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Methodological advances for the quantification of body movement and concurrently measured brain activity of exergame players

Doctoral thesis

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Metodiske fremskritt for kvantifisering av kroppsbevegelse og samtidig målt hjerneaktivitet ved bruk av exergames

Økt andel eldre i befolkningen kombinert med en prognostisert nedgang i antall helsepersonell nødvendiggjør økt bruk og utvikling av teknologiske løsninger for å begrense funksjonssvikt hos eldre mennesker. Exergames har vist seg å ha stort potensiale både som generell trening og etter en sykdom eller skade for å forbedre både fysisk og kognitiv funksjon. Imidlertid har det vært lite oppmerksomhet rundt spesifikasjoner om bevegelser og hjerneaktivitet som fremkalles under exergaming, hvordan disse påvirkes av exergame innstillinger og ikke minst, hvordan man samtidig måler og behandler bevegelse og hjerneaktivitet. Målet med denne avhandlingen er å bidra til utvikling av exergames som et verktøy for trening og rehabilitering ved å undersøke effekten av spillinnstillinger på bevegelsesegenskaper og kortikal aktivitet, og bevegelsesoppgave på automatisert EEG-artifakt forbehandling.

Resultatene viser at spillinnstillinger i exergames påvirker både hjerneaktivitet og bevegelsesmønster hos spilleren, og dette kan enten være positivt eller negativt for de ønskede treningseffektene. Derfor er det nødvendig å velge exergames med innstillinger som passer best for en spiller for å sikre maksimal effektivitet av et exergame. Videre er samtidig måling av kortikal aktivitet under exergaming mulig, til tross for tilstedeværelsen av bevegelsesartifakter. Rengjøring av EEG med artifact subspace reconstruction var best i den mest bevegelsesintensive oppgaven, noe som indikerte anvendbarheten for bruken i EEG samlet under exergaming. Disse resultatene baner vei for framtidig utvikling og bruk av avanserte EEG målinger som muliggjør analyse av kortikal aktivitet også i bevegelsesintensive exergames. Den resulterende kunnskapen kan bidra til fortsatt utvikling av mer målrettede og effektive exergames og gjøre det mulig for fremtidige studier å undersøke bevegelseskarakteristikker og hjerneaktivitet samtidig.

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Ovennevnte avhandling er funnet verdig til å forsvares offentlig for graded PhD i medisinsk teknologi.

Abstract

The aging population and a projected decline in the number of healthcare personnel necessitate the development and increased use of health technology to halt or delay functional decline in older adults connected to aging. Exergames in particular show great promise in both exercise and clinical contexts to train and improve both physical and cognitive function. However, there has been little attention to the specifics of movements and brain activity elicited during exergaming, how these are influenced by exergame settings and not in the least, how to concurrently measure and process movement and brain activity. The aim of this dissertation is to contribute to the development of exergames as a tool for training and rehabilitation by investigating the effect of game settings on movement characteristics and cortical activity, and of movement task on automated EEG cleaning performance.

Paper I investigated how two key game elements, game speed and the presence of obstacles, influence movement characteristics in 15 older adults playing a step-based balance training exergame. The task consisted of moving sideways to catch falling grapes and to avoid obstacles (falling branches), if present. Occasionally appearing chickens were caught by raising at least one arm over the head. Participants played the game for eight 2 min trials in total, at two speed settings and with or without obstacles. The 3D position of 22 retroreflective markers fixed to anatomical landmarks was captured using a motion capturing system. Calculated movement characteristics included step size, step frequency, single leg support, arm lift frequency, and horizontal trunk displacement. An increase in game speed resulted in a decrease in mean single support time, step size, and arm lift frequency, and an increase in cadence, game score, and number of error messages. The presence of obstacles resulted in a decrease in single support ratio, step size, cadence, frequency of arm lifts, and game score. Furthermore, an increase in step size from the first to the second trial repetition was observed. These results show that both game speed and the presence of obstacles altered movement characteristics with some changes considered beneficial and others detrimental

for the effectiveness of balance training.

Paper II aimed to assess whether concurrent electrophysiological measurements during exergaming are feasible and if so, whether cortical activity changes with additional cognitive elements. Twenty-four young adults first performed self-paced sideways leaning movements, directly followed by two blocks of exergames in which the same movement as input was used. The task of the exergame was to complete a 5 by 5 puzzle matrix. Puzzle pieces were selected by leaning towards them. The exergames were played in two difficulty levels. At the easy level, only the correct piece was shown, while two pieces were presented for the more difficult level. Brain activity was recorded using a 64-channel passive EEG system. Results showed that it is feasible to record brain activity in young adults while playing exergames. Five spatially different clusters of independent components were identified located frontal, bilateral central, and bilateral parietal. Significantly higher absolute theta power in the more difficult exergaming condition was found compared to the easy level and the self-paced movement. Both central clusters showed a significant increase in absolute alpha-2 power in the exergaming conditions compared to the self-paced movements.

In Paper III, the effect of task on the EEG artifact removal abilities of artifact subspace reconstruction was assessed. Using state-of-the art preprocessing algorithms is a precondition for artifact contaminated EEG recorded during more movement intensive exergames. However, the effect of the task on artifact subspace reconstruction has not yet been assessed. EEG recorded during three tasks was preprocessed manually and by the use of artifact subspace reconstruction using 10 cut-off parameters, which can determine the rigor of the artifact reconstruction. The mean cut-off parameter equivalent to the ratio of EEG removed in manual cleaning was strictest for the walking task. Quality indexes of independent components which give information about the repeatability of independent component decompositions were best for the walking and worst for the single-leg stance task across all cut-off parameters. Furthermore, quality indexes of independent components reached a maximum plateau for cut-off parameters of 10 and higher. Dipolarity was largely unaffected by the choice of the cut-off parameter. The number of independent components within each task remained constant, regardless of the cut-off parameter used. Surprisingly, ASR performed better in motor tasks compared to non-movement tasks. Furthermore, there was no benefit of using cut-off parameters less than 10.

The combined results of these papers show that game settings in exergames influence both brain activity and movement characteristics of the players, and this can be either beneficial or detrimental to the desired training effects.

Therefore, an informed approach is needed in order to achieve the intended benefit and effectiveness when choosing specific game settings in an exergame. Furthermore, simultaneous measurement of cortical activity while exergaming is possible, despite the presence of movement artifacts. The cleaning performance of artifact subspace reconstruction was best in the most movement intensive task, indicating its applicability for use in EEG collected during exergaming. This result paves the way for continued development of state-of-the-art EEG preprocessing algorithms that enable analysis of cortical activity also in movement intensive exergames, thereby allowing concurrent analysis of brain activity in specific areas during playing.

The resulting knowledge from all three papers can contribute to the continued development of more targeted and effective exergames and enable future studies to investigate movement characteristics and brain activity concurrently.

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Lastly, I would like to thank my friends and family, in particular my brothers Simon and David and my parents Frigg and Oskar for supporting me throughout my entire education.

[1]Knopfler et al., 1985

“All work and no play makes Jack a dull boy.”

– James Howell, *Proverbs in English, Italian, French and Spanish*

Contents

List of Publications

This thesis is based on the following peer-reviewed journal publications. The papers are open access and published by the international scientific journals listed below.

Paper I: Movement characteristics during exergaming

Anders, P., Bengtson, E. I., Grønvik, K. B., Skjæret-Maroni, N., and Vereijken, B. (2020a). Balance training in older adults using exergames: Game speed and cognitive elements affect how seniors play. *Frontiers in Sports and Active Living*, 2:54

https://doi.org/10.3389/fspor.2020.00054

Paper II: Brain activity during exergaming

Anders, P., Lehmann, T., Müller, H., Grønvik, K. B., Skjæret-Maroni, N., Baumeister, J., and Vereijken, B. (2018). Exergames inherently contain cognitive elements as indicated by cortical processing. *Frontiers in Behavioral Neuroscience*, 12:102

https://doi.org/10.3389/fnbeh.2018.00102

Paper III: Assessment of an EEG artifact cleaning algorithm

Anders, P., Müller, H., Skjæret-Maroni, N., Vereijken, B., and Baumeister, J. (2020b). The influence of motor tasks and cut-off parameter selection on artifact subspace reconstruction in eeg recordings. *Medical & Biological Engineering & Computing*, 58:2673–2683

https://doi.org/10.1007/s11517-020-02252-3

Abbreviations

Ag / AgCl electrode silver / silver chloride electrode

API application programming interface

ASR artifact subspace reconstruction

BCI brain-computer interface

BSS blind source separation

ECG electrocardiogram

EEG electroencephalogram

EMG electromyogram

EOG electro-oculogram

ERP event-related potential

fIC functional independent component

fMRI functional magnetic resonance imaging

fNIRS functional near-infrared spectroscopy

IC independent component

ICA independent component analysis

IMU inertial measurement unit

MEG magnetoencephalography

MoBI mobile brain and body imaging

PC principal component

PCA principal component analysis

RGB-D camera color and depth camera

SNR signal-to-noise ratio

List of Figures

Attributions

Figure 1.1:	*Wii-console* by *Evan_Amos*	🅭🄍
	Xbox-One-Kinect by *Evan_Amos*	🅭🄍
	Sony-PlayStation-Move-Controller by *Evan_Amos*	🅭🄍
	EyeToy_camera_1 by *Dave Pape*, remix	🅭🅯🄎
Figure 2.2 (a):	*Live Eikenes og Per Arvid Steen med PET MR-maskina* by *Geir Mogen / NTNU*	🅭🅯🄏
Figure 2.2 (b):	*Blonde fNIRS lady* by *Elisenicolegray*	🅭🅯🄎
Figure 2.3 (a):	*NIMH MEG* by *Unknown NIMH author*, edited	🅭🄍
Other figures:	are own creations, owned by the EXACT project group or screenshots of exergames made by SilverfitBV (Woerden, NL).	

