Enhancing VR Experiences with Smartwatch Data

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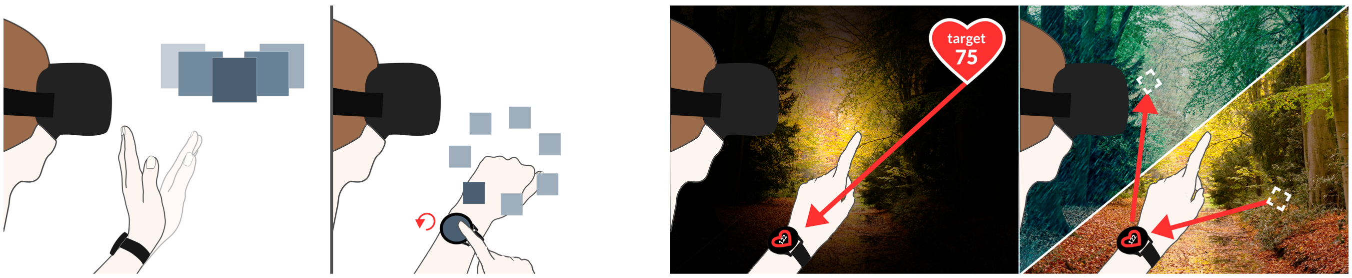

(a) (b) (c) (d)

Figure 1: Use case menu navigation: To browse through and select menu items, (a) left and right air swipe gestures and (b) touch gestures are used. Use case mental health: Health data is used to (c) gradually reveal the VE the closer the HR gets to the target HR and (d) predict the user's mood, automatically adjusting colours, weather and lighting conditions to reflect the user's current emotion (here: anger) or to counteract it.

ABSTRACT

Nowadays, smartwatches are widely used on a daily basis by a growing user base. They can constantly collect motion and health related data via different sensors such as accelerometer or heart rate sensors. This data offers new possibilities for designing VR experiences, interacting within VR, or enhancing a VR experience by adjusting it to its users. In this workshop paper, we explore the design space of smartwatch-gathered data for VR, focusing on how menu navigation can be facilitated by motion data for mid-air gestures and by the smartwatch's screen for touch-based gestures, and how health data can be used to automatically adjust the VE to encourage a relaxation of one's HR, and to reflect or counteract the user's predicted mood.

CCS CONCEPTS

• **Human-centered computing** → **Interaction devices**; **Virtual reality**; **Gestural input**; Graphical user interfaces; Haptic devices.

KEYWORDS

smartwatch, virtual reality, sensors, mental health, mood prediction

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1 INTRODUCTION

Immersive experiences in virtual reality (VR) support the interaction with the virtual world mostly through hand-held VR controllers. These controllers are limited to user input through different types of buttons and wrist motion tracking. Everyday wearables such as smartwatches or fitness trackers extend these input modalities and can additionally register user input through health data or touch gestures. Therefore, integrating smartwatches into immersive VR experiences expands the techniques users can use to interact with the virtual world and enables individually-tailored virtual environments (VE). Since smartwatches have increased and will continue to increase in popularity [34], they became ubiquitous computing devices, making their sensing instruments easily available for today's users in the commercial domain.

On the one hand, wrist-worn devices have common motion sensors embedded such as an accelerometer or gyroscope that track the local movement of the user's wrist or full-body movement, such as steps taken. Sensor quality of off-the-shelf smartwatches has been shown to allow for explicit interactions through, for example intentionally performed gestures [3, 42, 45]. On the other hand, since wearables were initially developed for the fitness domain, specialised body sensors, such as a heart rate (HR) sensor, pulse oximeter or thermometer, track users' vital signs. Such health data are usually not consciously controlled by users (although they can learn to a certain extent to intentionally influence their vital signs trough concentration and training), which offers objective data reading for input and could allow for more implicit interactions [31]. This type of data extends the capability of a VR system to sense the physical and mental state of a user in an objective and quantitative and adapt its parameters in response to the changes in readings. This is especially beneficial in health-related areas [25, 30, 36, 41].

Table 1: Overview of sensors for motion and health data. Smartwatches contain additional sensing instruments for the environment and other hardware components, for example for communication, mobile network and localisation which, though briefly mentioning them, we do not focus on in our paper.

data category	sensor	description
motion data	accelerometer	device acceleration along X,Y,Z axes
	compass/magnetometer	magnetic north direction and from this all other cardinal directions, orientation of the smartwatch
	gyroscope	angular velocity along device's X,Y,Z axes
health data	heart rate (HR) sensor	average number of heart beats per min (bpm)
	pulse oximeter	red and infrared sensors measuring the oxygen saturation of the blood (SpO2)
	skin temperature sensor	temperature of the skin

With this workshop paper, we take a first step in exploring the design space of using smartwatches to enhance VR experiences. We show how smartwatch data can enrich immersive experiences and address current problems and research gaps. Thus, we will first give an overview of the sensors and the corresponding data gathered by off-the-shelf smartwatches. Then, we present two specific use cases that use (1) motion data for mid-air gesture tracking and touch input, to highlight their benefits for VR menu navigation, and (2) health data to automatically adapt the VE to encourage relaxation and promote lowering of the user's HR, and to reflect or counteract the user's predicted mood. We will provide a basic overview of the benefits of using smartwatches as input devices for VR, highlight their positive impact on the user experience and help set the course for future research incorporating smartwatches as everyday proxies in VR.

