Integrated VR & EEG – The Best Practices for Real-Time Data Collection in Research

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Abstract

This paper presents a combined real-time monitoring workflow, headset-application procedure and offline inspection pipeline specifically for the OpenBCI Galea integrated dry-EEG VR system, addressing a methodological gap in current research. Existing literature recognises that dry electrodes achieve signal quality comparable to wet systems. However, guidance for obtaining quality data remains limited. We provide a step-by-step protocol for preparing and applying the Galea headset to optimise data quality, supported by author self-testing studies that evaluate the effectiveness of our real-time monitoring approach. Finally, we identify current limitations in packet stability and latency and recommend that future work prioritise these areas.

1. Introduction

With recent advances in integrated VR-EEG systems, there is a growing interest in the collection of physiological data within immersive experiences, especially in relation to cognitive workload, affective state or as a neuroadaptive interface. The majority of existing VR-EEG studies use offline analysis of recorded EEG data, providing little insight into real-time EEG monitoring or headset-specific procedures for using the integrated headsets for data collection while VR is in use. Regarding dry-electrode systems, electrode-skin impedance and signal quality vary considerably with the user's natural movements, indicating the need for continuous inspection to maintain signal quality (Chi et al. 2010, Lopez-Gordo et al. 2014, Harris et al. 2024). Rahman et al. (2023) used separate VR headsets and EEG-based BCI systems, leading to ergonomic limitations and reduced user comfort due to the need to simultaneously wear multiple head-mounted devices while maintaining reliable EEG signal acquisition. As integrated headsets, such as the Galea, become more widely adopted within research settings, establishing practical methods for real-time inspection and data collection becomes essential.

Currently, there is no procedural framework establishing the practical methods for both real-time signal inspection and the requirements for collecting high-standard EEG data from an integrated dry EEG headset. This paper addresses these gaps by presenting a novel approach to monitoring real-time data from the Galea headset and provides a detailed, validated procedure for applying the headset to a participant for successful data collection based on extensive testing conducted by the research team.

2. Background

Technological innovations in recent years have enabled the creation of biosensing-integrated VR systems. These systems utilise multiple different electrode types, each having their own benefits and limitations. Whilst wet electrodes have been considered the gold standard for this kind of research for quite some time, there are several issues with their use, including the time-consuming nature of their application. A recent survey found that experienced practitioners spent an average of 50 minutes on a full, methodical EEG application (Hoffman et al. 2024). This very heavily restricts participant flow.

Furthermore, as they rely on a wet electrolyte (e.g., saline) for conduction, the collected signal gradually degrades. This can be problematic for longer studies, but even in shorter studies, when comparing multiple smaller tasks, a slight degradation can mask the main effects of an experiment.

Due to the extended setup times for wet electrodes, the use of dry electrodes has gained attention due to the ease of setup and removal compared to gel electrodes. When comparing wet and dry electrodes, Lopez-Gordo et al. (2014) found that dry signals are closely correlated with those of wet electrodes at 90% or more. There are various differing dry electrode designs, including nanotube (Song et al. 2017) and pillar (Aghazadeh et al. 2021) electrodes, which have been explored over the past 9 years. These electrodes have the ability to surpass hair and enables direct contact with the scalp to provide acceptable EEG data recordings. The pillar electrodes having the most similarity to the conductive polymer active electrodes used by the Galea.

3. Methodology

This paper focuses on the best practices and methods for data collection with the Galea headset, using a Varjo Aero VR attachment with eye-tracking. This was chosen as a novel, standardised headset, commercially available to research institutions, though the methodologies for other comparable headsets may be similar. The modalities for this headset include ExG (EEG, EMG and EOG), PPG, and inertial sensors (Buxton et al. 2026, Table 1).

3.1. Real-time Monitoring and Signal Inspection

Real-time monitoring of physiological signals was implemented using a custom Python application that receives Galea's filtered time-series data via UDP stream. Each packet contains a JSON-encoded array of pre-processed EEG samples. In the current configuration, approximately 108 filtered packets are received every 10 seconds, giving an effective packet rate of 10.8Hz and an inter-packet interval of 92.6ms. This rate reflects the packet arrival behaviour post-network transmission, thus representing the practical end-to-end latency of the monitoring pipeline.

