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Temporal multimodal data synchronisation for the analysis of a game driving task using EEG

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ABSTRACT
Multimodal data channels such as bio-physiological signals are increasingly used in game-play studies to better understand players’ behaviours and their motivations. It is however difficult to perform any sort of conclusive analysis solely based on bio-physiological signals due to the complex nature of epistemic, semiotic and ergotic activities surrounding in-game activities and the artefacts facilitating player immersion. Thus a combined analysis of multiple data streams including in-game data and bio-physiological signals is indispensable to produce contextualised information from which a deep analysis of game mechanics and their effects can be performed.

Precise synchronisation in capturing multiple streams is required to generate valid inter-stream correlations and meaningful information. Typically there are no automatic mechanisms built in the game architecture or in commercial data logging systems for multimodal data synchronisation and data fusion. This paper presents a novel and generic technique based on inducing identifiable signature pulses in data channels to accurately synchronise multiple temporal data streams. This technique is applied and its capabilities are exhibited using a driving game simulation as an exemplar. In this example, driver’s in-game behavioural data is synchronised and correlated with their temporal brain activity. The concept of simplex method borrowed from linear programming is used to correlate between the driving patterns and brain activity in this initial study is provided so as to allow studying/investigating user behaviour in relation to learning of the driving track.

1. Introduction

Computer games are increasingly being used as a medium to study user affect in psychology and behavioural studies. To study a particular phenomenon, such as learning, perception or emotion, often the arbitrariness of real world activities makes for a difficult experimental setup to gather, track and analyse the provenance of data. Temporal data from human bio-signals e.g. Electroencephalogram (EEG), Electromyogram (EMG), Electrooculography (EOG), Galvanic skin response (GSR), etc. are often used to study the human behaviour with the reduced attitudinal and demographical influences. Unfortunately, such data are prone to noise and thresholding, weakening the correlations where evidence of temporal influences upon the multi-dimensional and subsetting operations during in-game activities to produce contextually meaningful information. Having well thought out and implemented game play mechanics would provide a context and immersive experience, by reflecting the temporal phenomena.

Contemporary Serious Games (SGs) are often represented through complex environments in which users are led to interact with many game-related elements and information. While SGs generally focus on a set of specific and recognisable purposeful activities (core mechanics) oriented towards specific learning outcomes, they also integrate a number of smaller, shorter, activities designed to engage players on different levels (secondary mechanics) and generate a state of flow for the player. Logging game play is a common practice in order to study a player’s in-game behaviour and monitor the efficiency of specific game elements. Behavioural knowledge gained through this approach could be used to assess the contribution of individual game mechanics (core or secondary) in supporting player engagement and learning. However, gathering and analysis of user behaviour is a multivariate process which requires more information than the mere logging of game context and player activity.
1.1. Synchronous logging of in game temporal data

The data captured in a game session can be classified as context independent and context dependent data [1]. Context independent data is normally external to the game, such as EEG, eye tracking, screen capture, etc., while context dependent data relates to the internal elements of the game such as score, lap time, driving speed, interaction with a game asset or character. Apart from enabling insights into the actual internal affective state of the player [2], context dependent and context independent data permits a more holistic understanding of the combined and interactive user-game system. Consequently, accurate synchronisation of multimodal data streams is critical to avoid parameter skews for analysis. Analysing task based operations (e.g. Event Related Potentials) require precise time measurements where the chronological ordering of events is crucial [3]. For example, if one wants to analyse P300 or N400 components in EEG signal, temporal alignment tolerance of the synchronisation should be in millisecond range rather than in seconds [4].

