489-1; EN 301 489-3; AS/NZS CISPR22 :2009; AS/NZS 4268 :2008; FCC CFR 47 Part 15C (identifers XUEEPOC01, XUE-USBD01)
Safety	EN 60950-1:2006; IEC 60950-1:2005 (2nd Edition); AS/NZS 60950.1:2003 including amendments 1, 2 & 3; CB Certifcate JPTUV-029914 (TUV Rheinland)
Lab Streaming Layer interface	Direct support
SDK	SDK Community (Free on Github) SDK Premium (Dedicated quotation)
Device Price	$799

Table 7: Emotiv Epoc EEG specs table

6 References

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[14] https://en.wikipedia.org/wiki/Time_Stamp_Counter

[15] https://github.com/sccn/labstreaminglayer/issues/118

[16] ftp://sccn.ucsd.edu/pub/software/LSL/Apps/Emotiv-beta.zip

A Appendix: artefact reduction test results

This table lists the percentages of correct classification for the first dataset.

			NR		FIXED		ENERGY		WAVELET	
			NO CAR *	CAR	NO CAR	CAR	NO CAR	CAR	NO CAR	CAR
Dataset 1	256 CHANNEL CONFIGURATIONS	SUBJECT 1	97.10	100.00	100.00	100.00	98.55	98.55	98.55	98.55
		SUBJECT 2	90.43	93.91	98.26	97.39	88.70	93.04	94.78	98.26
		SUBJECT 3	34.78	31.88	49.28	50.72	30.43	31.88	37.68	33.33
		SUBJECT 4	85.87	90.22	93.48	94.57	85.87	86.96	85.87	91.30
		SUBJECT 5	30.43	26.09	29.57	29.57	28.70	23.48	32.17	25.22
		SUBJECT 6	86.96	89.13	90.22	90.22	89.13	95.65	94.57	93.48
		SUBJECT 7	72.17	91.30	99.13	99.13	95.65	98.26	80.00	91.30
		SUBJECT 8	30.43	27.54	40.58	36.23	24.64	24.64	39.13	40.58
		SUBJECT 9	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
		SUBJECT 10	94.78	100.00	95.65	96.52	99.13	99.13	94.78	100.00
		SUBJECT 11	98.26	98.26	97.39	97.39	97.39	98.26	98.26	98.26
		MEAN	74.66	77.12	81.23	81.07	76.20	77.26	77.80	79.12
	64 CHANNEL CONFIGURATIONS	SUBJECT 1	97.10	97.10	97.10	97.10	95.65	97.10	97.10	97.10
		SUBJECT 2	88.70	90.43	91.30	93.04	89.57	89.57	89.57	89.57
		SUBJECT 3	37.68	33.33	33.33	33.33	39.13	39.13	39.13	34.78
		SUBJECT 4	75.00	70.65	78.26	78.26	75.00	73.91	82.61	79.35
		SUBJECT 5	39.13	37.39	40.87	37.39	34.78	36.52	37.39	44.35
		SUBJECT 6	95.65	96.74	92.39	92.39	95.65	96.74	95.65	95.65
		SUBJECT 7	57.39	72.17	71.30	80.87	79.13	75.65	71.30	77.39
		SUBJECT 8	30.43	28.99	26.09	27.54	21.74	21.74	33.33	24.64
		SUBJECT 9	99.13	98.26	100.00	99.13	100.00	100.00	100.00	99.13
		SUBJECT 10	82.61	89.57	86.09	91.30	89.57	93.91	88.70	93.04
		SUBJECT 11	98.26	98.26	99.13	99.13	98.26	98.26	98.26	98.26
		MEAN	72.83	73.90	74.17	75.41	74.41	74.78	75.73	75.75
	14 CHANNEL CONFIGURATIONS	SUBJECT 1	97.10	95.65	100.00	98.55	98.55	97.10	98.55	97.10
		SUBJECT 2	88.70	89.57	89.57	91.30	82.61	81.74	93.91	81.74
		SUBJECT 3	37.68	33.33	33.33	28.99	42.03	31.88	46.38	36.23
		SUBJECT 4	75.00	67.39	73.91	77.17	76.09	76.09	77.17	68.48
		SUBJECT 5	39.13	40.00	36.52	43.48	31.30	31.30	47.83	44.35
		SUBJECT 6	95.65	96.74	97.83	96.74	94.57	91.30	98.91	94.57
		SUBJECT 7	57.39	68.70	65.22	72.17	68.70	74.78	67.83	72.17
		SUBJECT 8	30.43	27.54	27.54	31.88	24.64	24.64	27.54	23.19
		SUBJECT 9	99.13	98.26	98.26	98.26	100.00	100.00	99.13	98.26
		SUBJECT 10	82.61	93.04	73.91	90.43	90.43	93.91	83.48	93.91
		SUBJECT 11	98.26	99.13	99.13	99.13	98.26	97.39	99.13	99.13
		MEAN	72.83	73.58	72.29	75.28	73.38	72.74	76.35	73.56