List of Tables

1 Introduction

Ættestup is the name given to several precipices in Scandinavia that served as ritual sites for senicides, according to Norse mythology[1]. People who were not able to support themselves anymore either jumped down a cliff or were forced to jump to their deaths. Although this practice is phased out in elderly care in Norway, the basic principle of having a good health and high levels of physical and mental functioning until the end of one's life is still a desirable goal. One key factor for a long and healthy life with high levels of functioning is physical activity (and of course, not falling from cliffs).

The challenges connected to an aging population are manifold and highly personal. Aging is accompanied by increased risk for diseases, chronic conditions, and functional decline. The number of people aged 60 years or older outnumbers children under five years, according to the world report on aging and health issued by the World Health Organization (2015). There is a need for a (cost-) effective method for the prevention of functional decline due to a sedentary lifestyle in order to relieve strains from the health sector.

Besides the functional decline connected to aging, older people are generally also more likely to encounter falls. Falls in older adults are among the main causes for hospitalization and institutionalization (Kannus et al., 2005) and significantly impact the cost burden on health care budgets worldwide (Heinrich et al., 2010). Both actual falls and fear of falling are associated with reduced activity (Hornyak et al., 2013; Yardley and Smith, 2002), which in turn increases the risk for developing chronic diseases.

[1]Gautreks saga: https://digitalt.uib.no/handle/1956.2/2887 — it is debated among scholars if senicides really happened. However, the answer to this question is out of the scope of this thesis.

1.1 From ættestup to exergaming

Developments in computer and sensor technology since the age of the Vikings led to new possibilities of aiding humans to maintain an active lifestyle and can thereby help to counteract the negative effects of aging. In our daily life, we are surrounded by sensor technology and computers such as those applied in smartwatches and mobile phones that track our health status and enable us to compete and connect digitally with other people through fitness apps.

In recent years, computer games that require bodily movements as inputs gained popularity in the consumer market. However, this is not a new concept. Already in the late 1970s and 80s, some arcade games required dance moves or similar bodily movements for playing a game. The modern terminology for those games is exergames[2]. Besides for entertainment, exergames can be used for serious purposes, such as rehabilitation after injuries or as a preventative measure for age-related decline in functioning.

1.2 Why exergames?

The main advantage of exergames is that even repetitive and otherwise boring tasks can become a fun activity if they are incorporated in a challenge, competition, or game. This concept is called gamification (Hamari et al., 2014). Gamification is the application of game-design elements, such as points and competition to tasks typically not associated with the term gaming.

Furthermore, exergames offer the possibility to add a cognitive element to a training task, potentially creating a dual task situation (Caetano et al., 2016, 2018; Schoene et al., 2011; Smith et al., 2011) which were shown to be beneficial for balance training (Zijlstra et al., 2008).

Exergames usually include a method for detecting the users' movements such as force sensitive mats or color and depth cameras (RGB-D cameras). Popular examples from the consumer market include Sony's EyeToy camera and Move controller, Nintendo's Wii fit and Wii Fit balance board, as well as Microsoft's Kinect, shown in Figure 1.1. Especially the two latter products in particular became popular among regular users, as well as researchers. The popularity among researchers was mostly due to the availability and ease of use of the systems, when used with the original software. Another important factor contributing to their popularity was an open and well-documented application

[2]As usual researchers are arguing about exact definitions for those games. In this thesis all games using bodily motions as an input will be referred to as exergames.

programming interface (API), as well as an active community support among researchers and people who like to "hack" technology. Those factors have enabled researchers to use the hardware for their own exergame creations.

Exergames have gained popularity both as a complementary tool or as a replacement for traditional exercise and rehabilitation (e.g. Mellecker et al., 2013), with the same or better effectiveness compared to usual care (Skjæret et al., 2016). In addition, exergames have been shown to have positive effects on physical activity in general (e.g. Fang et al., 2019; Höchsmann et al., 2016; Rhodes et al., 2017), as well as in specific rehabilitation settings (e.g. Baltaci et al., 2013; Laver et al., 2012).

Adherence to a prescribed training is potentially higher in exergaming interventions compared to traditional exercises (Skjæret et al., 2016). Furthermore, exergames are a cost-effective way to administer balance training (Stanmore et al., 2019).

Figure 1.1: *Common Christmas presents for researchers and kids alike during the 2000s (Nintendo Wii and balance board, left; Microsoft Kinect v2, top right; and Sony Move and EyeToy, bottom right).*

1.3 Are exergames just a toy?

The majority of commercially available exergames are designed for entertainment purposes and generally with a younger audience in mind. Even though exergames that are designed solely for entertainment purposes might require movements beneficial for training and rehabilitation purposes, a specifically designed exergame for this use case would presumably show even more advantages for the player. Exergames designed with a health purpose in mind are often marketed as wellness or fitness games, since those terms are not regulated in the EU's medical device directive (Directive 2001/83/EC, 2017). By avoiding terms like medical or rehabilitation in the title or description of an app or an exergame, no proof of their effectiveness is needed. However, this makes it more difficult to use exergames as a form of prescribed training or in rehabilitation, since they are not recognized as a form of treatment, but as a leisure activity instead. How can we move from using exergames as a toy to their implementation in practice and what methodological knowledge is needed to develop more targeted exergames for the use in training and rehabilitation?

1.3.1 Movement characteristics and the effect of exergame settings

Although exergames are increasingly used as a training or rehabilitation tool (e.g. Fang et al., 2019), the evidence about their effectiveness is inconsistent (Skjæret et al., 2016). One potential reason could be that we know very little about the actual movements performed by seniors while playing an exergame. This makes it difficult to properly interpret the effects, or the lack thereof, of exergame interventions. For example, it is common to adjust game settings such as game speed or to add cognitive elements (Van Diest et al., 2013) to keep the exergame player engaged. Changes to the game speed are often used to adjust the difficulty level of an exergame to the player's physical abilities, whereas adding cognitive elements can create dual task situations for e.g. balance training. However, the effect of these adjustments on movement characteristics is yet to be studied, so we do not know whether they are beneficial or detrimental for the intended rehabilitation or training purpose. This knowledge is crucial for the development of exergames that can be expected to be effective in rehabilitation and for maintaining physical functioning.

1.3.2 Cognitive functions and cortical activity in exergames

Besides providing physical training, exergames have the potential to train older adults' cognitive abilities through dual tasks, decision making tasks and discrimination tasks (Anguera et al., 2013; Zelinski and Reyes, 2009). It has been shown that there are synergistic benefits for the training outcome if physical activities are paired with decision-making opportunities compared to separate physical or cognitive interventions (Anderson-Hanley et al., 2012; Basak et al., 2008; Kraft, 2012; Yan and Zhou, 2009). However, most studies used cognitive tests or pre- and post-measurement designs instead of direct measurements of cortical activity during exergaming, since concurrent measurement of cortical activity during tasks that include vigorous movement was not possible until recently. Direct measurement of cortical activity during movements as already suggested in Makeig et al. (2009) is still in its infancy due to the difficulties connected to the low signal-to-noise ratio (SNR) of the electroencephalogram (EEG) recordings and the higher likelihood for the occurrence of motion artifacts. Only Baumeister et al. (2010) directly assessed brain activity during exergaming in a virtual golf-putting environment using EEG. Their EEG results revealed increased frontal theta power and decreased parietal alpha-2 power during virtual golf-putting compared to a resting period. An increase in frontal theta power indicated higher focused attention, whereas a decrease in alpha-2 power is linked to the quantity of sensory information processing.

