An Open Source Multi-Modal Data-Acquisition Platform for Experimental Investigation of Blended Control of Scale Vehicles

Peter Redmond
School of Computing
Dublin City University
Dublin, Ireland
peter.redmond6@mail.dcu.ie

Andrew Fleury
Transpoco Telematics
Dublin City University
Alpha Innovation Campus
Dublin, Ireland
andrew.fleury@transpoco.com

Tomás Ward
School of Computing
Dublin City University
Dublin, Ireland
tomas.ward@dcu.ie

***Abstract*—Currently many autonomous vehicles require a person to monitor the system and take over when an unexpected or unusual event occurs. A person may be able to monitor multiple such vehicles but a question arises as to how many, and how to measure the cognitive requirements. Brain Computer Interfaces (BCI) operating passively could aid in assisting remote operators in such tasks but there is as yet significant research to be undertaken before such technology becomes robust and effective. To this end we describe a platform for acquisition of multi-modal data for passive hybrid Brain Computer Interface (phBCI) development purposes. The open source system integrates electroencephalography (EEG), computer vision and a wearable inertial measurement unit (IMU) along with time-stamped event markers for a subject engaged in a set of driving-related tasks as applied to blended control of multiple vehicles. The vehicular control task is realised both with graded complexity simulations and physical scale autonomous vehicles. This platform has the following significant advantages: reduced experimental variability due to data acquisition system implementation decisions; ease of reproduction of experiments through shareable configuration information; and acceleration of open science dataset accumulation. Consequently this freely available open source platform has the potential to enhance the reproducibility of passive hybrid BCI experimental research.**

I. Introduction

Autonomous vehicles are becoming more and more ubiquitous[1]. Whilst these vehicles should do as much of the journey in autonomous mode as possible, the current state of the art depends heavily on a more blended control system, often requiring an operator to take over control[2] to maneuver the vehicle around unexpected obstacles or events, etc.

In the case of autonomous delivery vehicles for example, a future scenario would envisage such an operator having a number of autonomous delivery vehicles to monitor remotely and a question arises of how best to monitor the cognitive workload on this remote operator so that the operation of the service balances efficiency (i.e. have an operator monitor as many remote vehicles as possible) with safety[3] (i.e. an operator does not miss a potentially hazardous event). For example, as the increasing number of robots compete for the same cognitive resources, full attention cannot be given to every robot at once resulting in declines in concentration, attention or mental fatigue[4]. This is compounded even further when a robot requires assistance or rescue.

In this work, we describe a platform for the collection of physiological and behavioural data e.g. brain activity and other signals which may be related to operator state during driving-related tasks. In particular our focus is applied to the blended control of multiple vehicles capable of self-driving operation. This information has the potential to assist in the development of load sharing systems by detecting when an operator may be bored or overwhelmed by the task presented. This platform has been designed with the intention of supporting future work in the study of, for example, the combination of electroencephalogram (EEG) data with video and other sensor data to train a machine learning algorithm to predict task load. However, this paper is restricted to the description of the data-acquisition platform. The contribution of this paper is the presentation of the design, development and testing of a novel open source platform for integrated data collection and testing of human-robot interactions in the context of neuroergonomics specifically passive hybrid brain computer interfaces (phBCI).

II. Platform Overview

Fig.1 illustrates an overview of the platform consisting of two parts, the monitoring system and task load simulator which in turn consists of two different sub-task examples; simulated and scaled. The monitoring system collects multi-modal data from the remote operator while they are engaged in one of the two robot control related simulated tasks. The monitoring system also receives data from the task generator e.g. event markers or annotations, to register and correlate EEG events.

The task generators simulate operator related tasks as applied to blended control of multiple vehicles with increasing ecological validity.