To date configured solutions for multimodal data capture are ad-hoc solutions [5–10] and cannot serve as a holistic system. Almost every solution for multimodal data capture is interfaced with specific hardware or software tools from various vendors. Because of the ad-hoc interfaces, they are depended particularly to one or a family of data capture tools. Therefore it becomes obligatory to use multiple customised data logging solutions to satisfy different application scenarios. Assorted tools run on independent platforms, for instance different hardware or assorted software even if they run on the same hardware. In addition to the game logging, multiple data capture devices (e.g. EEG Capture Device, Eye Tracker, and Video Capture Device) also work as detached components in a data logging environment. Devices running on independent hardware or software platforms will naturally run asynchronously. Data captured from these isolated components are required to be synchronised by some means because data streams originating from these components must be temporally aligned to decipher the meaningful information. The temporal alignment can influence the information extracted in such a way that significant information of an activity is detected, undetected, or falsely detected. For instance, eye tracking data stream should be adequately aligned with the data stream from the in-game context in order to recognise what in the dynamic screen of the game could have caused the change in the eye data.

1.2. Driving task and game elements

A study using a driving game play was used in this paper to quantify driver performance and skills so as to gain a better understanding of a driver’s ability. The intention was to ascertain whether cognitive and motor skills from a driving game transferred to real world driving. The hypothesis that characteristics such as confidence, skills, capacity of learning, etc. in a gaming environment reflect similar skill sets for real-world driving, particularly since these activities align with requirements for Formula (F1) Student driver selection [11].

In this particular study, it is anticipated that learning is achieved via the repetition of the same game activities and a trial and error approach towards task completion. Drivers were asked to drive around the racing track against the clock. Driver abilities vary greatly depending on their real and simulated driving experience (i.e. driving games) and their knowledge of motorsports. The study therefore focused on the learning process rather than performance. The aim is to determine how accurately temporal data can be captured and fused to help document driver performance in the areas of braking point, corner entry, negotiating an apex and corner exit, prior to track days and race-driving tuition.

1.3. Game-driving task and psychophysiological analysis

Correlating driving performance and psychophysiological data, specifically monitoring the brain activity (using EEG) can potentially reveal the relationship between driving behaviour and the cognitive state of the driver [12–17]. However, the research in the area of distinguishing the above described skillsets from psychophysiological signals is not explicit. Neurometric studies and experiments for brain-based/driver applications are performed in tightly controlled environments (i.e., movement restrictions). It also limits the actual intended task and therefore not always feasible to perform the actual behavioural measurement during the recorded task [18]. A game-driving or real-world driving is essentially a mixture of various visceral and sensorial activities from which the driver has to respond [16,17,19]. The brain activity at an instance of driving corresponds to all these activities invariably.

The conventional practice of neurometric analysis is to ring-fence the study and hence reducing the number of parameters that can affect the experiment. Other activities are recognised as artefacts and the signals relating to these activities are considered as ‘noise’ in the signals. It might be neither possible to split the driving task into smaller key activities, nor reject other activities as artefacts in driving. Consider the task of negotiating a corner at speed, it involves hand-eye coordination and is associated to the driver’s confidence level. If a study has been performed to associate the confidence level using the affect state of the driver measured using EEG, separating the movements or visuals processing from task might breakdown the purpose of the study.

Although the action-chain (i.e., epistemic, semiotic and ergotic) relationships [20–22] of driving can be broken down into individual elements, the context of behaviour and cognitive organisation cohesion is more than the sum of its parts. The alternative approach is to extract patterns from combined modalities, car-related parameters (e.g., steering activity, pedal depressing, speed of driving, position on the track, etc.) along with neurometrics (mainly, EEG).

Consequently, a synchronised data capture of driving telemetry and psychophysiological data is critical for the combined analysis and for finding correlations. Since the outcome of the analysis is highly dependent on the synchronisation of independent data streams, a proven mechanism was required for the data capture and to verify the temporal alignment between data streams. This necessitates re-examining the assumptions about the data capture tools and the whole data stream pathway.

1.4. Paper contributions

The paper introduced the compelling need for the synchronised multimodal data capture in the Section 1. Issues related to EEG analysis in a game environment, specifically for driving were addressed in Section 1.3. Section 2 provides a background on issues related to the time synchronisation in data logging and standard strategies used to tackle the synchronisation problem are briefly reviewed here. As a solution to the synchronisation problem, Section 3 presents a novel and generic technique to temporally synchronise diverse multimodal data streams. Section 4 introduces the experimental task, a game-driving scenario as a case study. This section explains the data logging setup in detail with relevant data capture devices, also technically revealing potential flaws related to the temporal synchronisation of data streams. A driving game is used as an example scenario; however, the issues are generally encountered in many other gaming domains. Finally the accuracy and granularity of the synchronisation are critiqued by referring to the collected data.