Previous evidence (Baumeister et al., 2010; Eggenberger et al., 2016) suggests that the presence of cognitive elements in exergames affects cortical activation and suggests changes in cognitive control during and after game play. However, there is still sparse knowledge regarding cortical processing during exergaming. One of the reasons for this might be the time-consuming manual cleaning of highly contaminated EEG for which high level of EEG-expertise is needed. Automating the artifact removal process would be an important step forward to enable more research in this field.

1.4 Rationale for this thesis

Exergames seem to be a promising tool to increase physical activity in older adults in general, as well as in specific training tasks such as e.g. balance training for fall prevention. Previously, exergames have been shown to increase adherence and enjoyment of training and rehabilitation interventions in older adults (Skjæret et al., 2016).

However, the lack of knowledge about the interaction of exergame settings, movements and cortical activity in older adults makes it difficult to develop and further improve targeted and effective exergames. The aim of this dissertation is to contribute to the development of exergames as a tool for training and rehabilitation by investigating the effect of game settings on movement characteristics and cortical activity, and of movement task on automated EEG cleaning performance. This thesis contributes to this endeavor by answering whether changing the settings of an exergame, such as game speed and the presence of additional obstacles to avoid, alter movement characteristics and cortical activity in players. Thereby, future development of exergames can be based on empirical evidence and users of exergames can make more informed desicions when choosing a game for training or rehabilitation, to ensure maximum benifit for the player.

In an ideal world, cortical activity and movement characteristics would be recorded concurrently and assessed as a whole. Makeig et al. (2009) introduced the concept of mobile brain and body imaging (MoBI) in which bodily movements and cortical activity are recorded simultaneously. However, the concurrent recording of EEG during movements is challenging, due to the low SNR. Advances in our knowledge about and a better understanding of the technology used to filter noise and artifacts are needed in order to enable future research to apply the concept of MoBI. The papers this thesis is based on serve as stepping stones towards such future projects, with insights into the movement characteristics of older adults and cortical activity during exergaming (Paper I and II), and an assessment of a state-of-the-art automatic EEG artifact removal tool for tasks involving bodily movements (Paper III). In addition, the thesis presents a combined discussion of the results obtained throughout the projects and the lessons learned during this journey.

1.4.1 Paper I: Movement characteristics during exergaming

One major gap in our knowledge is that until now, only a few studies have focused on the movements of older adults during exergaming. In addition, no study has focused on the influence of obstacles and game speed, both commonly used to adjust the difficulty level of an exergame on elicited movement characteristics.

Therefore, the main aim of Paper I was to assess the changes in movement characteristics in older adults induced by variations in game speed and the presence of additional obstacles to avoid in a side-stepping exergame.

1.4.2 Paper II: Brain activity during exergaming

The cognitive involvement during exergaming is largely unknown. Until recently, the collection of usable EEG data recorded concurrently while performing a movement task was out of the scope of possibilities. However, with relatively recent developments in both software and hardware, the concurrent measurement of brain activity during exergaming might be within reach.

The main aim of Paper II was to assess the feasibility of concurrent EEG measurements during exergaming and to assess changes in cortical activity caused by additional cognitive tasks during a weight shifting exergame played in two difficulty levels.

1.4.3 Paper III: Assessment of an automatic EEG artifact cleaning algorithm

Recent developments in EEG processing that originated in the field of brain-computer interfaces (BCIs) led to the possibility for automatic processing of large amounts of EEG data that is contaminated with artifacts, such as in high-density movement EEG datasets. Artifact subspace reconstruction (ASR) is one promising example for such an algorithm, especially as a preprocessing step for analyses in source-space. It is commonly used for processing EEG. However, the only assessment of the artifact removal performance of ASR was based on an EEG dataset recorded during a simulated driving task (Chang et al., 2019). Compared to a simulated driving task, higher levels of artifact contamination can be expected during exergaming due to more vigorous movements. Testing such potential effects of the task on the artifact removal performance is therefore necessary for the use of ASR in a processing pipeline for EEG recorded during actual movement tasks.

The main aim of Paper III was to assess the quality and reproducibility of independent components (ICs) derived from EEG data that was preprocessed using ASR. The dataset consisted of continuous EEG collected during three tasks with different likelihood for causing movement artifacts.

Background 2

This chapter is intended to aid readers who are new to the field of movement- or neuroscience. Basic concepts of motion capture techniques, as well as the basics of EEG including the necessary signal processing steps and independent component analysis will be explained. Readers familiar with those topics may continue with chapter 3.

2.1 3D motion capture technology

Capturing the movements of a person or object in three-dimensional space is called 3D motion capture. A non-exhaustive list of possible methods for capturing movement data is presented in the following sections. Some methods presented rely on equipment worn by the user or participant. Those require, in general, more preparation time but deliver more precise results, resulting in a trade-off between measurement precision and preparation time.

2.1.1 Marker-based systems

If a point in 3D space is recorded by at least two cameras simultaneously placed at known positions in relation to each other, the point's position can be calculated. Commercial systems for 3D motion capture used in research and the movie industry use infrared light emitters and reflective markers or active markers with infrared LEDs placed on points of interest. This ensures easier recording of marker positions during daylight conditions. These systems usually consist of upwards of eight cameras to avoid marker concealment.

In studies involving human participants, reflective markers are usually placed on well-defined anatomical landmarks to track their position throughout an experiment. If more than one marker is used, then post processing might be necessary in order to ensure proper recognition of the markers by the software.

2.1.2 Markerless systems

Placing markers on the participant's body is tedious and requires skilled experts in anatomy. For applications which do not require highly precise measurements, other methods of collecting movement data may offer more benefits.

Camera-based systems

Cameras that record video images and depth simultaneously, so called RGB-D cameras, can be used to record point-cloud data of an object or a person. Algorithms can be used to calculate the position data of joints in a human body, based on the recorded point-cloud data. Infrared light is commonly used for depth measurement.

The commonly used Microsoft Kinect v2 (Microsoft, Redmond, WA) combines a video camera with a depth sensor using infrared light. It compares the recorded point-cloud data with a built-in proprietary database of known human poses, in order to generate a model of joint positions. The joint positions can be sent to a computer and used as an input for e.g. an exergame. An example of point-cloud data and skeleton joints can be seen in Figure 2.1.

Similar to the techniques described above, normal video data from multiple cameras can be used to reconstruct a 3D representation of objects using artificial intelligence or advanced algorithms vision to interpret the visual input. This became possible after major advances in the fields of computer vision and parallel computing.

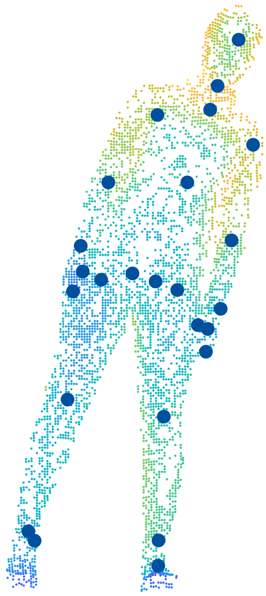


Figure 2.1: *Point-cloud data (smaller dots) and skeleton joints (larger blue dots) recorded using a Microsoft Kinect v2 during Study II.*

Inertial measurement units

A different approach for measuring the position of an object in 3D space is the application of three accelerometers perpendicular to each other. Data recorded using these accelerometers can be used to calculate changes in the position by numerically integrating the output signal twice. However, the double integration of the measured acceleration results in the displacement from the starting position plus a quadratic growing and accumulating error term caused by offsets, non-linearities and noise. In order to compensate for drift in the output signal, accelerometers are oftentimes combined with gyroscopes and magnetometers in so-called inertial measurement units (IMUs). In order to get a more robust estimation of the position of the sensor, IMUs use the information from the additional sensors to correct the accumulating error in the measurement.

IMUs are commonly used in mobile phones and smartwatches. The sensors are cheap and widely available as hardware development kits such as Arduino breakout boards, which makes them especially suited for rapid prototyping of e.g. gamified objects.

2.2 Cortical activity

Besides breathing and heartbeat, brain activity is what keeps us alive, literally and legally[1]. However, measuring the latter comes with unique challenges which will be explained in the following sections.

2.2.1 Overview of measurement techniques for cortical activity

In this section a selection of methods for the recording of brain activity will be presented and compared in terms of applicability for MoBI.

Methods using the brain's metabolism

Metabolism in the brain can be used as a proxy for measuring cortical processes. A consequence of higher metabolism is increased blood flow, which can be measured using functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS).