*NR + No CAR represents the case of no artefact removal.

This table lists the percentages of correct classification for the second dataset.

			NR		FIXED		ENERGY		WAVELET	
			NO CAR *	CAR	NO CAR	CAR	NO CAR	CAR	NO CAR	CAR
Dataset 2	256 CHANNEL CONFIGURATIONS	SUBJECT 1	88.80	86.40	87.20	85.60	92.00	92.00	87.20	87.20
		SUBJECT 2	80.80	91.20	92.00	92.80	78.40	92.80	83.20	91.20
		SUBJECT 3	51.20	52.00	48.00	52.80	55.20	52.80	51.20	52.00
		SUBJECT 4	51.20	58.40	44.00	45.60	48.00	48.80	53.60	55.20
		SUBJECT 5	38.40	38.40	61.60	62.40	44.00	46.40	36.80	41.60
		SUBJECT 6	91.20	87.20	78.40	80.00	86.40	82.40	90.40	87.20
		SUBJECT 7	65.60	68.80	86.40	84.00	72.00	76.80	66.40	72.00
		SUBJECT 8	24.80	22.40	25.60	24.00	24.80	24.00	28.80	22.40
		SUBJECT 9	88.80	93.60	92.00	91.20	92.80	94.40	87.20	93.60
		SUBJECT 10	80.80	85.60	77.60	77.60	75.20	74.40	80.80	84.00
		SUBJECT 11	89.60	91.20	96.00	95.20	89.60	91.20	90.40	91.20
		MEAN	68.29	70.47	71.71	71.93	68.95	70.55	68.73	70.69
	64 CHANNEL CONFIGURATIONS	SUBJECT 1	84.00	87.20	81.60	82.40	81.60	84.00	88.00	87.20
		SUBJECT 2	89.60	91.20	81.60	87.20	80.80	87.20	88.00	91.20
		SUBJECT 3	52.80	51.20	52.80	57.60	56.80	50.40	55.20	56.00
		SUBJECT 4	48.80	52.80	47.20	47.20	50.40	56.00	48.80	48.80
		SUBJECT 5	33.60	35.20	33.60	28.00	23.20	28.00	41.60	40.00
		SUBJECT 6	94.40	92.80	86.40	87.20	92.00	92.80	94.40	91.20
		SUBJECT 7	57.60	60.80	52.00	58.40	53.60	55.20	61.60	64.80
		SUBJECT 8	26.40	21.60	24.80	23.20	21.60	22.40	31.20	28.80
		SUBJECT 9	88.00	90.40	84.80	87.20	88.80	89.60	86.40	89.60
		SUBJECT 10	68.00	68.00	70.40	68.80	67.20	65.60	68.00	70.40
		SUBJECT 11	87.20	88.80	86.40	88.80	90.40	92.80	88.00	92.80
		MEAN	66.40	67.27	63.78	65.09	64.22	65.82	68.29	69.16
	14 CHANNEL CONFIGURATIONS	SUBJECT 1	84.00	82.40	84.00	86.40	79.20	84.80	83.20	84.00
		SUBJECT 2	89.60	92.80	84.00	90.40	92.00	92.80	85.60	92.00
		SUBJECT 3	52.80	50.40	55.20	52.00	48.80	47.20	52.00	48.80
		SUBJECT 4	48.80	52.80	48.80	47.20	44.00	45.60	47.20	48.00
		SUBJECT 5	33.60	34.40	34.40	35.20	32.00	28.00	37.60	37.60
		SUBJECT 6	94.40	92.00	92.00	94.40	91.20	89.60	94.40	92.00
		SUBJECT 7	57.60	61.60	43.20	47.20	58.40	58.40	58.40	66.40
		SUBJECT 8	26.40	19.20	22.40	24.00	16.80	18.40	29.60	21.60
		SUBJECT 9	88.00	89.60	84.00	87.20	83.20	83.20	85.60	90.40
		SUBJECT 10	68.00	68.80	60.00	62.40	64.00	68.80	66.40	68.80
		SUBJECT 11	87.20	87.20	73.60	88.00	84.80	88.00	85.60	87.20
		MEAN	66.40	66.47	61.96	64.95	63.13	64.07	65.96	66.98

