Modelling Physiological Sensor Noise to Movement-Based Virtual Reality Activities

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Abstract: This position paper proposes the hypothesis that physiological noise artefacts can be classified based on the type of movements performed by participants in Virtual Reality contexts. To assess this hypothesis, a detailed research plan is proposed to study the influence of movement on the quality of the captured physiological signals. This paper argues that the proposed plan can produce a valid model for classifying noisy physiological signal features, providing insights into the influence of movement on artefacts, while contributing to the development of movement-based filters and the implementation of best practices for using various associated technologies.

1 INTRODUCTION

The use of physiological monitoring has become an essential tool for multidisciplinary studies leveraging interactive virtual reality (VR) devices and digital games for the purpose of studying human-based behaviours. Some examples include neuroscience (Bohil et al., 2011), the study of emotions (Montana et al., 2020), human-computer interaction (Liapis et al., 2015), affective computing (Lopes et al., 2017), learning (Bavelier et al., 2012), and healthcare (e.g., rehabilitation (Howard, 2017), therapy (Norrholm et al., 2016; Bohil et al., 2011) and pain management (Hoffman et al., 2011)). VR in particular provides high-fidelity immersive experiences, allowing individuals to physically interact with virtual environments, which can be advantageous for rehabilitation (Howard, 2017) and exposure-type therapies (Bohil et al., 2011). The main constraint, however, is that physiological devices are not prepared for this type of intensive interaction, a pattern that has been observed in several studies using these tools (Kritikos et al., 2019; Solbiati et al., 2021; Dey et al., 2022; Higuera-Trujillo et al., 2017; Petrescu et al., 2020). Literature suggests several methodologies on how to mitigate this problem (Lopes and Boulic, 2020; Järvelä et al., 2014), but such methods often rely on minimising movement as much as possible, which is counterproductive to the core advantages of using VR in the first place.

Given the integral nature of movement and interaction required from VR experiences, this position paper argues that the influence of movement on the signal quality of recorded physiological data should be adequately explored, thus proposing a step-by-step research plan towards that goal. In particular, this paper asks the question: "Given a set of pre-defined movements, can we associate each movement type with a classifiable artefact pattern?". Thus, the hypothesis is that the noise artefacts themselves, which are specifically obtained within this context, could be classified based on the type of movement that was conducted by the participant.

For the resolution of this problem, the development of a VR application is needed to enable the collection of both physiological and participant body movement data. This VR application serves as a stimulus, offering the participant objectives and incentives to move repetitively over the course of a game playing session. Physiology can be collected through high-quality physiological sensors, while body move-

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ment can be captured through high-definition video cameras and motion capture (mocap) systems, paired with internal information from the VR system headset and controllers movement information. The different granularities offered by these technologies provide sufficient detail on how a participant moves their body in relation to the appearance of a noise artefact. By analysing the captured signals and the different levels of noise over time, the hypothesis considers that patterns will emerge based on how participants move their bodies during the game playing session, which in turn can be modelled accordingly. Furthermore, such patterns may be user-dependent, providing additional solutions for user-centric filtering techniques.

The expected outcome of such a research plan would be a model capable of classifying noisy physiological signal features while accounting for different granularities of participant movement. Furthermore, an extensive study and compilation of the influence of movement on the appearance of artefacts in physiological data could be constructed based on all observations collected from this type of experimentation. We argue that such study could provide (i) models for noise detection identifying noise source, (ii) a foundation for the construction of specific movement-based filters through pattern recognition, and, (iii) methodologies and best practice design patterns for systems employing such technology.

2 BACKGROUND

The use of VR for the study of human-based phenomena is a comprehensively explored subject (Lopes and Boulic, 2020; Jawed et al., 2021; Hoffman et al., 2011; Norrholm et al., 2016). This is unsurprising when considering the potential of such technology due to its immersive capabilities, which allow individuals to physically interact and walk within virtual environments. Furthermore, these environments are highly malleable and offer an extensive degree of control, which in turn allows therapists, psychologists and other professionals to safely tailor these treatments to each individual patient (Ćosić et al., 2010).