Section 5 demonstrates how temporal synchronisation can be utilised to correlate the brain activity and the events related to driving. Simplex correlations [23] between EEG data and driving
related telemetry data are discussed here. The purpose of this analysis is twofold. While several new methods of associating the brain activities with the events related to driving are being presented, the authors also want to emphasise the fact that these unprecedented ways of analysing the game-activity would not have been possible without the achieving a tight temporal synchronisation.

2. Related work

Synchronising data streams can be achieved by time-stamping every sample with a central or external clock. However, this is not always a practical solution because of the limitations in accessibility to the internal architecture of games and commodity data capture devices. It is very common to use a data capture device which is usually a proprietary piece of hardware or software; where only the data is streamed out from the device. Although games and device manufactures provide Application Program Interfaces (API) or a Software Development Kit (SDK) to access the data, access to the core event or the streaming loop is restricted. Therefore it is inevitable to comply with the standard data stream provided by the games or the capture devices.

Software based data logging systems are typically custom built (with many existing as third party ad hoc solutions) to collect data from relevant devices’ data streams. Data streams from multiple sources suffer variable amount of latencies and jitters in their pipeline from the source to the data logging system [24,25]. A general solution to deal with the non-deterministic latencies is to introduce a jitter buffer. However this extra buffering also adds to the overall latency [26]. Interoperability becomes an issue since typical data logging systems running on general purpose operating systems (OS) suffer further non determinism in OS related aspects such as task scheduling, context switching, communication protocols and buffering, etc. [27,28].

The accuracy of a signal processing architecture (e.g. Social Signal Interpretation Framework (SSI) [29]) is dependent and the recognition of tasks will be affected by the temporal characteristics of streams supplied to it. Misalignments in the input signal streams can influence the output generated by a tool which fuses the data from multiple signal streams. Therefore the samples from multiple streams are needed to be indexed with regard to a common time reference so that the processed output can also be referenced to the input streams and hence can be related to the source activity.

The common approach used in data logging systems is to synchronise all logged channels with one primary channel. Inherently, this primary channel can be a global timing device. Samples from every stream will be marked with a frame number from the primary channel, using it as the index. The TRUE Architecture by Microsoft Game Studios [30] presents a system for recording data for studying user behaviour in a PC software or a gaming console. This architecture looks at streams of data and logs sequences of events along with the timestamp. Captured video is also synchronised with the event timestamps and indexed based on the events. While this demonstrated the efficient retrieval and navigation through large data sets of game play to identify potential problematic areas in a game, fine grained time synchronisation issues are not addressed in this work. In addition to the time stamping, context related events occurring in the games are marked by emitting a unique signal, for example using parallel port byte or a transmission control protocol (TCP) packet. This message is consumed by the data logger and time stamped and/or inserted alongside the other data streams [3]. Emitting events to external software i.e. to data logging software needs access to some features of the game via a SDK or API. In contrast to consciously emitting events Bannach et al. [31] suggested a way of detecting events and synchronising streams according to the events. An un-ambiguously detectable data signature in data streams were used to synchronise streams in this technique. This technique is adopted in this work for synchronising multiple data streams.

3. Generic source data based synchronisation using synthesised pulses

The problem with Bannach et al.’s [31] approach to estimate the time offsets is that, finding a universal, action that could spawn an unambiguously identifiable characteristic data signature in every data channel is extremely difficult. For example, finding a common detectable pattern in across physiological data streams, software logging and audio visuals is a difficult challenge. As a solution, this paper presents a modified technique from Bannach et al.’s source data based synchronisation [31] approach. In contrast to finding a common comprehensible pattern across multiple modalities, using a reference calibration device is proposed here. The primary purpose of this calibration device is to induce pulses or signatures in corresponding data streams, independently. Selecting a suitable pulsing method depends on the physical nature of the signal and the corresponding data stream. Generally it is not difficult to find an exclusive calibration pattern for each different modality, for instance using light/LED flashes for video capture, buzzers for audio, electromagnetic induction on cables for physiological capture to name a few.