*NR + No CAR represents the case of no artefact removal.

This table lists the percentages of correct classification for the first dataset, but only for the subjects with medium-high scores (the “poorly accurate” subjects have been excluded)

			NR		FIXED		ENERGY		WAVELET	
			NO CAR *	CAR	NO CAR	CAR	NO CAR	CAR	NO CAR	CAR
Dataset 1	256 CHANNEL CONFIGURATIONS	SUBJECT 1	97.10	100.00	100.00	100.00	98.55	98.55	98.55	98.55
		SUBJECT 2	90.43	93.91	98.26	97.39	88.70	93.04	94.78	98.26
		SUBJECT 4	85.87	90.22	93.48	94.57	85.87	86.96	85.87	91.30
		SUBJECT 6	86.96	89.13	90.22	90.22	89.13	95.65	94.57	93.48
		SUBJECT 7	72.17	91.30	99.13	99.13	95.65	98.26	80.00	91.30
		SUBJECT 9	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
		SUBJECT 10	94.78	100.00	95.65	96.52	99.13	99.13	94.78	100.00
		SUBJECT 11	98.26	98.26	97.39	97.39	97.39	98.26	98.26	98.26
		MEAN	90.70	95.35	96.77	96.90	94.30	96.23	93.35	96.39
	64 CHANNEL CONFIGURATIONS	SUBJECT 1	97.10	97.10	97.10	97.10	95.65	97.10	97.10	97.10
		SUBJECT 2	88.70	90.43	91.30	93.04	89.57	89.57	89.57	89.57
		SUBJECT 4	75.00	70.65	78.26	78.26	75.00	73.91	82.61	79.35
		SUBJECT 6	95.65	96.74	92.39	92.39	95.65	96.74	95.65	95.65
		SUBJECT 7	57.39	72.17	71.30	80.87	79.13	75.65	71.30	77.39
		SUBJECT 9	99.13	98.26	100.00	99.13	100.00	100.00	100.00	99.13
		SUBJECT 10	82.61	89.57	86.09	91.30	89.57	93.91	88.70	93.04
		SUBJECT 11	98.26	98.26	99.13	99.13	98.26	98.26	98.26	98.26
		MEAN	86.73	89.15	89.45	91.40	90.35	90.64	90.40	91.19
	14 CHANNEL CONFIGURATIONS	SUBJECT 1	97.10	95.65	100.00	98.55	98.55	97.10	98.55	97.10
		SUBJECT 2	88.70	89.57	89.57	91.30	82.61	81.74	93.91	81.74
		SUBJECT 4	75.00	67.39	73.91	77.17	76.09	76.09	77.17	68.48
		SUBJECT 6	95.65	96.74	97.83	96.74	94.57	91.30	98.91	94.57
		SUBJECT 7	57.39	68.70	65.22	72.17	68.70	74.78	67.83	72.17
		SUBJECT 9	99.13	98.26	98.26	98.26	100.00	100.00	99.13	98.26
		SUBJECT 10	82.61	93.04	73.91	90.43	90.43	93.91	83.48	93.91
		SUBJECT 11	98.26	99.13	99.13	99.13	98.26	97.39	99.13	99.13
		MEAN	86.73	88.56	87.23	90.47	88.65	89.04	89.76	88.17