The use of physiological sensors is often a crucial aspect when studying the influence of certain stimuli on humans. VR is attractive for these studies due to the immersion offered to its participants and the close relationship individuals can have with their virtual avatars. This psychological phenomenon is known as embodiment (Kilteni et al., 2012), where the participant associates their own body with that of the virtual avatar, which can increase the effectiveness of stimuli presented in the virtual environment (Slater, 2017). Thus, the effectiveness of using such a technology to study specific human behaviours, while maintaining patient safety and controlling all possible outcomes of the virtual environment, is clear. Examples of VR applications being used as a stimulus include the study of human emotion (Montana et al., 2020), learning effectiveness (Bavelier et al., 2012), brain activity for neuroscientific phenomena (Bohil et al., 2011), psychological therapies (Norrholm et al., 2016) and rehabilitation (Hoffman et al., 2011; Howard, 2017).

The advantage of using VR is also a core reason why it can be so difficult to collect physiological data. Participant movement can lead to several problems when it comes to collecting this data, as micro to macro movements can induce noise and artefacts, requiring thorough methods for filtering the signal (Bian et al., 2019), and in the worst case having to discard them (Lécuyer et al., 2008). Through our extensive analysis of the literature, we observed a constant trend in dealing with this exact recurring problem, where signals often had to be discarded, despite the use of state-of-the-art physiological recording devices (Kritikos et al., 2019; Solbiati et al., 2021; Dey et al., 2022; Higuera-Trujillo et al., 2017; Petrescu et al., 2020). Given that head tracking and 3D interaction are fulcral components of the embodiment experience, it is not possible to remove them without compromising the use of VR in the first place. It is also worth noting that, even for interactive systems that present a lower degree of movement than VR applications—such as traditional desktop gaming applications—the problem persists, albeit to a lesser extent (Lopes and Boulic, 2020; Järvelä et al., 2014).

The most common solutions in the literature often focus on filtering these artefacts with traditional methodologies such as low- and high-pass filtering techniques (Bian et al., 2019; Kritikos et al., 2019; Solbiati et al., 2021; Dey et al., 2022; Higuera-Trujillo et al., 2017; Petrescu et al., 2020), threshold filtering, and signal decomposition (Yuan et al., 2019). Despite these methods being used extensively, they are still sensitive to specific muscle contractions and movements, forcing experimenters to exclude these signals completely (Kritikos et al., 2019; Solbiati et al., 2021; Dey et al., 2022; Higuera-Trujillo et al., 2017). Alternative electrode placement, and even sensor types such as bracelets, have also been explored (Borrego et al., 2019; Sra et al., 2019), as certain parts of the body can experience less stress and muscle contractions than parts subject to traditional electrode placement (Lopes and Boulic, 2020). The downside of placing electrodes on unconventional locations is that the signals collected present a lower signal to noise ratio than when collected in common locations. Such locations are also not devoid of potential noise, and given a lower amplitude signal, can still result in discarded data points (Borrego et al., 2019). To address this problem, some have suggested to completely avoid or minimise the presence of noise through meticulous protocol and task design where certain movements and conditions are avoided (Lopes and Boulic, 2020; Järvelä et al., 2014). However, this is quite limiting, as movement and interaction are a crucial aspect of VR applications (Jawed et al., 2021; Hoffman et al., 2011; Kilteni et al., 2012; Slater, 2017; Howard, 2017), and limiting these features will severely hinder the experience and put into question its use in the first place.

Classifying noise is not a novel approach, with research often focusing on determining if noisy patterns consistently emerge from signals (Park and Lee, 2020; Sweeney et al., 2010; Chowdhury et al., 2013). If such patterns are proven to be consistent and allow for a means of classifying them with a high degree of accuracy, methods for filtering this noise become possible through the use of pattern recognition techniques.

Previous studies have attempted to find patterns in movement-based noise classification through the use of accelerometers (Chavarriaga et al., 2013; Kunze and Lukowicz, 2008) and electromyography (Yang et al., 2017), with various degrees of success. This position paper proposes an alternative solution for studying movement-based noise patterns. This alternative consists of a VR experiment where participants are asked to perform a series of repetitive minor tasks specifically targeting body locomotion and muscle activity, forcing them to move in very precise ways. Extracted data, consisting of common physiological signals (ECG, EDA, EMG and Respiration), mocap measurements, and depth camera recordings, can then be analysed to determine the relationship between specific movements and the observed noise artefacts.