2 MOTION AND FITNESS DATA

This section provides an overview of the sensors and other hardware components of commercially available smartwatches. In addition, data acquisition is discussed, including the utilisation of the companion architecture to gain access to sensor data.

2.1 Smartwatch Sensors

To identify the built-in sensors, we analysed 61 wearables (smartwatches and fitness trackers) from the six most popular manufactures worldwide (Apple, Xiaomi, Huawai, Samsung, Fitbit, and Garmin) [35]. We divided all available sensors into three different categories, based on the type of registered data (motion, health, and environment). Because the focus of our paper is user-generated input, we will concentrate on motion tracking and health data (see Table 1). The most common sensors that we have encountered are accelerometer (92%) and HR sensor (92%), followed by gyroscope (67%), compass/magnetometer (46%), pulse oximeter (26%), and skin temperature sensor (18%). Sensing instruments measuring the environment include a microphone, a barometer, an air temperature sensor, and an ambient light sensor. Smartwatches also offer hardware components facilitating communication (Wi-Fi, near field communication (NFC), Bluetooth), mobile network (LTE, UMTS), and localisation (GPS, GLONASS, GALILEO, QZSS, Beidou). Modules for user feedback include a touch screen, a speaker and a vibration motor.

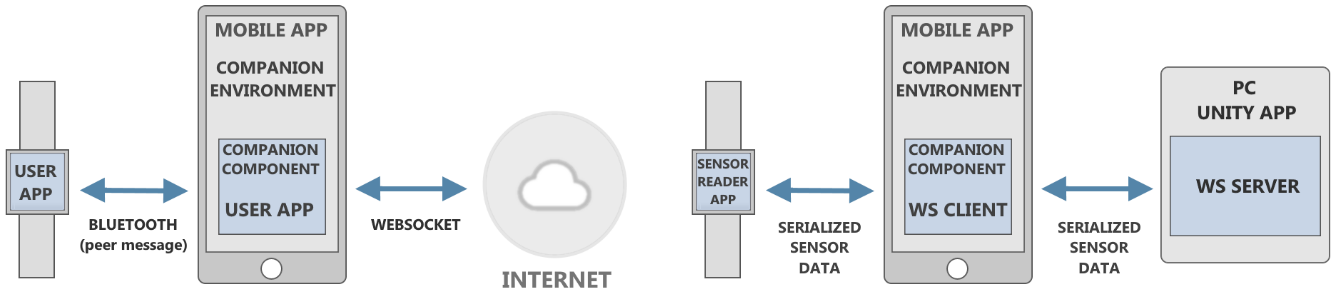
2.2 Sensor Data Acquisition

The built-in sensors provide a fixed set of raw data fields from which further information is computationally derived. A much larger set of aggregated data contains estimations of various parameters such as body battery, stress level, or sleep quality. The available types of the raw data and estimated parameters depend on the device's features.

To allow third party applications access to these data, most smartwatches provide a form of Web API. However, this approach is not suitable for scenarios in which real-time, high frequency readings from sensors are required (e.g., wrist/hand movement tracking, gesture recognition). Although the optimal solution would be to connect directly to the smartwatch via *Bluetooth*, many manufacturers do not provide such a direct link for practical and security-related reasons. Instead, many smartwatches communicate with the "outside world" using a *Companion Model* (shown in Figure 2a) - a framework allowing smartwatch applications to run a companion component on a phone or tablet device (inside a sandboxed runtime environment). The smartwatch side can outsource tasks to more powerful mobile device and later retrieve the result. For example, they utilise a mobile device's internet connection to fetch weather data, and after it has arrived - present it to the user.

Our framework for obtaining and sending raw, real-time data from smartwatch sensors (shown in Figure 2b) to a Unity application makes use of the *Fitbit Companion API*. The main objective is to acquire raw sensor readings from the Fitbit Versa and relay them to the Unity application for further processing and examination. In our system, (1) the smartwatch application obtains batched sensor readings and sends them via companion peer socket to (2) the companion component on a mobile device (*Android*), which relays this data via websocket to (3) the Unity application running on the PC.