The Python script runs a dedicated listener thread that handles packets without blocking the Tkinter (GUI Display) event loop. The script parses the packets from JSON and adds each packet to a per-channel dequeue buffer. The buffer length is fixed (200 samples), corresponding to approximately 18–19 seconds of visible history, with a display update rate of 80ms (12.5fps). As the visualisation is updated more frequently than the receipt of packets, new data received results only in a gradual change in the channel trace over time.

This setup provides an oscilloscope-style display (Figure 1) allowing up to ten channels of data to be displayed, each of which scales independently to its own amplitude range, allowing quick visualisation of electrode contact and confirmation of signal stability during preparation and experiment procedures.

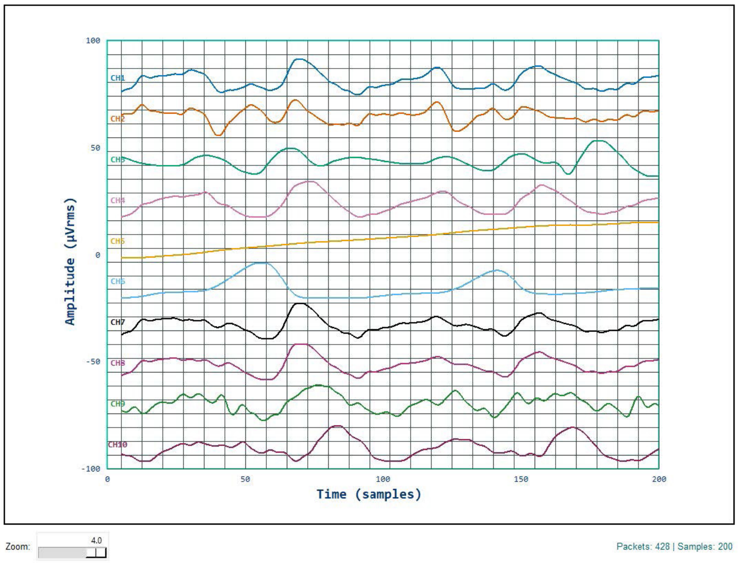

Figure 1: An oscilloscope-style display visualising the EEG channels from the Galea.

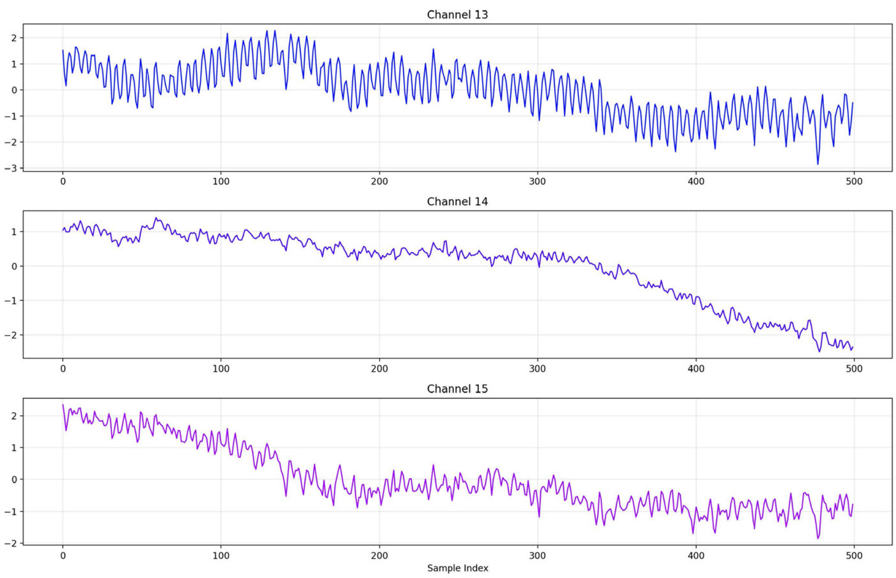

Figure 2: Brainflow EEG Multi-channel (13–15) visualisation plot, these channels refer to Parietal lobe EEG recordings, which is mainly responsible for spatial awareness, an area likely to be affected by Stroke.