III. Monitoring System

Whilst there are many ways to measure physiological and behavioural data[5], there is no one sensor that can give full

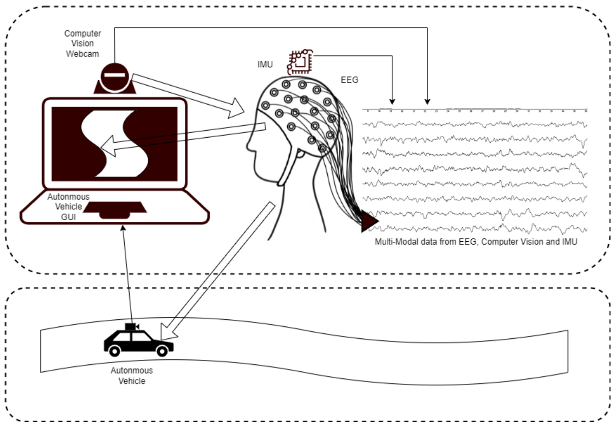

Fig. 1. Platform overview using scale autonomous vehicle task generator.

information on how a person is responding to a particular task. For this platform, we employ use of the following sensors and systems:

- Electroencephalogram
- Computer Vision
- Inertial Measurement Unit

A. Electroencephalogram

Brain-computer-interfaces (BCI) offer a communication pathway between a brain and an external device. By measuring the brain's electrical activity, EEG is the primary signal of interest for translating brain state into data with suitable processing[6]. EEG data can be used to monitor the brain including cognitive workload. It is understood for example that the latency and amplitude of a person's evoked potential corresponds to improved cognitive abilities[7]. Evoked potential can be measured in real time using EEG sensors and the equipment we used in this project for monitoring such brainwave activity is the Ant Neuro eego rt 16 channel wearable EEG system[8] as depicted in Fig.2.

Fig. 2. The Ant Neuro eego rt 16 channel wearable EEG system.

B. Computer Vision

EEG is an inherently noisy signal, evoked potential for example is detected by averaging over several trials. As contamination of eye movement and blink artifacts in EEG recording makes the analysis of EEG data more difficult and could result in erroneous findings[9], using video and computer vision algorithms in synchronous with the EEG data can potentially be used to identify and remove ocular and ambulatory artifacts from the EEG data. Computer vision algorithms can also be employed to monitor attention levels directly[10]. Video of

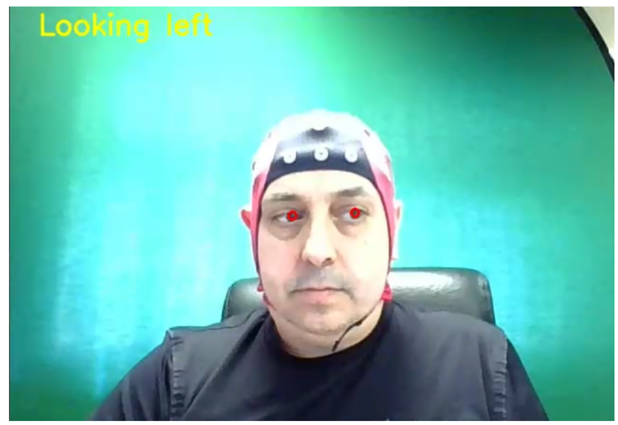

Fig. 3. Eye tracking computer vision

the subject performing the tasks is recorded and this is run through our computer vision (CV) software post experiment as illustrated in Fig.3. Using OpenCV[11] existing and bespoke open-source algorithms, our software outputs various time stamped data such as head and eye tracking, changes in blink frequency, yawn detection, pupil dilation, eye's widening, etc[12]. Such information can be employed to indicate changes in attention level[13]. We can also employ CV to detect causes of distractions such as when the subject is using a cellphone for example[14].

C. Inertial Measurement Unit

Whilst we can detect head movement in 3D using CV algorithms, another sensor we employed for increased accuracy is the IMU. An IMU is a sensor that contains an accelerometer and gyroscope, and commonly a magnetometer. It measures acceleration and angular velocity and is small enough to be attached to an EEG cap to allow for accurate head tracking. We employed a head tracker system using the Arduino Nano 33 BLE with an embedded 9 axis inertial sensor[15]. This open source software is originally designed for FPV head tracking of remote control aircraft. Fig.4 depicts the open source GUI with pan, tilt, and yaw graph. Our branch of the software has an added function of outputting the tracked coordinates.