This reference calibration device will be connected to the data capture system, where the channel latencies/offsets will be measured using this device as the reference. Predominant steps involved in this calibration process are listed below.

1. The round trip time of sending a command to the calibration device and getting an acknowledgement will be measured.
2. A command will be sent to the device to synthesise patterns in each channel, all at once or one-by-one. Patterns will be induced in the data channels upon receiving this command.
3. The latency of the induced patterns will be measured in every channel and individual time offsets can be estimated as follows.

Figure 3.1 illustrates the spawned synchronisation data-signature and the differences in the latencies of the signals.

The Command latency (Tcl) can be related to the Round Trip Time (RTT) of the calibration device. In addition to latency in data stream paths (Tpath), jitter buffering also creates additional delays (Tjitter) on the signal before they are received by the data logging system [26]. Essentially both of these components contribute to the overall latency in a channel (Tlatency).

\[ T_{cl} = \frac{T_{RTT}}{2} \]

\[ T_{latency} = T_{path} + T_{jitter} \]

The latency (Tlatency) in a channel is equivalent to the latency in the spawned data signature, which can be measured by the delay between the time of inducing the synth pulse and the time it appears in the captured stream. The measured delay (Tdelay, i.e. d1, d2, d3) comprises the actual channel latency and the command latency. Therefore the latency in a channel can be represented as below.

\[ T_{latency} = T_{delay} - T_{cl} \]

4. Case study: temporal synchronisation of driving game logging and psychophysiological signals

Data was recorded in a driving simulation environment to understand drivers’ behaviour, and performance on a racing track.
In this case the aim was to monitor a player’s activities in relation to mastering the specific corner sequence of braking, corner entry, apex taking and corner exit.

4.1. Data capture setup

Codemasters Formula 1 game was used as the simulation engine to provide the actual driving experience. Three dimensional visuals of the game were rendered using the DepthQ stereoscopic projector onto a power wall with active wearable shutter glasses. Logitech G27 racing wheel and pedals with force feedback system were connected with the game engine as the driving controls. Telemetry data including, car’s parameters such velocity, position of the car on the track and engine speed and drivers activities such as throttle, brake and steering angle are streamed out by the game engine via user datagram protocol (UDP) at the rate of 50 Hz. Visuals rendered by the game engine were captured as a phase alternating line (PAL) video with 25 frames/s. A video camera is also used to capture the driver and surroundings at the same frame rate. Electrodes were attached to the driver’s head, in order to monitor Electroencephalographic (EEG) activity. EEG signals were captured at 2048 Hz using Mindmedia Nexus 32 physiological monitoring device. Fig. 4.1 illustrates the arrangement of devices and the information flow.

In addition to the driver, an observer was also linked in the data capture setup. The task of the observer was to identify milestones and incidents manually during the game. The observer performed this by pressing predefined keys on a PC keyboard. The observer is also provided with the real-time visualization of the captured EEG Data, Telemetry, and video streams. The observer’s input was used to aid quick analysis, for example, to point out interesting aspects on every lap, with the hope of future rigorous and to identify and fix any sensor faults while the experiment was carried out.

Main practical concerns related to the data capture setup and devices are addressed throughout the rest of this section.

4.2. Jitter on the data streams

The EEG capture device API delivers the data by means of a call-back function. Having no control over this call-back frequency, other than setting a constant value while configuring, a jitter is observed in this signal (Fig. 4.2). This behaviour is expected in a general purpose OS such as windows and in the universal serial bus (USB) communication channel used by the EEG capture device. A similar observation is seen in the telemetry UDP packets as well. Additionally telemetry stream UDP packets were received approximately at 46 samples/s. This greatly deviates from the pre-set frequency of 100 Hz. Network dynamics and UDP packet loses or the simulation engines internal design might have created this deviation. The jitters can be removed by introducing additional First-In-First-Out (FIFO) buffers. UDP stream’s actual frequency is monitored by counting elements on the FIFO, in fixed intervals. This observed frequency is used as the real frequency in the analysis.