3 RESEARCH PLAN AND METHODS

The objective of the proposed research plan is to model noise artefacts of physiological data recordings generated by participant body movement. The optimal final result would be the construction of a model capable of classifying these noise artefacts based on the type and intensity of movement that generated them. Furthermore, considering the objective of classifying movement specifically, an additional question can be made relative to "how movement data granularity can influence the accuracy of such models". Therefore, the proposed study requires collecting movement data from a wide range of sources, such as real-time mocap data, depth cameras, and VR tracker technologies. By leveraging these different types of movement-based data, various types of classifiers can be constructed. Lastly, by exploring the relationship between physiological noise and movement, a compilation of all the phenomena, difficulties, and best-practices can be made available to the research community. This type of document can have extensive benefits for future experimental design solutions using these technologies, ideally reducing the amount of data that has to be discarded.

Although the proposed plan is focused on VR experimentation, its output can have implications beyond this scope, namely in biomedicine and healthcare. More specifically:

- Noise artefact detection.
- Immediate filtering in real-time applications.
- Associating movements to noise patterns, offering contextual information to experimenters.
- Personalised signal filters to each individual, usable for post-processing analysis rather than more general methods (e.g., low- and high-pass filter).
- Measure and monitor physiological sensor sensitivity according to body type, movement and limb articulation, for development of more robust sensor technology.

This paper proposes five milestones to achieve this research plan:

M1 Experimental design and activity definition.

M2 VR experiment implementation.

M3 Motion capture integration.

M4 Data collection.

M5 Pre-Processing, feature decomposition, data analysis and modelling.

The following subsections describe each milestone in detail in addition to its sub-objective milestones, demonstrating possible temporal overlap between these and the core milestones.

M1. Experimental Design and Activity Definition

The goal of this milestone is to survey the requirements needed for accomplishing the proposed research goals. These requirements include: defining the first phases of the experimental protocol; an effective development and deployment strategy of all software developed and hardware integration; and safeguarding the privacy and confidentiality of participant data.

The experimental protocol and methodology will need to be submitted to the relevant ethics board to ensure compliance with General Data Protection Regulations (GDPR) .

M1 is divided into three sub-milestones:

M1.1. Requirements Survey. For a successful experiment it is first necessary to evaluate what and how data will be collected. We will start by defining a series of movement types and classify them based on their intensity ("is it a low-key or an assertive movement?", for example), degrees of freedom (e.g., upper or lower body movement, articulations) and muscle activation. In-game triggers (or flags) will also need to be defined to distinguish between the different activities and effectively parse the data in post-processing. Lastly, development considerations—such as surveying the relevant libraries, software and hardware integration methods needed for the development of the applications—are also a requirement.

M1.2. Experiment Design. Given an initial set of movements, a series of VR playful activities will be designed and developed (see M4). These consist of visual and active metaphors that will be used to help the participants establish the intended movement, to common menial tasks repurposed for VR interaction. Examples include the movement of pushing or pulling a door; pressing a button at different heights; walking through a sidewalk; moving away from an incoming object; and using a laser pointer to emphasise certain words in a presentation. To further aid participants, it is necessary to define how hints and visual aids will be displayed and animated, where the objective is to reduce ambiguity. Such activities can be disguised as a playful game experience for the most part, offering participants the opportunity to engage with the task for more natural movement. Furthermore, given that interaction using a mocap environment is slightly different than that of a traditional VR experience, it is important to consider both approaches in the design process. More specifically, to guarantee experimental consistency, it is necessary to determine how movements in one approach translates to the other, possibly giving preference to movements that are easier to translate between approaches.

Expected Outputs

1. A document with ethical procedures, data treatment and hosting solutions compliant with GDPR.
2. Core movements survey effectively tagged based on articulations, intensity and muscle activation.
3. Survey of initial VR design, including interface and movement mockups detailing consistency of the experimental design between the traditional and mocap versions of the VR application.
4. Prototyping and refinement of the application design.

M2. VR Experiment Implementation

The core objective of this milestone is the development and integration of external devices into the main experimental application (or game). This milestone also includes the testing of mocap integration and the piloting/deployment strategy, in parallel with M3 and M4, respectively. It is divided into three sub-milestones:

M2.1. Design. This milestone addresses the design aspect of the application, defining how participants and experimenters interact with it and how information is communicated to them. If certain design choices end up not working within the testing and piloting stage (milestone M2.3), these will return to this design phase to be refined using the knowledge obtained from user testing.