By combining physiological data and behavioral data from the different modalities of EEG, CV and IMU systems, a greater representation of operator response to cognitively challenging tasks can be achieved[16]. This data-set may potentially be used to train a machine learning system to infer

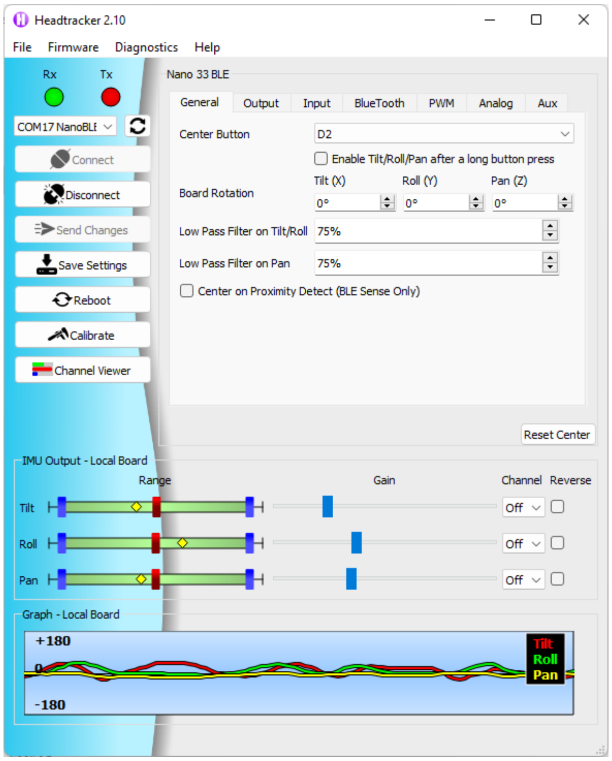

Fig. 4. Open-source Head Tracker GUI

cognitive state from the video data only, as wearing EEG and other sensors may prove impractical in real world operational settings. This goal is that of the lager project of which this data capture platform is a part.

IV. Task Simulators

For the purpose of illustrating the data collection platform, we collected multimodal data using two operator task generating systems. However, our open-source platform is not limited to any particular task system and can for example, be used in conjunction with packages such as PsychoPy[17]. PsychoPy is a free cross-platform package allowing researchers to run a wide range of experiments in the behavioral sciences. There are two main scenarios used during the experimental sessions to generate tasks. The first scenario is an abstracted task simulator designed to be run at three levels in game form. The second scenario is real world robot operator role using scale autonomous vehicles.

A. Cognitive Loading Game

The game is designed to simulate various discrete tasks types that may occur during a blended control operation. The game tasks that the player (operator) must control are:

1) Keep a ball moving around the screen perimeter by clicking when it stops.
2) Keep a constantly leaking water level between two limits by clicking a valve.
3) Answer simple math questions.
4) A Stroop colour word test (SCWT)[18].
5) Turning off lights when they illuminate.

Tasks 1 and 5 simulate reactions to something suddenly occurring whereas Task 2 is predictable. Tasks 3 and 4 take some mental focus to accomplish. The reaction time for each task is recorded and a score is calculated from the average reaction time for all tasks.

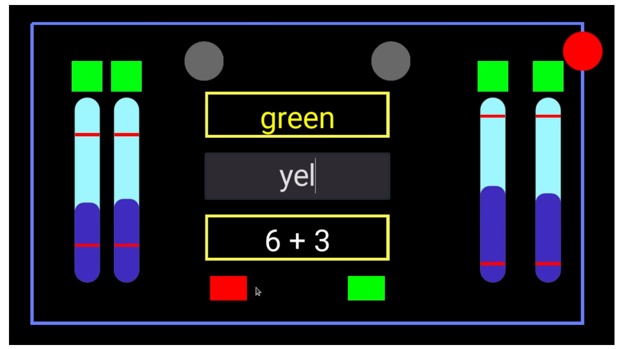

Fig. 5. Task Simulator Game at Level 3.

The game is presented in three levels played by an operator for 10 minutes each. In the first level, the event changes are rare so that the operator has very little to do for the 10 minutes of game play.

The second level is designed to be more challenging but still achievable. There is a constant stream of tasks but no overlapping tasks. During this level, the operator is not over-tasked but also does not have cognitive space for external distraction.