The maximum throughput of our prototype system is 8kb per second, allowing us to send data simultaneously from accelerometer (3 floats), gyroscope (3 floats) and orientation readings (4 floats) at the maximum rate of 200Hz (although reading rate is constrained by Fitbit hardware to 100Hz). In order to manage such high frequency sampling and to conserve CPU cycles, the smartwatch app obtains a batched reading four times per second, resulting in 25 consecutive samples per query. Those are send eight times a second to the Unity application.



(a) Companion Distributed Application Model

(b) Our Companion-based Prototype for obtaining real-time sensor data

Figure 2: Companion-based approach used to obtain real-time sensor data.

3 SMARTWATCH DATA FOR VR INTERACTION

To explore how data collected by smartwatches can enrich immersive virtual experiences and which current problems and gaps can be addressed, we explored two use cases. We discuss (1) how motion data can be used for mid-air gesture tracking and touch input for VR menu navigation, and (2) how health data can be used to automatically adapt the VE in order to encourage relaxation and promote lowering of one's HR, and to reflect or counteract the user's predicted mood.

3.1 Use Case One: Smartwatch-Based Gestures for VR Menu Navigation

For the first use case, we analyse how smartwatch-based gestures can improve menu navigation in VR. We discuss both, mid-air and touch-based gestures.

3.1.1 Mid-Air Gestures. Due to the smartwatch's unique position around the wrist close to the user's hand, the motion sensors pick up finger and hand movements. Early studies have shown that collected data from off-the-shelf smartwatches allows the tracking of (1) distinct gestures [42, 45], and (2) real-time tracking of body posture [24] and arm posture [32, 33]. Equipping both wrists with a smartwatch could even allow for tracking gestures of both hands simultaneously, as well as enabling two-hand gestures.

Using smartwatches for gesture and motion tracking in VR bares potential for hands-free interaction, reducing the need for handheld VR controllers. It also offers ergonomic advantages over the visual/camera-based hand tracking, as the users' hands do not have to stay elevated to remain within the camera's field of view (FoV). Using the user's wrist rotation for the interaction in VR has already been explored in the context of a mobile VR game [15], and a smartwatch was tracked in VR for 6-DOF hand movement with additional two cameras and marker detection [16].

In a preliminary experiment, we explored the feasibility of using smartwatch-based gestures for menu navigation and item selection in VR. We found that each gesture was associated with distinct patterns in observed sensor data. The strongest patterns emerged for gestures such as air swipes and wrist flicks (gentle, but brisk left and right rotations). Our initial findings show that even simple, naive approaches were sufficient for accurate gesture recognition, without the need for more resource-demanding methods, such as spectral analysis or machine learning techniques. This is an important finding because less computation usually means better responsiveness, especially when computational power is limited, like on mobile devices.

Since our initial findings showed strong patterns for air swipe and wrist flicks, using them for the menu navigation in VR could be a reliable solution. We imagine that gentle left and right air swipe gestures could be used for browsing through items in a horizontally arranged graphical user interface (GUI) (as shown in Figure 1a), a brisk air swipe to jump to either the first or last menu item, depending on the swipe direction. Due to the rotational movement of wrist flicks, we see their application for navigating circular GUIs, for example rotating them, or charging the currently highlighted item. To select an item within these menus and to confirm the item selection, we imagine using an air or surface tap as gesture.

3.1.2 Touch-based Gestures. Besides mid-air gestures, smartwatches, further, offer touch input for menu navigation, introducing another set of smartwatch-based gestures for VR. By matching the physical smartwatch with it's virtual representation, users can perform familiar touch gestures such as a swipe or a tap on the physical screen. Navigating through the menu is, therefore, augmented with passive haptic feedback.

Such passive haptic feedback has been shown to improve the interaction with two-dimensional GUIs [20]. Further, it would be beneficial to anchor the GUI to the smartwatch, since menus can be thus easily moved in and out of the FoV. [18]. We have also considered using two smartwatches in tandem - placing each smartwatch on one of the user's wrists. This could allow for separate, independent menus, that could be attached to either of the user's hands. Potential use cases could include context-dependent menus.

In particular, we envision three ways of menu navigation using touch input. (1) Two-dimensional buttons could be presented on the virtual smartwatch screen itself, for example for *yes/no*-selections. (2) A two-dimensional GUI extends the space of the screen and by swiping left or right on the screen, the menu is moved. (3) A circular GUI is arranged around the virtual smartwatch and by performing circular motions on the screen, the menu rotates (as shown in Figure 1b). For selecting a menu item, users could tap on the screen, which could further be augmented by vibrotactile feedback. Such subtle vibrations of the smartwatch could also be used to gain users' attention to look at the virtual GUI, for example when a confirmation from the user is required.