M2.2. Core Implementation. This milestone focuses mainly on the process of integrating the features designed in M1 and implemented in M2.1, where a continuous debugging process is essential to guarantee a robust application. This particular milestone will be developed in proximity with the next milestone (M2.3), which will continuously report bugs and problems to be fixed.

M2.3. Testing and Piloting. This milestone consists of two different phases of quality assurance of the application: testing and piloting. The goal of testing is to discover potential software breaking instances. Piloting will consist of assessing the application with the purpose of determining (a) the usability of the application from an experimenter and participant point of view, and, (b) how the application performs on-site once deployed. This will provide an overall view of the application's reliability and collect data from participants to improve its usability and potentially optimise the experiment protocol.

Expected Outputs

Several increasingly stable versions of the application, followed through an internal Git repository and weekly feature and bug reports, are expected during this milestone. Simple prototypes are initially expected for observing and validating if the core movements defined in M1 are being effectively achieved. Alpha versions of the system for iteratively implementing and testing features then follow. A subsequent beta version of the feature complete system will be extensively tested for debugging and usability. Lastly, a stable build of the application is the final expected output of this milestone.

Potential Pitfalls

Unexpected issues need to be considered, especially considering that the project uses several technologies that work in tandem for its effectiveness (i.e., game engine, VR devices, and physiological recorder). Thus, it is important to be aware of hardware limitations, especially once deployed. The interactions must also have a degree of recording effectiveness to maintain a coherent noise to signal ratio and avoid flat signals (e.g., knocking off sensors during interaction, or impossible movements due to cable management limitations). Thus, an insistence on an initial prototyping phase with rudimentary 3D assets, such as testing the reliability of the chosen movements, is crucial. If some movements are found to be unrealistic to perform, others will then be chosen from the list compiled in M1.

M3. Motion Capture Integration

This core milestone deals with the integration of the selected mocap system within the Lab Streaming Layer middleware suite[1]. Furthermore, to leverage the granularity of movement capture by such a device, additional data visualisation software needs to be developed, allowing the overlap of an ambiguous representation of a participant's avatar with the captured physiological signals. This would allow the observation of the small variations of body movement over time and how it influences noise on physiological signals. M3 is split into two additional milestones:

M3.1. Middleware Integration. This milestone exclusively addresses the integration of a mocap data stream, with the purpose of outputting the captured data into a centralised synchronisation middleware system. This will simplify data processing and analysis in M5, as all time-series (i.e., physiology, mocap, and game metrics and triggers) will be effectively synchronised. It also offers a way of increasing the accuracy of automated triggers sent by the game, allowing automated parsing scripts to cut the data according to each activity or other requirements (e.g., collecting baseline).

M3.2. Body Motion Visualisation System. This milestone focuses on developing a simple body rendering system capable of extrapolating the mocap data by generating a 3D visualisation of the participant's body movement. Avatars will consist of faceless representations of participants and will accompany the physiological signals. This allows experimenters to visualise a side-by-side comparison of specific events with the different collected physiological channels (e.g., ECG, EDA, EMG and Respiration). Such a system can be built using a game engine and various assets that use mocap data to create 3D animations. Considering this has no dependencies with the experimental application itself, it can be built in parallel with M2.

Expected Outputs

1. Update of the internal data collection middleware integrating the selected mocap system.
2. Mocap data visualisation software.
3. Independent validation of the fidelity of data collected through the data collection middleware.

M4. Data Collection

This core milestone consists primarily of the deployment phase, where the experimenter will collect the necessary data for statistical analysis. This consists of conducting several trials of the different movements defined in M1. This milestone is dependent on both M2 and M3, as for this process to take place the application must be fully integrated and functioning.

During this milestone experimenters need to follow a strict experimental protocol, programmed within the application, which will present all the movements the participants are required to make. Ideally the application will be sufficiently autonomous to (a) minimise experimenter mistakes, (b) start collecting data as soon as the experiment begins, and, (c) guide participants effectively over the course of the experiment. The experimenter will have their own interface to visualise (a) the physiological data in real-time (in case any adjustments are necessary during the experiment), and, (b) what the participant is doing in-game.

[1] https://labstreaminglayer.org/

Expected Outputs

1. An experimental dataset, including all expected data types: physiology, mocap vectors, camera skeletal features, in-game markers, participant questionnaires, and demographics.
2. Dataset manual, including instructions for parsing and description of all data types in the dataset.
3. Automatic parser script providing an initial treatment of the data, which will be included with the dataset.