The third level has multiple overlapping tasks and it is generally not possible to keep up with all of the tasks. An example screen shot of the simulator game at level 3 is shown in Fig.5. Although the tasks within each level have no priority order, the objective is to keep completing tasks oldest to newest to minimise the delay count build.

The objective of the varying the task level is so that for example, the different levels of task simulation may be used to investigate the changes in physiological data and behaviour that occurs when a person is switched between under-loaded to overloaded situations during task operation. The game software output stream consists of a sequence of events, rates and annotations to the physiological data-stream. This software package is presented open-source python on our GitHub server[19].

B. Small Scale Autonomous Vehicles

While simulations and game-play are useful for reproducibility, the psychological risk and stress associated with attention retention is reduced[20]. To generate more ecologically valid data as related to blended control of autonomous vehicles, we have employed the supervision of small scale autonomous vehicles. A low cost open source example of such scale autonomous vehicles, is a platform known as Donkey Car[21].

The Donkey Car project website describes how to build and train an open source scale autonomous vehicle. An operator

Fig. 6. Donkey car small ($\frac{1}{10}$) scale autonomous vehicle navigating a 5mx5m printed road.

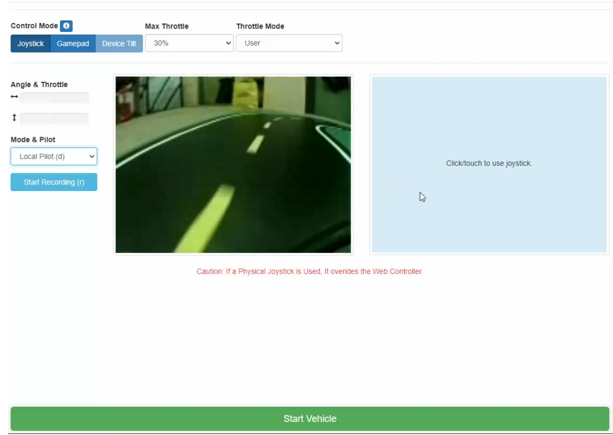

Fig. 7. Donkey car small scale autonomous vehicle onboard web UI with first person view.

can connect to a Donkey Car using a web based user interface (UI) and can see the car's view in first person (FPV) as in Fig.7 along with other telemetry data. The operator can also take control of the car through the UI to both train and operate the vehicle. Training consists of an operator driving along the track a number of times (circa 10 laps) and recording video from the on-board camera. We have designed a 5m x 5m track that is printed on a vinyl mat for a $\frac{1}{10}$ scale Donkey Car as depicted in Fig. 6. Some additional useful training data can be achieved by placing obstacles on the track and recording how the operator avoids them. It is further useful to record corrective moves such as returning to the track in case of over or under steer. Training should be done at various speeds.

As for the case with the simulated tasks, we have three levels of workload for the scale autonomous vehicles. For level 1, we have only one car on the track and if well trained, the car should have no problem navigating the track autonomously while the operator observes the FPV. In this case, it is easy for the operator to become distracted as they will have little if any engagement. For level 2 we add an additional vehicle. Now the operator must interact and assist if the two vehicles will collide or need to overtake. It is more common in this scenario for the vehicle to lose track of the road and require re-orientating by the operator. For the third level, we add another vehicle or reduce the training level of the vehicle. With this, the operator must take control more often and many collisions and corrections occur. This platform is fully open-source[21] and can be used for as a starting point for further annotations to the physiological data. Modifications to design files and 3D printing files can be found at our GitHub server[19].