In fMRI strong magnetic fields are used to induce spin in hydrogen atoms. The spin can be detected by sensitive radio antennas. This gives information about the structure and type of tissue in a body. The hemodynamic response can be measured in fMRI using blood-oxygen-level-dependent imaging (Chou, 2008). Specially shielded facilities, usually in a hospital, are needed to record the radio frequencies emitted by the spinning hydrogen atoms. FMRI offers comparably good spatial but low temporal precision. However, fMRI is not suited for MoBI applications, since the machines are neither wearable, nor portable as shown in Figure 2.2 (a).

Similar to fMRI, fNIRS measures the haemodynamic response as a proxy for cortical activity. The measuring mechanism behind an fNIRS system is the same as in pulse oximetry. Infrared light of different wavelengths in the spectral interval between 700 and 900 nm is emitted by a light source and subsequently recorded by optodes[2] placed in an array on the scalp or on the forehead. Due to the optical characteristics of skin and bone tissue, infrared light passes through those layers until it reaches the haemoglobin in the blood vessels. The light absorption properties of oxygen saturated and unsaturated

[1]Norwegian law regarding the determination of death: *Forskrift om dødsdefinisjon ved donasjon av organer, celler og vev, § 2. Stadfesting av døden:* https://lovdata.no/forskrift/2015-12-21-1813/§2

[2]"electrode" for light

haemoglobin are different from each other and further depended on the wavelength. At 810 nm oxygenated and non-oxygenated haemoglobin have the same absorption properties. The relative concentration of oxygenated haemoglobin can therefore be calculated using a modified version of Lambert-Beer's law (Beer and Beer, 1852; Bouguer, 1922; Lambert, 1892). This results in measurements with high spatial, but low temporal precision compared to methods using the brain's electrical activity. FNIRS systems are easy to use, light and portable. This makes them usable for MoBI applications as shown in Figure 2.2 (b).

(a) (b)

Figure 2.2: *Methods for measuring brain activity using blood flow (a) functional magnetic resonance imaging and (b) functional near-infrared spectroscopy.*

Methods using electrical activity

Synchronized activity of neurons can be measured using their magnetic field or the voltage differences measured between two scalp sites.

Synchronized neural currents induce weak magnetic fields. In magnetoencephalography (MEG) an array of highly sensitive magnetometers, sensitive enough to measure the changes in the magnetic field, is used in a scanner as shown in Figure 2.3 (a). MEG scanners are large and require shielding against magnetic interferences, similar to the measures used in fMRI. This prohibits the recording of moving participants.

The remaining chapter will focus on EEG and the challenges connected to the recording of usable data during participant movements. The aforementioned measurement methods all come with distinct advantages and disadvantages.

However, for the measurement of brain activity during movements only fNIRS and EEG are suitable. The remaining section will focus on EEG, since this method for acquiring cortical activity was used in Studies II and III.

(a) (b)

Figure 2.3: *Methods for measuring brain activity using electrical activity (a) magnetoencephalography and (b) electroencephalogram.*

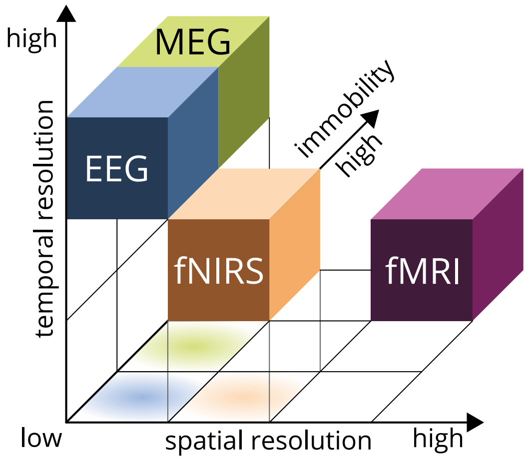


Figure 2.4: *Comparison of the temporal and spatial resolution, and mobility of systems for measuring cortical activity. Adapted from Mehta and Parasuraman (2013).*

2.2.2 Electroencephalogram

An EEG records electrical activity of neurons measured invasively by inserting electrodes through the skull or non-invasively by measuring differential voltages between two electrodes placed on the scalp (Berger, 1929). Surface EEG amplitudes have more than 90 % of its energy content between 1 and 30 Hz, and typically range between 10 and 100 μV (Thompson et al., 2008). The electrical activity is caused by excitatory and inhibitory postsynaptic potentials in apical dendrites of neurons. EEG activity is mainly generated by pyramidal cell postsynaptic potentials, shown in Figure 2.5. Only synchronized activity due to interaction between the cerebral cortex and thalamus can be recorded (Sazgar and Young, 2019).

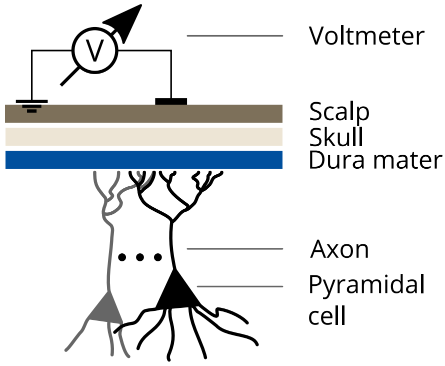


Figure 2.5: *Anatomy of dendrites, skin and bone layers of the head, and a simplified measurement setup for electroencephalogram.*

In contrast to other methods such as fMRI and fNIRS, EEG has higher temporal, but lower spatial resolution, as shown in Figure 2.4. Furthermore, EEG systems are mobile and can therefore potentially be used for capturing brain activity during body movements. Electrodes are usually placed using the international 10-20 system as shown in Figure 2.6.

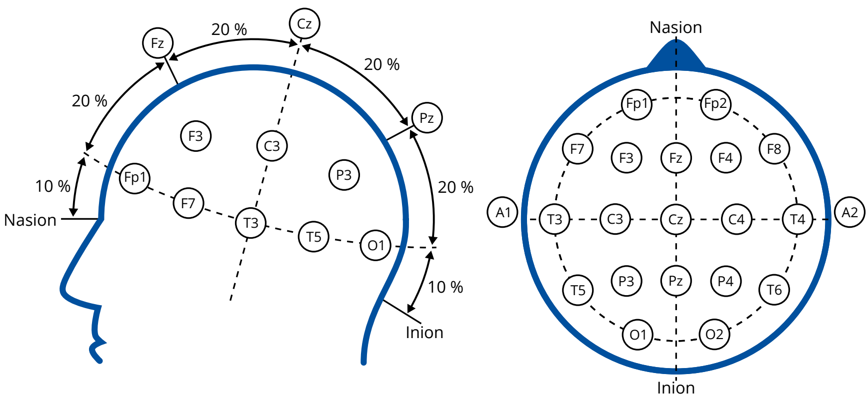


Figure 2.6: *Electroencephalogram electrode placement according to the international 10-20 system.*

The recorded electrical activity from the scalp can be divided into four main frequency bands as shown in Figure 2.7. Increased or decreased activity in certain frequency bands can be used to diagnose certain diseases by clinicians.

The mathematical description of an EEG signal can be seen in Equation 2.1. The measured EEG on the surface of the scalp is a product of the source activity S and a mixing matrix A plus an error term η to account for all types of artifacts, noise and measurement imperfections.

$$X = A\,S + \eta \tag{2.1}$$

2.2.3 Artifacts

Differential voltages measured on the surface of the scalp using an EEG system are a mixture of brainwaves, and biological and non-biological noise, as shown in Figure 2.7. Regardless of their origin, noise and artifacts need to be removed from the signal in order to analyze brain activity. The likelihood for the occurrence of some types of artifacts can be omitted by instructing the participants to avoid certain behaviors, such as sudden movements or the tensing of facial muscles. Other types of artifacts are unavoidable, either because they are necessary to maintain homeostasis of the participants (e.g. heartbeat) or unavoidable due to the research question (e.g. movement task).

Biological sources of noise and artifacts

There are three prominent biological sources of noise that originate from bodily functions.

The first source is the electrical activity of skeletal muscles, measured as electromyogram (EMG). In traditional EEG research movements of the participants, and thereby EMG activity, is restricted to a minimum to avoid contamination of the EEG signal (Gwin et al., 2011).

The second source is the orientation of the eyes and their movement measured as electro-oculogram (EOG). An EOG measures the corneo-retinal standing potential between the cornea and foveal sclera. Eye movements and blinks induce electrical changes that can be measured, in the case of EEG as unwanted artifacts. Participants in an EEG study can be instructed to reduce the number of eye blinks and to minimize eye movements if the research question permits this.

The third source is the electrical activity of heart muscle, which is measured using an electrocardiogram (ECG). For obvious reasons heartbeat can not be avoided.