Initial testing was designed to enable the commencement of a Galea session directly from within Python, bypassing the Galea GUI. The current infrastructure and parsing facilities already exist within the framework, the real-time monitoring application demonstrates the potential for the development of a stand-alone acquisition pipeline. This could reduce operator workload, eliminate the need for switching software during experiments and improve alignment between VR events and recorded physiological data.

A complementary offline visualisation pipeline was created to inspect recorded sessions. CSV files exported from the Galea GUI were processed by a Python script using the Brainflow Data-

Filter module to load the data and plot each EEG channel (Figure 2). Channels can be plotted individually or displayed as multi-panel figures, simplifying the interpretation of signal features across successive sessions. Basic normalisation was applied to highlight amplitude differences.

4. Discussion

Integrated Dry EEG Headset Procedure: Based on the studies conducted by the research team, we propose the following procedure for preparing an integrated dry EEG headset for optimal data collection.

First, prepare the headset by ensuring the electrodes are clean, residue-free, and the electrode straps have been undone; loosen the fasteners and encourage the participant to put the headset on themselves – visor first, then assist in moving the remainder of the headset into place. Secondly, tighten the rear strap and adjust the visor angle so the headset sits comfortably, then tighten the top electrode straps and fasten. Finally, attach the ear clips and check for any twisted, dislodged or removed electrodes.

The effective packet rate of 10.8Hz places clear constraints on the types of analysis that can be conducted in real-time. Whilst this rate is sufficient for monitoring electrode contact or identifying any unwanted signals, this would not be sufficient in its current capacity for applications requiring millisecond-level synchronisation, such as closed-loop neuroadaptive control of VR events. The use of UDP presents additional considerations, including packet loss and out-of-order arrival, which can be expected at lower packet rates. This reinforces that the stream should be treated as monitoring-grade in its current form.

The filtered time-series data stream also lacks metadata, such as time stamps, which limits its use for detailed signal interpretation. Although, the offline workflow shown in Figure 2, provides higher-quality visualisation for post-hoc inspection, it does not address the limitations of real-time stream. However, it does provide the output from the Galea GUI in a much more readable and user-friendly format.

Despite these constraints, the monitoring tool substantially improves participant preparation efficiency through the provision of immediate visual feedback. It enables the exploration of a Galea GUI-free session with the potential of developing a stand-alone acquisition pipeline that could inform real-time adaptation via neurofeedback.

5. Conclusion

This paper presents a novel approach to collecting and analysing data in near real-time, providing a foundation that could support adaptive environments and tasks within a closed-loop system, once higher-frequency or more informationally rich data streams are achieved. A procedure detailing the ideal prerequisites for collecting EEG data using an integrated dry EEG headset derived from findings and testing conducted by the research team. Finally, the limitations of the real-time monitoring approach are identified and addressed appropriately.

Future work in real-time monitoring will build upon the current platform by increasing robustness and informational richness of the data stream. The current stream rate of 10.8Hz is adequate for setup and quality checks, but higher-frequency streaming or time-stamped packets are required for use within a closed-loop neuroadaptive application or synchronisation with VR events. In terms of the networking framework, exploring alternative transport layers or adaptive buffering strategies could reduce packet loss at low rates, while extending initial work on a Galea GUI-free session would enable a stand-alone acquisition pipeline. Together, these suggested developments have the potential to advance the workflow from a monitoring-grade tool to a flexible, research-ready platform capable of supporting closed-loop neuroadaptive control and more advanced experimental designs.

Future studies will continue to focus on incorporating integrated dry EEG headsets, resulting in a deeper evidence base for future iterations to the optimal practices established within this paper. Examples of intended future work by the authors include:

- A Biosensing-Enhanced Neuroadaptive XR Rehabilitation system informed by the biosignals provided by the Galea to infer a user's physiological state and adapt accordingly in real-time.
- A Platform-Agnostic Multimodal Neurophysiological Sensing in Game-Based Interaction to regulate and identify autistic traits among adults.
- A Highly-Realistic Human Avatar based approach to detecting differences in Facial Emotion Expression Recognition, both in terms of ability and cognitive processing, focused on observing differences between the general population and people with Autism.

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