# Measuring user physical activity in a virtual reality environment

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**Abstract**

Virtual reality (VR) is getting traction in rehabilitation. A crucial factor for its success will be the development of valid metrics of physical activity and their usability by physiotherapists and patients alike. Using the case of SyncVR's physiotherapy app for Oculus Quest, this work aims at developing such metrics using VR-recorded movement data. A second contribution will touch the prototyping of a corresponding visualisation tool. Machine learning models will be tested to automate activity recognition of the app users. The project can be viewed on GitLab, here.



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# Introduction

Virtual reality (VR) is becoming increasingly a hot topic (and alas a buzzword). In rehabilitation, VR is getting traction too, possibly thanks to the affordance of stimulus control, ii) real-time performance feedback and iii) gamified, safe and immersive environments [Rizzo and Kim, 2005]. However, a large number of recent VR rehabilitation solutions - `XRHealth`, `GonioVR`, `InMotionVR` and the subject of this project, `SyncVR` - might be struggling with i) developing a set of valid, reliable and accurate metrics for VR physiotherapy exercises and ii) integrating these metrics in the broader context of the therapy.

From a data science perspective, they face three major challenges: i) movement data recorded by VR applications shows volume (e.g. 60 frames per second), ii) there is velocity (e.g. real-time feedback) and iii) results need to be intelligible to physiotherapists and their patients. Using VR-recorded movement data in order to develop and visualise these metrics motivates this work.

Currently, popular VR applications are mostly concerned with interactions with the virtual environment, ignoring the effect of user actions in the real world. For example, in a goalkeeping game players would move in a virtual football field to catch balls with their hand-held controllers. The game engine will i) measure whether the hand and the ball (virtually) intersect and ii) act accordingly. In other terms, VR devices do not analyse movement data beyond what it is needed by the application to run.

On the other hand, physiotherapists currently rely on goniometers and heuristics to measure the performance of their patients during traditional and VR treatments. In addition, they might not be able to fully grasp what patients using VR physiotherapy apps are doing at all times. Developing physical activity metrics based on the VR-recorded movement data would thus address both issues concurrently.

The objective of this project is thus to design and prototype a complex system that could help answering the following questions:

**RQ1** What metrics could be used to measure the performance of patients using a VR physiotherapy app?

- How could these metrics be developed and gauged?
- What machine learning methods could be applied to develop them?

**RQ2** What visualization tools could be best suited to present these metrics?

- How would different user groups (e.g. physiotherapists and patients) benefit from these visualisations?

## Related work

The use of VR for medical applications, especially in physical rehabilitation, has long been studied as it affords precise stimulus control, immersive, dynamic, 3D environments and performance tracking and recording [Rizzo and Kim, 2005, Birckhead et al., 2019, Hochstenbach-Waelen and Seelen, 2012]. Moreover, VR could bring several advantages to the patients undergoing treatment. In fact, VR enhances the rehabilitation of patients [Streicher et al., 2018, Laver et al., 2017], while ensuring error-free learning [Rizzo and Kim, 2005], reducing levels of distress [Li et al., 2011] and minimising kinesophobia [Chen et al., 2017].

Objective metrics have to be defined in order to measure task performance, progression in rehabilitation [Sveistrup, 2004, Hochstenbach-Waelen and Seelen, 2012, Rizzo and Kim, 2005] and improvements in patients ADL [Birckhead et al., 2019]. However, the development of such metrics based on the VR recorded performance is non-trivial, as biomechanical, physiological and technical constrains have to be to taken into account [Strimpakos, 2011, Lockhart and Weiss, 2014].

Human activity recognition (HAR) could be conducted by mining sensor data from mobile devices (mostly accelerometers and gyroscopes) [Kwapisz et al., 2011, Lockhart and Weiss]. From a machine learning standpoint, this ties strongly to the classification of physical activities during VR physiotherapy sessions. However, limitations have been identified in the deployment at scale of such HAR models [Stisen et al., 2015], possibly due to heterogeneity in the experimental setups in terms of data collection methods, sample structure, hardware specs and data processing and analysis techniques [Lockhart and Weiss, 2014]. In this regard, deep learning models such as Long Short-Term Memory (LSTM) could be successfully applied to HAR classification problems and possibly overcome some of the above limitations [Donahue et al., 2017, Saeed, 2020].

Finally, the visualisations of such metrics must be developed with a user-centered approach [Rado et al., 2009, Ploderer et al., 2016]. Such visualisations could include include both performance (i.e. movement topology) and result (i.e. movement outcome) feedback [Hochstenbach-Waelen and Seelen, 2012]. In fact, physiotherapists could use a dashboard that shows objective patient data before or during consultations to assess patient engagement and their performance over time [Rado et al., 2009]. Moreover, an intuitive visualization tool affords a more active involvement of the patients in the rehabilitation process and an increased probability of effective transfer training [Rado et al., 2009]. In fact, physiotherapists have to identify the extent to which a specific skill or a general familiarity with the training context is being transferred [Sveistrup, 2004].

# Methodology

### Use case

The development of the metrics and their visualisation will be focused on a specific physiotherapy app, developed by SyncVR. At the time of writing (March 2020) and for the purpose of this work, the app offers six games, including goalkeeping, fruit picking and object catching. The app is designed for Facebook Oculus Quest, a standalone VR device comprising one head-mounted display (HMD) and two hand controllers. The app runs at 72 fps and automatically logs the global position and rotation of the three markers. This data is then offloaded to a PC and then securely shipped back to SyncVR.