Non-biological sources of noise and artifacts

Non-biological sources of noise and artifacts are caused by imperfections in the measurement chain. Neither amplifiers nor electrodes are perfect. The risk of occurrence of unwanted signals due to technical reasons can be mitigated with careful preparation of the study participant. Common examples are impedance changes of electrodes or electrical line noise. In traditional EEG experiments, minimal behavior models are used to reduce the likelihood for artifacts caused by movements. The use of active EEG electrodes that perform an impedance conversion at the measurement site can help to reduce the likelihood for artifacts and noise.

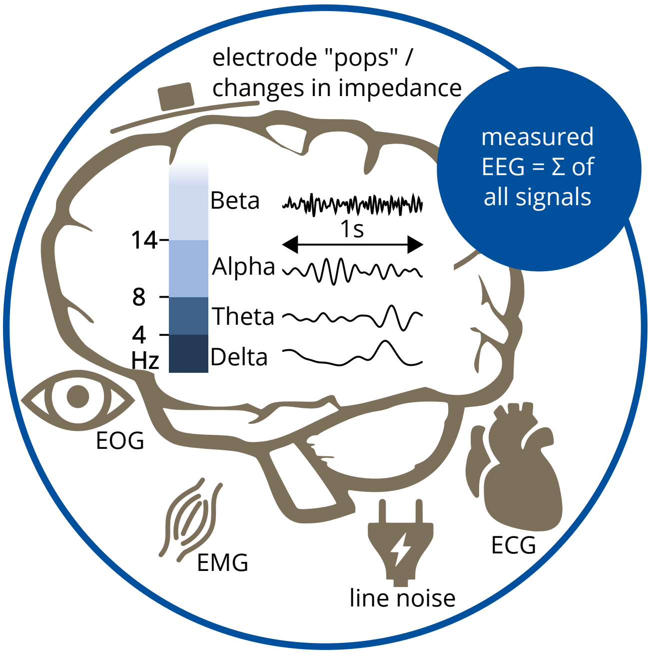


Figure 2.7: *Frequency bands of brain activity and common sources of electrical noise and artifacts. EOG: electrooculogram, EMG: electromyogram, ECG: electrocardiogram.*

2.2.4 Preprocessing

It is necessary to remove unwanted noise and artifacts from EEG in order to proceed with further analysis steps. Preprocessing or cleaning steps usually include the removal of line noise, band-limitation and down sampling. Cleaning is always a compromise between removing the unwanted parts and keeping what is important. One would never wash a *marius genser*[3] using bleach, but only gentle soap. Similarly, when cleaning EEG data, a compromise between noise and artifact removal and conservation of the brain signal needs to be found. Examples of EEG data in various preprocessing stages acquired during Study II are shown in Figure 2.10 (A) — (C).

Band limitation

Frequencies of interest in EEG recordings are usually on the lower end of the spectrum and generally below the frequency range of muscle activity. This can be used as an advantage for EEG data processing, since the part of the signal that represents an EMG can be excluded using a low-pass filter. Band limited and re-referenced EEG data is shown Figure 2.10 (A).

Manual cleaning of artifacts

Artifacts in otherwise relatively clean EEG can be removed manually by excluding time series contaminated with biological and non-biological artifacts. This results in a loss of data, with the remaining signal not being affected by this method of cleaning. Manual removal of artifacts has been the gold standard for many decades. However, with more powerful hardware, computationally expensive and complex algorithms may clean EEG equally well or even better than a human can do while being faster and lossless at the same time. Manually cleaned EEG data is shown in Figure 2.10 (B). The vertical red lines in the EEG time series are a result of removed data in between.

Channel rejection

If a channel of an EEG recording is contaminated with noise throughout the measurement setup, it is sometimes unavoidable to remove it completely before conducting further analyses. Excessive noise in a single channel can be caused by high impedance between skin and electrode or excessive EMG contamination.

2.2.5 Blind source separation and their application for EEG preprocessing

If an observation is a linear and stationary mix of more than one unknown independent source signals, blind source separation (BSS) can be used to recover original components of the signal.

[3] Traditional Norwegian woolen sweater

Principal component analysis

Principal component analysis (PCA) is a decorrelation technique that ensures maximum uncorrelation between output pairs ($\langle u_i u_j \rangle = 0$, for all $i,\ j$). By rotation of the coordinate system, the geometrical distance to each data point on the plane is minimized. The origin of the coordinate system is also adjusted in a way that the distance to each point is at a minimum. A PCA is well suited for Gaussian noise separation. As a consequence, the standard deviation of the resulting principal component (PC) in the new coordinate system is lower than in the original. PC are the highest energy components in the data set. Furthermore, PCA can be helpful for detecting outliers, since the lower standard deviation in the new coordinate system makes it easier to detect outliers.

Independent component analysis

Independent component analysis (ICA; Bell and Sejnowski, 1995; Hyvärinen and Oja, 2000; Makeig et al., 1996) is a signal processing method to separate independent sources that are linear mixed and recorded using several sensors. Using an ICA, a multivariate signal X recorded using m sensors and of the duration T (see Equation 2.2) can be decomposed into n independent signals S (see Equation 2.3) using an unmixing matrix.

$$X = (x_1(t),\ ...,\ x_m(t))^T \tag{2.2}$$

$$S = (s_1(t),\ ...,\ s_n(t))^T \tag{2.3}$$

The original independent non-Gaussian signals $S \in \mathbb{R}^{K \times T}$ are mixed using a mixing matrix $A \in \mathbb{R}^{M \times K}$, before they can be recorded as $X \in \mathbb{R}^{M \times T}$ shown in Equation 2.4. M denotes the number of sensors used, K denotes the number of individual sources and T stands for the time. Contrary to Equation 2.1, there is no additional noise or error term η. For ICA decomposition, noise and artifacts are considered non-brain sources of activity and can therefore be found in the matrix S.

$$X = A\,S \tag{2.4}$$

Under the precondition that the mixing is stationary, an unmixing matrix can be determined. The unmixing matrix W in Equation 2.5 is used to transform X to S using Equation 2.6. However, A is unknown and can not be measured.

Therefore, e.g. a gradient descent function to maximize kurtosis can be used to approximate W.

$$W = A^{-1} \tag{2.5}$$

$$S = W\ X \tag{2.6}$$

In contrast to a band-pass filter or a Fourier transformation, an ICA can be used to isolate in-band noise, such as EMG (Brown, 2000). The number of discovered independent sources is limited by the number of sensors used. Furthermore, it is important to use a relatively clean EEG signal as input for an ICA, since noise and artifacts manifest in the matrix S as sources of activity because they are usually of higher amplitudes compared to EEG. By removing as much noise and artifact contamination as possible, the maximum availability of independent sources for brain related source activity is ensured.

An ICA decomposition is based on a number of assumptions such as: (1) the mixing of sources is linear, (2) propagation delays are negligible, (3) component time courses are independent and the (4) number of components is less than the number of channels. Linear mixing of sources is ensured, since the majority of the EEG signals' energy is below 1 kHz and each time instance can be considered separately, so the quasistatic approximation of Maxwell's equation holds (Hämäläinen et al., 1993). Furthermore, electrical signals travel close to the speed of light. As a consequence, delays are negligible n the timescale used in EEG analysis. Moreover, even though component time courses are not completely independent, most ICA algorithms use a maximum projection algorithm to find solutions that are maximally independent. In order to represent all sources present in e.g. the cortex, at least as many sensors need to be used as there are sources. However, the number of synchronized local field potentials S and the number of noise sources is unknown and most likely higher than the number of sensors. ICA applies a cut-off for sources that do not contribute much to the EEG signal. Previous research showed that EEG measurements with the aim of analyzing data in source-space should at least consist of 32 sensors (Troy M et al., 2012). More sensors are of benefit if additional noise is to be expected.

The cocktail party

After numerous difficult sections, it is time to relax and have a drink at a cocktail party (Cherry, 1953)[4]. At a cocktail party, there are usually many people talking to each other. A band performs some light jazz in the background, which adds to the relaxing atmosphere. Later in the evening, the band changes genre and plays loud dance music instead. It becomes more difficult to follow the interesting conversations. Fortunately, ICA can help. Figure 2.8 (a) shows a stylized version of a cocktail party. Sound is very difficult to represent on paper or a screen, so it is changed out with color instead. In order to understand what the three sources (K interesting people who speak S) say, the noise (by now an annoyingly loud band) must be filtered out. By placing a number of sensors (M microphones) in the room, the recorded sound (channel data X) can be fed into a computer that runs a BSS script, for example ICA, to decompose the independent sources of the signal (speech and music).