4.3. Asynchrony of EEG and telemetry streams

These two streams originate from highly dissimilar sensor nodes. The path taken by EEG samples can be described sequentially such as, generated by the hardware, transmitted through the optical fibre, retransmitted by the USB device, received by the API and finally reaches the data capture framework’s realm. Since there is no apparent knowledge available to model the path taken by these samples the relative temporal offset between these two streams cannot be estimated directly.

4.4. Using a reference device to calibrate streams’ temporal offsets

For calibration purposes an in-house built embedded device (Fig. 4.4) is used to induce spiky changes in EEG and simulator...
telemetry streams. The calibration device was initially programmed to estimate a Round Trip Time (RTT) of a command (command to induce a data signature) and to get the respective, symmetric acknowledgement. Measuring RTT can be also affected by the OS timing issues and jitters discussed in the Section 2. As a consequence of this, the RTT is estimated using multiple trials (Fig. 4.3) in order to get a better estimate.

After the RTT estimation, the calibration device is programmed to induce a signature in the data stream. Every stream’s time offsets were then estimated individually by spawning individual calibrating actions such as inducing spike waves on the EEG sensors using digital pulses, blinking Light Emitting Diodes (LED) on video streams, using gyros attached to the embedded devices to sense the steering wheel rotation etc.

Temporal offsets for the EEG and video streams were estimated using the method described above and by inducing spikes on their individual data streams. However a slightly different method was used to estimate the offset in the telemetry streams from the game engine.

Inertial data captured using the reference device was used to calibrate the telemetry streamed from the game engine. One off calibration was performed to measure the telemetry offset. The reference device with the inertial measurement modules was mounted onto the steering wheel and pedals so that the offset between the inertial data stream and individual telemetry streams can be measured. Both telemetry and inertial data streams are examined for the calibration signatures such as sharp turns on the steering wheel and quick depresses on the pedals. Distinctive changes in data streams related to the calibration signatures were recognised and used to evaluate the offset between these streams. Once this offset is measured and using the known latency of the reference device (this is equivalent to the latency comprised in the inertial data stream) the actual latency of individual telemetry channels were evaluated.

4.5. Evidence of synchronisation of driving activity and EEG

The EEG signals and car telemetry shown in Fig. 4.5 respectively illustrate the correlation between the drivers muscle activation of the actuations on the game controllers (steering wheel and brake and gas paddles). EEG Signals were filtered here using Butterworth – band pass (20–50 Hz) filter so that the muscle artefacts are clearly visible and hence the synchronisation can be validated. Muscle artefacts are typically filtered out in EEG analysis and disregarded, but this information is effectively used here for the purpose of synchronisation.

Muscle activity is a common artefact in EEG signals which can be manually observed, therefore it is used here to evident and validate the synchronisation of the captured signals. Accuracy of the temporal alignment of EEG and driving telemetry can be visually examined using the muscle actuations, which corresponds to a driving activity, i.e., driver is changing over from full throttle to brake and subsequently performing a turn in an apex in the track. It should be noted that in this case muscle artefacts present in the EEG data stream were exploited to validate the synchronisation, and hence the signals are filtered to enhance the muscle artefacts. Nevertheless it is common to filter out muscle activities while performing a comprehensive EEG analysis but the concept of synchronisation will remain unchanged.

5. Brain activity and driving patterns

Having addressed the synchronisation related issues described and with temporal alignment of captured driving telemetry and
EEG data justified reasonably, the methodology was used to study the driving pattern of 14 drivers, including 7 gamers with more than 500 h of formula 1 gaming experience, 2 real formula 1 drivers and 4 rally drivers.

The main aim of this study was to demonstrate how synchronised data logging and multimodal data fusion, i.e. multiple data streams (psychophysiological signals, game, and telemetry) can be useful in documenting the process of learning. In this case, learning to corner at speed; braking, corner entry, apex and corner exit. Synchronised driving activity data provides the necessary information for documenting the learning process from a purely numerical perspective. Such data also allows for determining learning and exploration patterns regarding a task.