Potential Pitfalls

The most relevant risk with this milestone is signal degradation due to sensors being knocked off by participants or hardware failures. The extensive testing in M2 attempts to mitigate this problem by offering the experimenter a set of monitoring features that will help assess the quality of the signal during experimentation. This means experimenters will have real-time information about the signals being recorded and after each trial may pause the experiment and re-adjust the electrodes on participants for more efficient capture. Although the objective of the experiment is to capture signal noise, it has to be able to do so in the ideal capturing conditions, or more precisely, some trace of the original signal must still be present in the recording for a model to be able to adjust and effectively remove the noise.

As an additional contingency, a small visualisation software should be made available for the experimenter, so that they may parse and visualise all captured signals from that session and access its quality and conduct a superficial analysis. If the signal is deemed inadequate it is tagged as "damaged" and placed in the dataset with this condition. A replacement participant will then be recruited to replace these trials and obtain the expected number of trials as defined in M1.

M5. Pre-Processing, Feature Decomposition, Data Analysis and Modelling

This milestone will consolidate all activities related to the treatment, cleaning, pruning, parsing, analysis, and modelling of the data collected in M4. It is divided into three sub-milestones, which will consider the observed results and recent state-of-the-art approaches that may benefit the study.

M5.1. Cleaning and Parsing Trials. The first sub-milestone is dedicated to cleaning, analysing, and parsing the raw signal values. This will include developing several data visualisation scripts. Despite the core objective of this proposal, some form of data pruning will be considered, such as "dead" signals caused directly by the disconnection of sensors.

M5.2. Time-Series Analysis. Signals are analysed with respect to their baseline value, and all movements in each category will be compared to this baseline through polynomial regression. This will allow researchers to understand the delta fluctuations between baseline and movement trials. This will also be done for trials within the same movement category with the purpose of learning if a large distance exists between these trials. Furthermore, the correlation between signals within the same movement category will also be investigated; the goal is to determine if a high correlation is still present within a signal despite artefacts being present during this movement. This will allow reseachers to observe if a natural tendency exists between the actual body movement and the artefacts that appear in the signal.

M5.3. Categorising and Machine Learning Methods. One of the main objectives of this experiment is to learn if certain artefacts can be categorised based on the movement type, i.e., if we can categorise noise artefacts based on the movement of an individual. As a first methodology, the intent is to use a technique such as PCA or UMAP (Fachada et al., 2016; Du et al., 2023) to reduce the dimensionality of the signal and apply an unsupervised learning approach such as *k*-means clustering. This will provide an initial observation of the data patterns to test the hypothesis that certain noise artefacts correlated with a specific movement create specific clusters. It is important to consider that this proposal is not limited to this type of methodology. Given its exploratory nature, techniques such as supervised learning, forecasting, and others can be also be explored.

Expected Outputs

1. Anonymized and clean dataset usable for dissemination purposes (including the raw unprocessed data).
2. Detailed report on the findings and observations related to the questions asked in M1.
3. Detailed report on good and optimal practises of physiological data-collection in VR applications with a high-degree of movement.
4. Statistical models capable of categorising noise based on movement types or common features it presents.

Potential Pitfalls

The knowledge obtained through this work will result in several studies and methods about the effects of movement on physiological signals. Thus, even if models prove difficult to train, many of the methodologies can be used to improve how this data can be collected, in turn enhancing the overall quality of data collection in studies involving VR.

4 CONCLUSIONS

This position paper proposed a step-by-step research plan to study the influence of movement on the quality of physiological data captured during VR sessions, putting forth the hypothesis that the noise artefacts can be classified based on the type of movements performed by participants. The main outcome of such study would be a model capable of classifying noisy physiological signal features, providing insights into movement's influence on artifacts and contributing to the development of movement-based filters and best practices for using the associated technologies.

Although the purpose of this research is to specifically study VR movement, the application of all the knowledge assembled throughout its implementation could be applied towards a wide range of healthcare based applications. As discussed, VR has been extensively used for psychological treatment, rehabilitation, and even distracting patients from painful procedures. Observing the relationship between gross motor activity and the noise captured from sensors could foster the development of new methods for increasing sensor robustness, while avoiding an increase in cost. In conclusion, by offering a better understanding of the movement-signal relationship—therefore allowing higher-quality data collection in VR sessions—this research proposal can potentially lead to cheaper and more effective VR treatments for improving the health and well-being of patients.

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