3.2 Use Case Two: Health Data for Mental Health in VR

Using digital tools to support health management are on the rise [10, 36] and have become even more pronounced due to the COVID-19 pandemic [7]. Gathering health data from smartwatches can enable a VR system to sense the user's physical and mental state, which offers more objective data than self-reports and more holistic data than current VR controllers and HMDs. This form of implicit input [31] can result in individually-tailored VR experiences.

Thinking about smartwatches and VR, the benefits for physical health immediately come to mind, for example to better track the effectiveness of sportive VR games [44]. However, against the backdrop of COVID-19, it is beneficial to develop ideas to use health data to improve VR mental health management. Although user acceptance of such has been already highlighted [25], concrete use cases of how health data can enrich VR are currently lacking in literature. Thus, we will introduce our ideas on implicit smartwatch input to relax one's HR and to include mood predictions in a VE.

3.2.1 Relaxation of Heart Rate. Many areas within mental health management make use of VR as an affective medium [30], whose immersive VEs can evoke emotional states similar to reality [28]. The two most prominent forms of interventions within this field are exposure therapy in which patients practice coping strategies for various anxieties in a save environment [30], and relaxation practices, in which meditation [8, 27], stress reduction [38, 39, 43], and mindfulness strategies [22, 26] are taught. Both approaches rely on tracking the user's progress through the state of their relaxation, achieved mostly through self-reports or via bio-signal measurements as higher bio-signals are connected to stress and excitement [19] and indicate being highly activated [6]. These are measured mostly in two ways: either by the HMD "listening" to the user's breathing rhythm as performed in many commercially available relaxation games [23, 40] but which is only one entity of relaxation and not a reliable measure, or via cumbersome and costly equipment like headbands, electrodes, and trackers [1, 9].

Using the smartwatch's health data instead could more efficiently track implicit body reactions of the average user, effectively providing objective measurements on the effectiveness of therapeutic interventions. Further, this could also improve the user experience, widening the target group of mental health VR apps. In detail, we imagine that HR and stress level could be visualised and made audible in a VE. As an objective to increase one's relaxation, the surrounding environment could get gradually revealed the more the user's HR synchronises with the target HR (as shown in Figure 1c). Further, objects could pulse and move with the target HR and increase in colour over time.

3.2.2 VE Adjustments based on Mood Prediction. Being able to identify one's feelings is often a cognitively demanding task for patients [17], however, being aware of one's emotions has been shown to improve one's mental well-being [2]. In order to promote emotional awareness through visualisation, technologies such as VR promise to "open up" the user to their emotions more effectively than classical approaches [14] by offering a virtual space for complex performance-based artistic expression [5] and individually designed therapeutic environments [13].

Despite the good preconditions, few VR applications encourage an active altercation with one's feelings: Either users can choose a VE fitting to their own mood (or eliciting a certain emotion [21]) *before* entering a VE, for example by choosing different surroundings or colour-themed "mood worlds" [37], or they are able to manipulate their surrounding *within* a VE, for example by making it rain in NatureTreks VR [12]. Such manipulation is very limited and not yet very common in VR mental health apps. Thus, we see an expandable field for development regarding personal mood integration in VR.

Some related works have shown the feasibility of mood predictions [11]. On the premise that feelings are overlapping complex experiences that can be categorised by a pleasance/valence and an arousal/activation dimension [29], several health data can be used to draw a conclusive picture of one's mood: the higher the HR [6], the higher the physical activity (measured by step counts [4, 19] and accelerometer [11]), the more consistent the movement (sampled by a low variance in the accelerometer's x-coordinate) [6], or a combination of these [11], the higher the self-reported level of pleasance and activation.

Effectively, easily accessible health data gathered by smartwatches can be used to allow for a certain level of automatisation in the process of visualising one's feelings. This is especially beneficial for users struggling to define own emotions, as it can provide an objective representation of one's emotional state which supports self-reflection. As an example, we imagine a VE which, based on mood predictions of the health data, automatically adjusts the light and weather conditions, colours, and movements of animals to visualise one's mood (see Figure 1d). It could then gradually change these entities to improve one's mood, as related works have shown that those have an emotional impact [21].

4 CONCLUSION & FUTURE WORK

Smartwatches as everyday items are worn by more and more people. This paper is a first step to explore the design space of how data gathered by a smartwatch can enrich an immersive virtual experience. We demonstrated how smartwatches (1) facilitate gesture recognition in VR for menu navigation and item selection, using mid-air and touch-based gestures, and (2) provide implicit data about the physical and mental state of a user that can be used to improve a user's relaxation and to automatically adapt a VE to the user's mood. As highlighted by our concrete use cases, incorporating smartwatches into VR offers numerous possibilities for future research.

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