5.1. Experimental setup

The Silverstone circuit was selected for the study. Each participant drives the Red Bull Racing RB7 Renault car, with no other cars on the track. The car was configured for automatic gear shifts, 197° of steering angle and all other assisted driving controls (breaking, stability control, etc.) disabled. To provide a more immersive environment full cockpit view, force feedback steering and stereoscopic three dimensional rendering were enabled. Lap count, lap time and shortest lap time are displayed on the screen while all other information displays (e.g., track position, track guidance marks, comments) were turned off. Fig. 5.1 shows the driving environment and the rendered 3D visual.

All drivers were trained on the Melbourne Grand Prix circuit before they were allowed to enter the Silverstone circuit. The training was to familiarise the driver to the controls, the car, and adapt themselves to the simulated environment (i.e., depth perception, motion sickness, and steering response etc.). Once the driver felt competent, they were asked to complete as many laps as possible within 30 min in the test session on the Silverstone circuit.

EEG data was collected in a 10–20 system using an electro gel cap. Drivers were strapped to the driving seat using seat belts and a head-neck restrain setup similar to a HANS device [32]. These restraints emulated an environment similar to a real F1 car and helped to restrict intense body movements, hence reducing severe artefacts in the EEG.

Driver activity over a specific region on the track (Fig. 5.2) was selected. The ‘Stowe’ corner was selected as it is a high-speed corner with a long approach straight leading into a large radius curve. It is anticipated that drivers will contemplate risks as they learn to deal with this corner. Additionally, Stowe tests the confidence and the attention/concentration of the driver since maintaining a high entry and exit speed critically impacts on the overall lap time. The A telemetry capturing module was built to automatically generate a marker in real-time whenever the car enters and exits Stowe. The automatic generation of markers allows instantaneous extraction

![Fig. 4.4. In-house built embedded device with inertial measurement modules mounted.](image)

![Fig. 4.5. Synchronised EEG and driving telemetry signals. EEG signals were filtered using Butterworth – band pass (20–50 Hz) filter.](image)

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of temporally aligned data, i.e. ready to use data segments during or after the driving session.

5.2. EEG processing

EEG analysis was performed in both time domain and frequency domain, mainly based on the signals from frontal lobe electrodes (F3, Fz, and F4). Signals are filtered using 4th order Butterworth filter, using hi-pass to remove the DC component and low-pass to remove the high frequency noise. Actual cut-off frequencies are selected according to the specific analysis performed which are alpha band 8–12 Hz, and beta 13–21 [34, pp. 112–120]. Thereafter the filtered signal has been transformed into frequency domain to observe power of the frequency power spectrum. Frequency transform was performed in 1s windows, with the window stepping of 10 ms. The frequency transform was scaled based on the length of window (number of points) to conserve the signal power; although the importance was given to the relative variation of the frequency spectrum than the absolute values. Various representations of the frequency power values have been presented throughout this section. The colour map used to represent the frequencies varies from blue to red corresponding to the minimum and maximum frequencies in the considered timespan.

5.3. Artefacts and noises

A driving task involves various activities that could influence the EEG recording, such as muscle activities in the head region, eye blinks, etc. Body and head movements also cause slight movements in the EEG cap, affecting the impedances in the electrodes, consequently introducing many noise sources in the signal. Artefacts occur more frequently in driving compared to a controlled experiment, e.g., an Event Related Potential (ERP) experiment with limited predefined events and responses. The standard practice is to automatically or manually detect and reject artefacts [35,36]. However doing this for an EEG signal collected during a driving task would result in highly fragmented strips of signals unsuitable for continuous brain activity analysis [37,38]. Event locking is a common methodology in EEG studies of signals before and after the event. Thereafter the signals will be averaged over many events and/or various participants [35,39–41]. The difficulty with this approach is isolating and distinguishing a discrete cognitive event in a driving task.