*NR + No CAR represents the case of no artefact removal.

This table lists the percentages of correct classification for the second dataset, but only for the subjects with medium-high scores (the "poorly accurate" subjects have been excluded)

			NR		FIXED		ENERGY		WAVELET	
			NO CAR *	CAR	NO CAR	CAR	NO CAR	CAR	NO CAR	CAR
Dataset 2	256 CHANNEL CONFIGURATIONS	SUBJECT 1	88.80	86.40	87.20	85.60	92.00	92.00	87.20	87.20
		SUBJECT 2	80.80	91.20	92.00	92.80	78.40	92.80	83.20	91.20
		SUBJECT 4	51.20	58.40	44.00	45.60	48.00	48.80	53.60	55.20
		SUBJECT 6	91.20	87.20	78.40	80.00	86.40	82.40	90.40	87.20
		SUBJECT 7	65.60	68.80	86.40	84.00	72.00	76.80	66.40	72.00
		SUBJECT 9	88.80	93.60	92.00	91.20	92.80	94.40	87.20	93.60
		SUBJECT 10	80.80	85.60	77.60	77.60	75.20	74.40	80.80	84.00
		SUBJECT 11	89.60	91.20	96.00	95.20	89.60	91.20	90.40	91.20
		MEAN	79.60	82.80	81.70	81.50	79.30	81.60	79.90	82.70
	64 CHANNEL CONFIGURATIONS	SUBJECT 1	84.00	87.20	81.60	82.40	81.60	84.00	88.00	87.20
		SUBJECT 2	89.60	91.20	81.60	87.20	80.80	87.20	88.00	91.20
		SUBJECT 4	48.80	52.80	47.20	47.20	50.40	56.00	48.80	48.80
		SUBJECT 6	94.40	92.80	86.40	87.20	92.00	92.80	94.40	91.20
		SUBJECT 7	57.60	60.80	52.00	58.40	53.60	55.20	61.60	64.80
		SUBJECT 9	88.00	90.40	84.80	87.20	88.80	89.60	86.40	89.60
		SUBJECT 10	68.00	68.00	70.40	68.80	67.20	65.60	68.00	70.40
		SUBJECT 11	87.20	88.80	86.40	88.80	90.40	92.80	88.00	92.80
		MEAN	77.20	79.00	73.80	75.90	75.60	77.90	77.90	79.50
	14 CHANNEL CONFIGURATIONS	SUBJECT 1	84.00	82.40	84.00	86.40	79.20	84.80	83.20	84.00
		SUBJECT 2	89.60	92.80	84.00	90.40	92.00	92.80	85.60	92.00
		SUBJECT 4	48.80	52.80	48.80	47.20	44.00	45.60	47.20	48.00
		SUBJECT 6	94.40	92.00	92.00	94.40	91.20	89.60	94.40	92.00
		SUBJECT 7	57.60	61.60	43.20	47.20	58.40	58.40	58.40	66.40
		SUBJECT 9	88.00	89.60	84.00	87.20	83.20	83.20	85.60	90.40
		SUBJECT 10	68.00	68.80	60.00	62.40	64.00	68.80	66.40	68.80
		SUBJECT 11	87.20	87.20	73.60	88.00	84.80	88.00	85.60	87.20
		MEAN	77.20	78.40	71.20	75.40	74.60	76.40	75.80	78.60

*NR + No CAR represents the case of no artefact removal.