For the context of EEG, the multivariate signal X is the measured sensor data, S are the ICs calculated based on the synchronized local field potentials generated in the cortex and unwanted noise (see Figure 2.7). A simplified example of brain signal propagation within the brain is shown in Figure 2.9 (Onton and Makeig, 2009).

Using the ICs of an EEG signal instead of the measured signal X can aid comparability between participants, since the signal propagation is affected by the individual's brain anatomy.

[4]Please keep it non-alcoholic. I don't want to get in trouble with my previous employer.

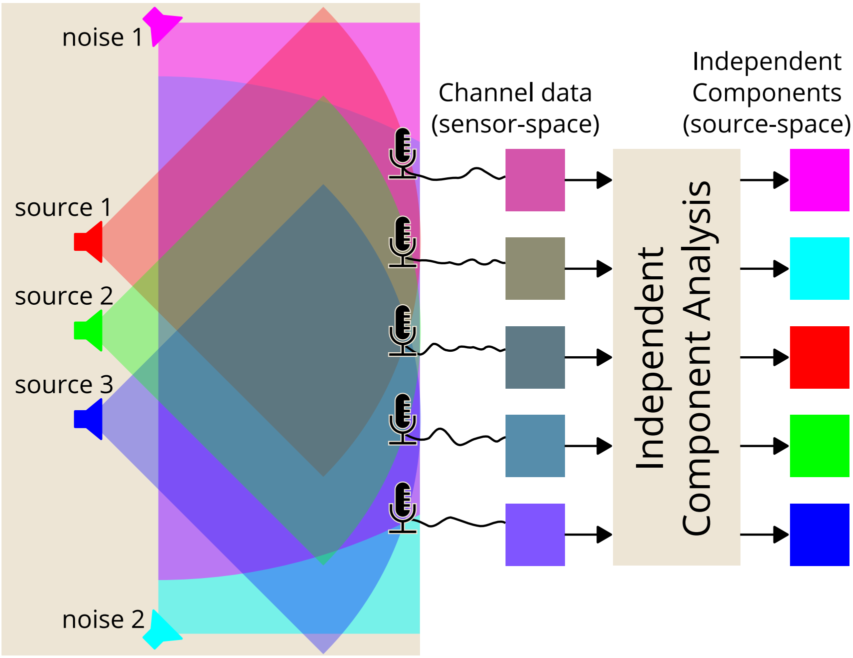


Figure 2.8: *Idealized example of an independent component analysis.*

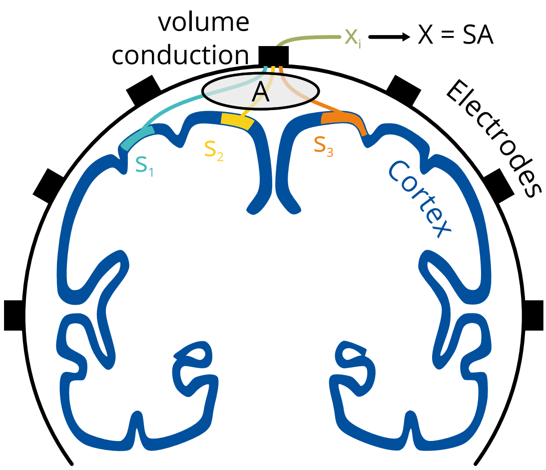


Figure 2.9: *Synchronized local field potentials and their propagation to scalp electrodes.*

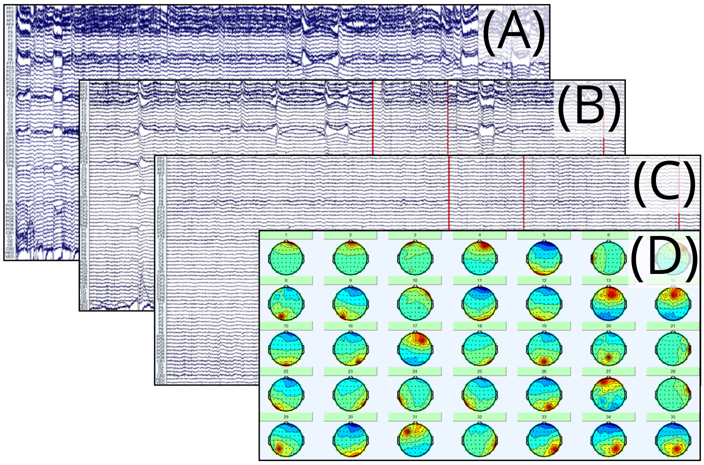


Figure 2.10: *Preprocessing steps in EEGLAB used in Study II. (A): EEG data after band limitation line-noise removal and re-referencing. (B): EEG data after manual rejection of non-stereotypical artifacts using visual inspection. (C): EEG data after removal of stereotypical artifacts using the results of the independent component analysis. (D): Source localization of brain activity.*

Artifact subspace reconstruction

ASR (Kothe and Jung, 2016; Mullen et al., 2015) can be used to remove non-stationary, non-stereotypical and high-variance signals from EEG recordings. The removed data is then reconstructed using a spatial mixing matrix. EEG data before and after cleaning with ASR can be seen in Figure 2.11.

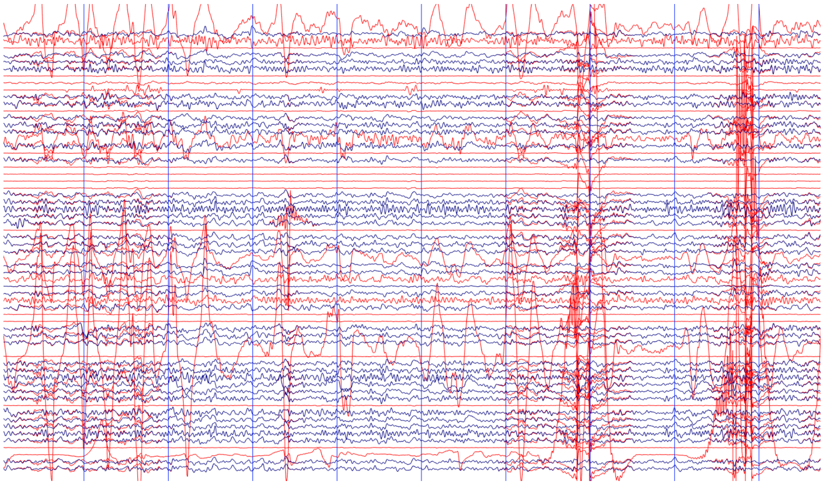


Figure 2.11: *EEG data before (red traces) and after artifact removal using artifact subspace reconstruction (blue traces).*

ASR uses a manually or automatically chosen reference signal $X_c \in \mathbb{R}^{Q \times M}$ of the duration M with low artifact content from the EEG recorded using Q sensors. A PCA is then applied to a short sliding window $X \in \mathbb{R}^{Q \times N}$ of the duration N in order to calculate the PCs $V \in \mathbb{R}^{Q \times Q}$ of X. PCs whose variance σ_k exceeds a threshold $t\left(v_k\right)$, derived from X_c. Removed PCs are reconstructed using linear combination of the remaining non-artifact contaminated PCs.

Back-projection of PCs to the sensor-space used the linear operator in Equation 2.7. The threshold operator $U \in \mathbb{R}^{Q \times Q}$ is chosen such as $U_{ki} = 0$ if the variance σ_k is larger than the threshold $t\left(v_k\right)$, otherwise $U_{ki} = 1$. M is the projected matrix square root of the covariance matrix C of X_C as shown in Equation 2.8 such that Equation 2.9 is fulfilled. The linear operator in Equation 2.7 is applied to $x(t)$ as shown in Equation 2.10.

$$R = V\ M\ \left(M \circ U\right)^{\dagger}\ V^T \tag{2.7}$$

$$M = V^T \bar{M} \tag{2.8}$$

$$\bar{M}\bar{M}^T = C \tag{2.9}$$

$$\hat{x}\left(t\right) = Rx\left(t\right) \tag{2.10}$$

The thresholds are computed using the PCs $W \in \mathbb{Q}^{Q \times M}$ of the reference data X_c. Subsequently, component activations Y are calculated using Equation 2.11.

$$Y = X_c \, W^T \tag{2.11}$$

For each y, mean m and standard deviation s are calculated, so that a per component threshold z can be obtained as shown in Equation 2.12. This equation includes a tuneable cut-off parameter c. Recommendations for the selection of c can be found in Chang et al. (2019).

$$z = m + c\, s \tag{2.12}$$

Subsequently, the threshold $t\,(v)$ can be calculated using Equation 2.13 and 2.14.

$$Z = \mathrm{diag}\,(z)\;\; W^T \tag{2.13}$$

$$t\,(v) \equiv \|Zv\|_2^2 \tag{2.14}$$

Using the example of the *marius genser* again, ASR can remove in-band noise or in this case in-yarn noise from the pullover by patching parts of the contaminated wool based on a reference knitting pattern X_C obtained from the same pullover (unstained part). Figure 2.12 shows an example of a dirty pullover with the traditional Norwegian *marius* knitting pattern. The pattern represents the recorded EEG data in sensor space X. The EEG is depicted as channel data as rows on the "y-axis" over time as loops on the "x-axis". The pullover is contaminated with dirt stains in the yarn (in-band noise and artifacts, e.g. lower spectrum of EMG) and superficial mustard stains (out-of-band noise and artifacts, e.g. line noise). The latter can be removed using e.g. a notch filter. ASR uses the clean reference data X_C to reconstruct the color of the dirt stains within the yarn (in-band noise, discolorations). The resulting reconstructed pullover is a closer resemblance of its original, uncontaminated state compared to the dirty version. To assess the source material, the pullover can now be un-knitted to form balls of wool using an ICA.