An experimental system built with consumer game equipment and EEG capture is limited in many ways compared to an exclusively built laboratory setup used in psychophysiological studies, e.g., cost and quality of the equipment, signal to noise ratio, interferences by external sources and activities, etc. Body movement is a significant source of noise particularly since it is almost impossible to maintain a ‘rigid’ posture or abstain from body sway. These are uncontrolled parameters as result of combined game immersion and motor reflex as in a real-world racing environment, whereas parameters are carefully controlled in a scientific experiment so that one specific concept can be isolated and studied independently. The contrast here revolves around using a force feedback steering wheel and pedal box as opposed to a game pad with thumb-stick controls. Therefore, the approaches followed in a controlled environment are not always practical in a more realistic environment.

As a consequence, rather than establishing a unique signal or pattern, it is preferable to identify the trends relating to action-chain relationships in the EEG data. Potentially driving activity can be explained more reliably and accurately by one or more sequences of abstract action-chain relationships. Therefore it is important to know what happened at a specific moment in the environment to understand and interpret the EEG. The basis developed by the tight synchronisation provides and enables the correlation of recognisable actions performed by the user at any specific time.

5.4. Interpreting the ‘noisy’ EEG using synchronised telemetry

The possibility of revealing some useful information from artefacts is considered here. Instead of removing signal components, which are deemed to be artefacts or noise in conventional EEG, they are retained. For example, signatures of white noise (appears in all frequencies) could represent a muscle artefact or disturbance caused by a movement in the electrodes, cap, cables, etc. (see Figs. 5.3 and 5.4). White noise is identified by vertical lighter lines in the frequency spectrum, some of which are associated with the driver’s physical activities on throttle whereas horizontal lines represent alpha activity. Therefore such a white noise may be considered as an indication of the driver’s body movement and verified further if it also corresponds to a driver activity captured in driving telemetry. Observing the continuous variation in alpha power (horizontal colour changes) it can be visually justified that every rise in alpha is not due to an artefact and hence the data still contains usable information, therefore it does not need to be disregarded completely (see Fig. 5.3).
6. Results and discussion

From an observational perspective, mistakes made by drivers and the type of alpha and beta activities immediately prior to or during mistakes being made were investigated. Equipped with such data it is then possible to further the causes for mistakes associated with attitude parameters such as concentration (Beta) or attention (Alpha). The resulting analysis below suggests several cases where the synchronised data from EEG can further document an observation and potentially provide better feedback towards learning or skill acquisition.

In Fig. 5.5, the driver makes a mistake at the breaking point; brakes too late, thus missing the corner’s entry point, apex and corner exit. The cause of the mistake is clearly seen from the telemetry record and trajectory of the car in lap 2 compared to laps 1 and 3. A possible interpretation of brain activity correlated to the incidents in the driving is given below.

It can be speculated at this stage that alpha monitoring could provide information as to why a driver might have missed their braking point. Research has shown EEG alpha power fluctuations to correlate with processing of the visual network and between the visual cortex and the rest of the brain. Interestingly, these effects are unique for the alpha band and not observable in other frequency bands [42]. The braking zone is highlighted in red, meaning that the driver is emitting high alpha thus appearing quite relaxed and still possibly performing mental calculations, working with memory [43–46]. Upon missing the breaking point, the alpha reading shift towards low alpha (blue) and full attention to the task at hand. It can be speculated that this could illustrate the moment in which the driver realises that he/she is not going to make the corner entry or the apex and possibly run off the track. While speculative, the shift of activities in the EEG bands appears to match the expected experiential sequencing of events on track. In this context, the later part of the corner is particularly telling as the driver is focusing his/her attention towards re-positioning the car on the track. Fig. 5.6 illustrates further examples from a novice driver, highlighting the alpha attenuation when coming close to the kerb or overshooting. Similar interpretations were derived by performing cause and effect analysis [47] for all 14 drivers.