### Data collection and methods

Currently, the app is used only in the Netherlands. Moreover, additional data could be recorded by enrolling subjects and let them use the app. This would not compromise the validity of the experiment, since the focus of this work is not to test the efficacy of the VR solution itself. Related to this, data could be recorded in a laboratory setting (giving subjects scripts and video recording them) and then manually labelled in order to create a training sample for machine learning models such as LSTM.

It has to be noted that all data is anonymised and that SyncVR and its partners are responsible for managing patient personal data. Moreover, should the data collection be conducted using lab subjects, appropriate consent forms will be handed out.

Different methods could be explored to answer the two research questions:

RQ1 Uni-channel scales (e.g. 1:1 metric:axis), multi-channel scales [Strimpakos, 2011] and machine-learning models such as LSTM, with appropriate training data [Donahue et al., 2017, Saeed, 2020];

RQ2 A dashboard with a combination of plots, heatmaps and mo-cap animations;

The software stack will include ML-oriented Python libraries (pandas, numpy, scikit-learn, keras), dashboard tools (Flask, JavaScript, CSS) and possibly cloud solutions (AWS EC2 and S3).

### Evaluation

After defining clear testing goals and completing the prototype, the evaluation will focus on user feedback on the metrics [Nielsen and Landauer, 1993] and model evaluation [Tharwat, 2018]. For the visualisation tools, a system usability scale survey (SUS) [Brooke, 1996] and a semi-structured survey on UX [Cawthon and Moere, 2007] will be conducted. It is planned to complete the testing with 5 users, a commonly accepted number of observations.

### Initial results

Data customarily created has been extracted from the app and analysed using Python libraries. Minimal data cleaning had to be conducted (e.g. rescaling Euler angles into a [-180,180] range) before observing meaningful movements. It is possible to observe two head rotations straight-to-right and one straight-to-left (leftmost plot) and one extension (centre plot). In general, the device seems to track well the markers.

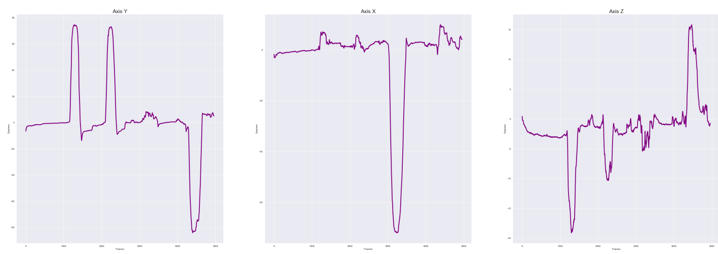


Figure 1: Head rotation

Moreover, a first iteration of the visualisation tools has been conducted, using a commercial solution, Moveshelf. It is possible to observe both a snapshot of a mo-cap with a humanoid replaying the user app actions and a plot of the corresponding head range of motion (ROM).

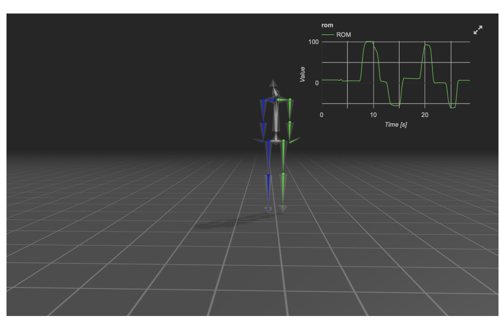


Figure 2: Mo-cap prototype

# Project plan

The project plan below uses the following convention: [D] stands for developmental work, [W] stands for writing work.

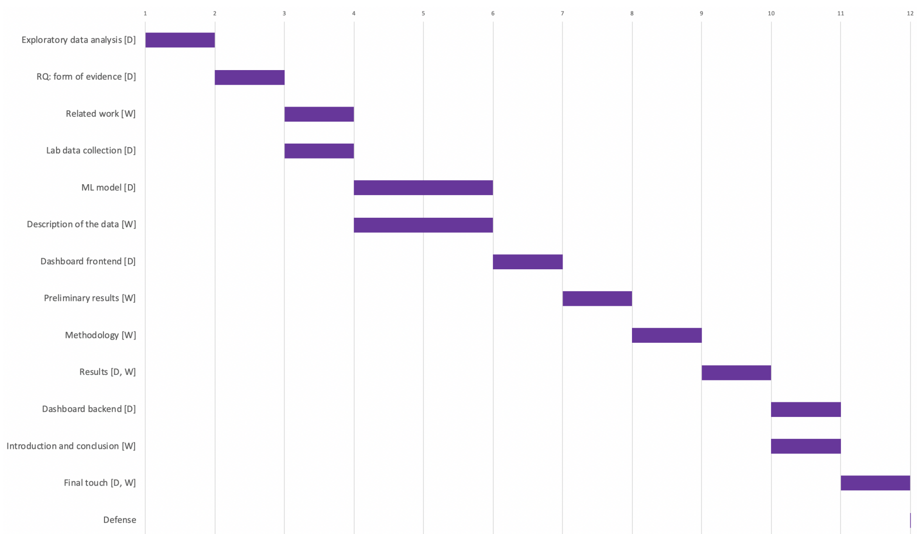


Figure 3: GANTT chart

# Risk assessment

| | Effect | Measure | Risk |
|---|---|---|---|
| **Data collection** | Lack of sufficient data | Manual recording | High |
| **Backend speed** | Frontend not loading | Local deployment | Medium |
| **User feedback** | Lack of users for prototype validation | Online sessions | High |

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