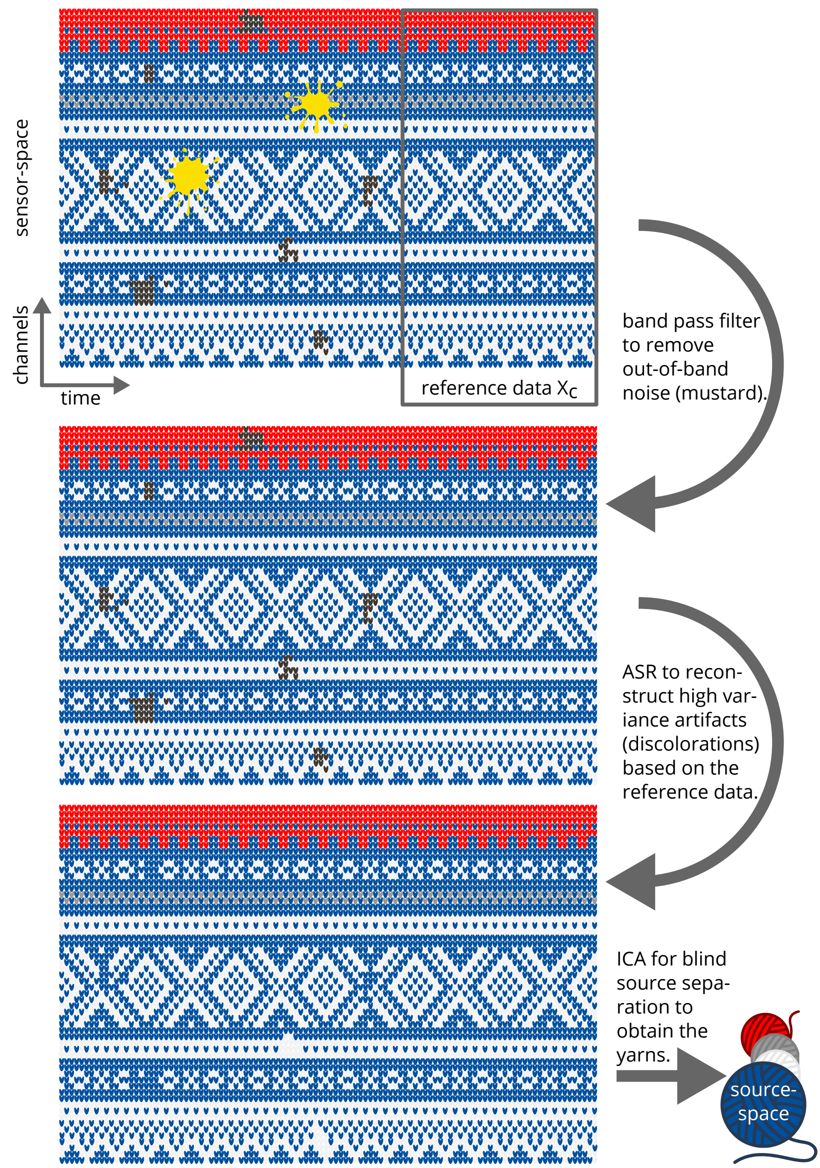


Figure 2.12: *Marius electroencephalogram pattern.*

Graphical abstracts 3

The following pages show graphical abstracts for Paper I — III. A more detailed description of the methods and results follows in Chapters 4 — 5. Furthermore, a comprehensive discussion across the three papers and the PhD project in general can be found in Chapter 6, with a conclusion in Chapter 6.6.

Paper I: Balance training in Older Adults Using Exergames: Game Speed and Cognitive Elements Affect How Seniors Play (Anders et al., 2020a) in Figure 3.1.

Paper II: Exergames Inherently Contain Cognitive Elements as Indicated by Cortical Processing (Anders et al., 2018) in Figure 3.2.

Paper III: The influence of motor tasks and cut-off parameter selection on artifact subspace reconstruction in EEG recordings (Anders et al., 2020b) in Figure 3.3.