While high alpha is interpreted as a state of still brain, i.e., relaxation or performing internal mental calculations, working memory [43,46], beta represents a busy activity, anxious thinking, or actively concentrating [44,48–50] process. Fig. 5.7 shows the drivers brain switching between alpha and beta activities. Low alpha power was observed when the driver overshoots the track then he/she regulates the throttle and corrects the path back to the track.
the normal position. This is justified by the notion of alpha attenuation i.e., increased attentiveness [43–45]. The example in Fig. 5.8 illustrates a situation in which both alpha and beta activity can be combined in order to further explain a mistake and cognitive load in compensating the error. The switch between alpha and beta frequencies in the apex can be observed here, i.e., driver switching between relaxed, possibly internal calculations, working memory modes (high alpha) to attentive (low alpha) [43,46], and busy, anxious thinking, active concentration (high beta) modes [48,49]. In this case, the error occurs at mid-corner while negotiating the corner’s apex. At this stage of the task, the driver’s attention should shift towards the corner’s exit and target the white track demarcation line on the side of the track for maximum exit speed.

In this particular case, there might be several reasons as to why the driver has run off the track, e.g. carrying too much speed in the corner and/or misjudge the corner exit point. Fig. 4.4 is however suggesting that the driver might not have been as attentive as he/she should have been towards the apex of the corner. High alpha towards the apex of the corner would suggest that the driver is quite relaxed at this point. Low beta further is correlating as it suggests that the driver in this case is not showing high levels of concentration (blue). Once off the track, alpha levels reduce, thus suggesting attention is fully returned while beta activity slowly rises (yellow/red) towards re-joining the track.

While this approach cannot at this stage be used as a definite and conclusive mechanism for interpreting player performance, it...
can be used in conjunction with other game-related performance and logged activities so as to further determine the reasons motivating player behaviours and enhance the quality of feedback that can be offered to the player.

7. Conclusion

A novel and generic technique to synchronise independent data streams captured in a gaming session has been detailed and demonstrated in the paper. The technique described in this paper neither depends on nor needs to have knowledge about the internal architecture or the core timing loop of the game to measure the end-to-end timing inconsistencies between the environments (i.e., where real-world user activity happens) and the data capture endpoint (i.e., the data is being available to capture along with the temporal information).

Cases study that records video, driving telemetry and EEG data was used to demonstrate the accuracy of synchronisation of these multimodal data streams for neurometric analysis. The proposed synchronisation method is generic and applicable to any data stream.

This paper demonstrated how the achieved precise temporal synchronisation across multimodal channels was exploited to create in depth interpretations of the in game activity. This approach provides fresh opportunities for using commercial of-the-shelf games to study user behaviour in-relation to the in-game data logging. Consequently it enables a vast majority of games not intentionally designed for research to be used for scientific and methodological research. The development of such a generic technique for temporal synchronisation opens up a wide range of possibilities in the areas of psychology, game studies, cognitive sciences and experiential-based multimodal studies. This technique is beneficial to the Serious Games community in the sense that it offers a quick method for a synchronised real-time documentation of learning activities by combining explicit and implicit data gathering. The synchronisation technique discussed in this paper, for instance, currently being used experimentally in synchronising game events for psycho-physiological studies and for studying cognitive aspects of computer aided design task. From a multi-modal perspective, this approach presents the benefit to develop a flexible and fast approach to experimenting with complex experimental designs by significantly reducing the complexity of experiment technical implementation.

8. Future work

The presented work highlighted the potential of interpreting the driving based on EEG and in game data. The difficulty in tightly
controlling the environment and ring fencing a particular activity in the driving task creates difficulties in employing conventional neurometric approaches. Consequently authors are constrained to choose a flexible approach of using time synchronised multimodal approach to interpret the data. Cause and effect analysis have been performed manually to describe patterns in the EEG power spectrum [47]. Current and future work will focus on automatic classification and documentation of the driving activity. Differences in previous experiences in gaming or driving task and driver individualities create a challenge in building up a large data-set. The reliability and performance of automatic methods rely on finding statistically suitable methods and adequate amount of training data for classifiers. Using the time synchronisation techniques presented the future direction of the work leads towards a real-time, closed-loop system that can feedback into the game or to the driver to influence driving experience.

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References