V. Synchronisation

Because we have 5 different sources of data, we must have a method of synchronising all of these together to produce a single data-set for each task. The sources are:

- EEG data
- IMU data
- Video of subject and CV processed data
- Video feed from simulator/Donkey car web UI
- Mouse/keyboard events

Each data packet is timestamped with ticks when captured. In addition a visual and physical marker is generated at the beginning and ending of a session to recognise any drift within the sequence. This is achieved by having the subject tap the EEG cap with the mouse button introducing a technical artifact into the EEG signal. The subject does this three times to indicated the beginning of the session and twice to indicated the end. This tapping can be seen by the subject's camera, is sensed and recorded by the EEG cap and the IMU (Fig.9) and mouse events are recorded by the input to simulator or donkey car controller. To ensure the video feed is synchronised, a small mirror is placed behind the subject to capture the screen information on the subject's camera. Any drift can be detected using this technique. In our experiments, the data was manually synchronised using the three/two sets of spikes in the data, however, it is envisaged that this could be automated in future experiments where the number of sample are larger. Further refinements to the platform will use Lab Streaming Layer (LSL) and similar techniques[22] to automate the synchronisation of the data streams.

VI. Results

Although at the time of writing our results are preliminary and mainly for use of fine tuning the synchronisation steps, our vision system correctly identified and tagged 100% of ocular blinks as depicted in Fig.8 for example. Such annotated data stream from combined CV processed video and EEG data and can be potentially used to remove ocular artifacts from EEG data. Similarly, the synchronised IMU data can potentially be used to remove ambulatory head movement from the EEG data. An example of the graphed output is depicted in Fig.9. The full open source code for the simulator, video capture, CV system and IMU can be found at our GitHub repository[19]. The raw and processed data-sets are available from our Zenodo repository[23]. It should be noted the for data protection, only the post-processed video data is available from Zenodo.

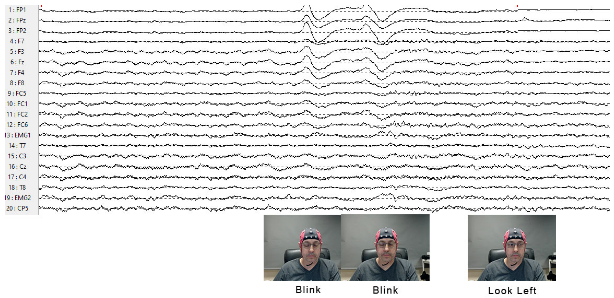

Fig. 8. EEG graph with CV identified blink annotations (IMU data not displayed)

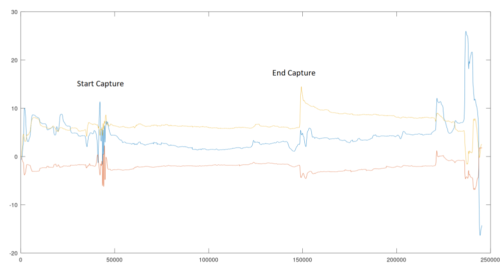

Fig. 9. Sample of IMU Head Tracking stream showing synchronisation peaks. The three lines depict Pan, Tilt and Yaw motion in degrees over time in milliseconds.

VII. Further Work

Our next steps in this work are to conduct experiments with more subjects so to produce a large number of data-sets which we make available at the project's Zenodo repository for the purposes of data mining and the development of machine learning systems in the context of hybrid passive BCI. Currently the sensor capture systems are loosely coupled and future work considers tighter integration of the data acquisition software into a single monolithic application to simplify synchronisation and operation. We are currently investigating LSL to assist with the automation of this process. This will facilitate improved synchronisation among the incoming sensor data streams. To further assist this, real-time vision processing will reduce the post processing requirements.

VIII. Conclusion

We have described a new open platform to capture multi-modal data-sets including event markers for the purposes of accelerating passive hybrid Brain Computer Interface research. The system consists of EEG, eye tracking and wearable IMU streams along with event markers while users supervise generated task from simulated tasks and scale autonomous vehicles. Each of the generated task systems has 3 distinct levels of load, easy, manageable, and overwhelming. The preliminary results with synchronised video, EEG and IMU data identified and tagged ocular and ambulatory movement that can be used to clean inherently noisy EEG artifact data. Overall the system can contribute to enhancing EEG-based passive hybrid BCI research through improving experimental reproducibility. This is achieved through ease of sharing of experimental set-ups, a reduction in sources of experimental error due to technical implementation idiosyncrasies, and if community-adopted, acceleration of shareable open datasets for mining and algorithm development with a concomitant impact on independent algorithm performance verification activities.

Acknowledgment

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