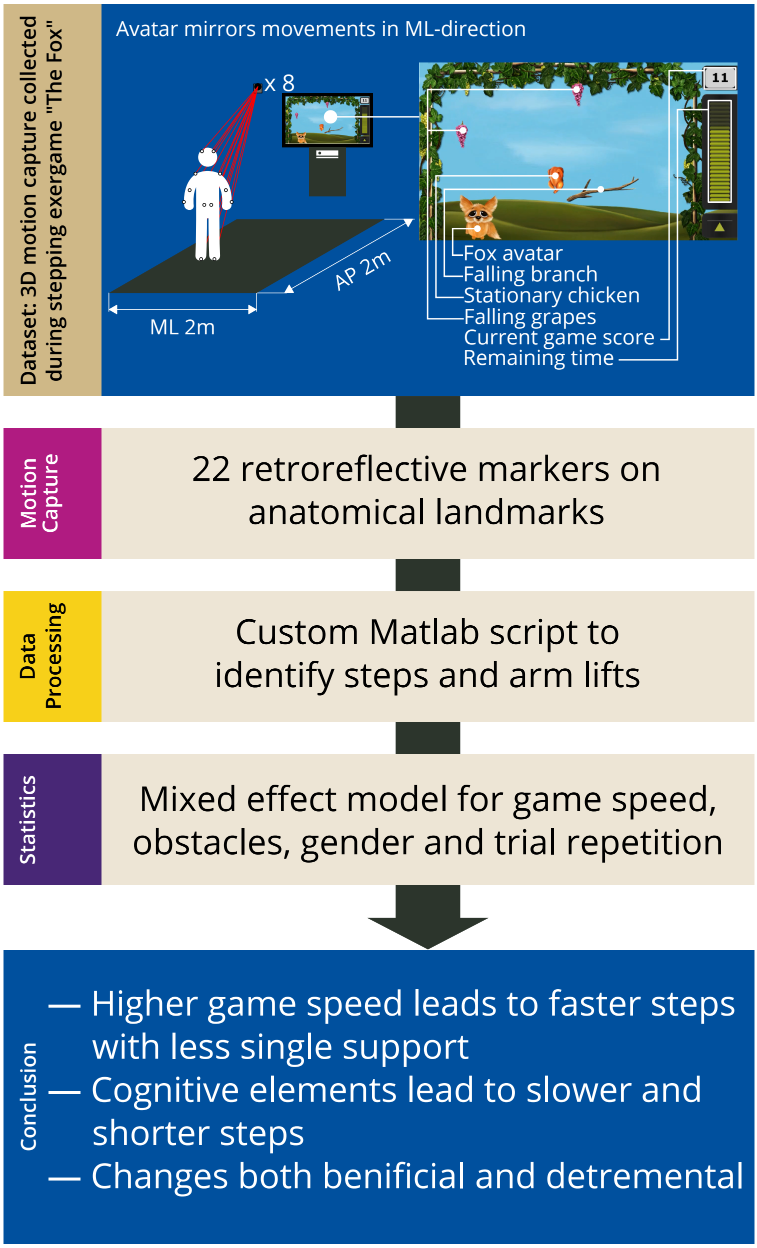


Figure 3.1: *Graphical Abstract of Paper I.*

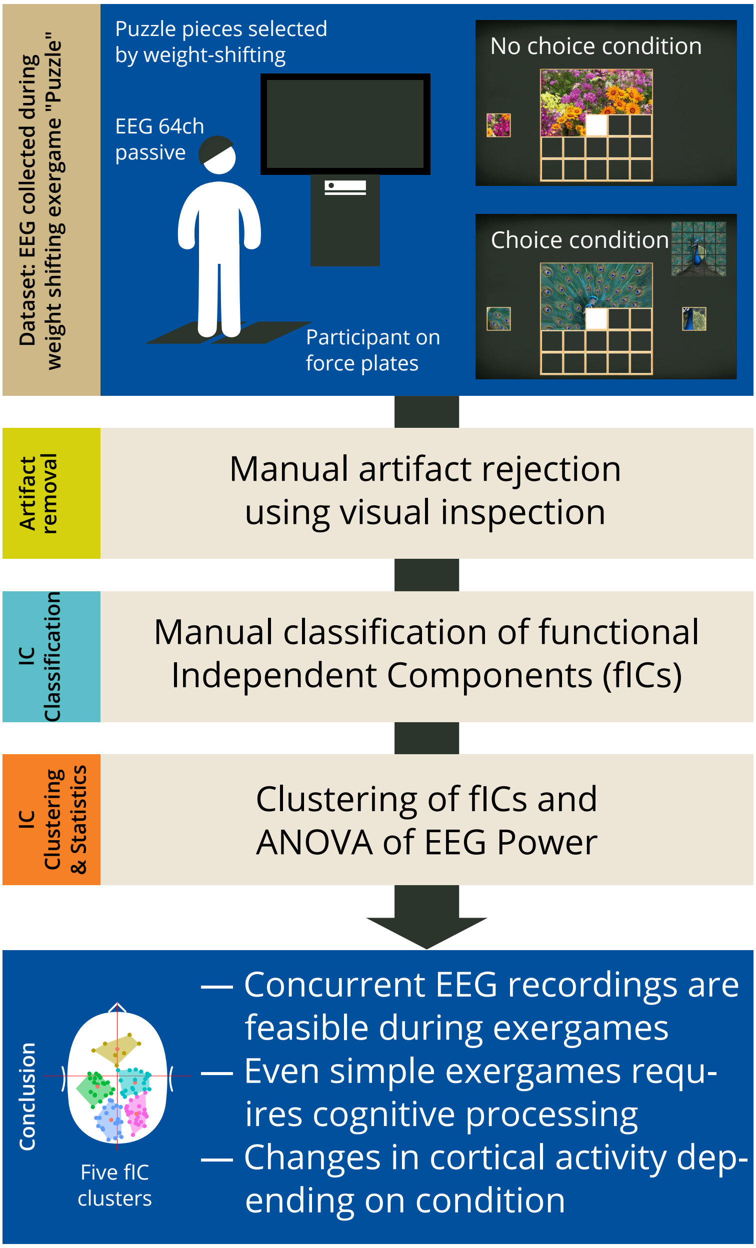


Figure 3.2: *Graphical Abstract of Paper II.*

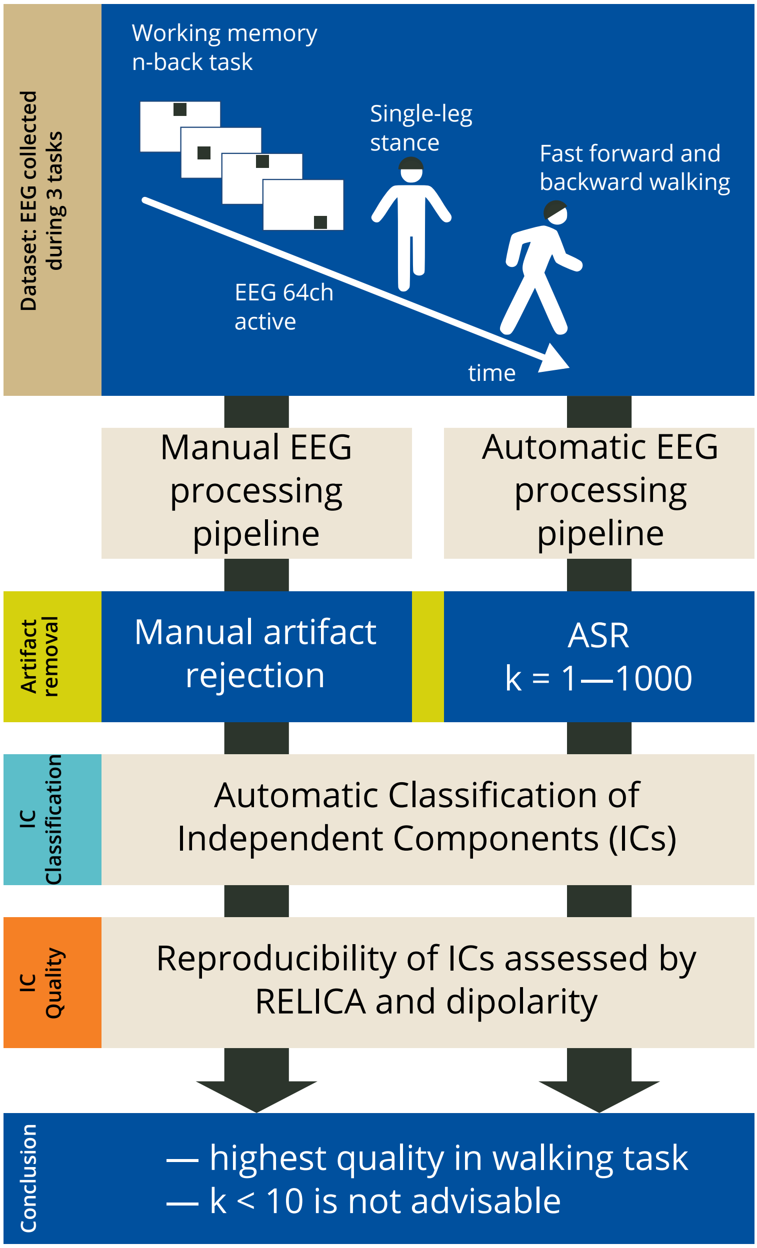


Figure 3.3: *Graphical Abstract of Paper III.*

Methods 4

This thesis is based on three studies conducted at the Norwegian University of Science and Technology (NTNU) in Trondheim, Norway (Studies I and II) and at Paderborn University in Paderborn, Germany (Study III). The protocols for studies conducted in Norway were approved by the Regional Committees for Medical and Health Research Norway. All procedures performed during the study conducted in Paderborn were in accordance with the ethical standards of the institutional review board of the University of Paderborn. All studies were performed in accordance with the Declaration of Helsinki and its later amendments. The data collected in each study was published in separate papers (Study I — Paper I, Study II — Paper II and Study III — Paper III). All participants gave their informed consent before entering in each study.

4.1 Study designs and study sample characteristics

The three studies this thesis is based on were experimental lab studies. All participants in the three studies were part of a convenience sample of independently living and healthy participants. For Study I older adults aged 65 years or older served as participants, whereas in Studies II and III young adults in the age group between 18 and 30 years were recruited. An overview over the demographics of participants in each study can be seen in Table 4.1.

Table 4.1: *Demographics, place of data collection and study sample size of all studies (M: mean; SD: standard deviation; TRD: Norwegian University of Science and Technology NTNU, Trondheim, Norway; PAD: Paderborn University, Paderborn, Germany; ♀: female, ♂: male).*

Study	Age M ± SD yrs.	Height M ± SD cm	Weight M ± SD kg	Study site	N ♀ — ♂
I	73.7 ± 4.4	172 ± 4	68.6 ± 8.4	TRD	7 — 8
II	24.6 ± 2.1	175 ± 10	74.8 ± 11.8	TRD	12 — 12
III	23.2 ± 2.6	172 ± 3	63.8 ± 4.4	PAD	5 — 0

4.2 Exergames and Equipment

Due to the difference in scope of the three studies various equipment was used for data collection. In Table 4.2 an overview of the equipment used is presented. Further details can be found in the following subsections.

Table 4.2: *Overview of the exergames and equipment used in Studies I, II and III.*

Study	Exergame	Movement capture	EEG system
I	*The Fox*	3D motion capture	—
II	*Puzzle*	force plates	64ch, passive
III	—	—	64ch, active

4.2.1 Exergames

The software part of the commercially available exergame system Silverfit3D (SilverfitBV, Woerden, NL) used in Studies I and II was provided free-of-charge. The commercially available system consists of a computer, a screen and an RGB-D camera (e.g. Microsoft's Kinect v2). The intended use of the complete system is for rehabilitation and training purposes in care facilities. In contrast to the majority of available commercial exergames, Silverfit3D (SilverfitBV, Woerden, NL) is certified as a medical product.

In Studies I and II, we used a laptop, a Kinect v2 (Microsoft, Redmond, WA) and a 55" (139.7 cm) TV screen to run the exergames. The free and open-source cross-platform streaming and recording program Open Broadcaster Software Studio (Bailey and the OBS Project Contributors, 2017) was used to record the screen output of the exergames in Studies I and II.

The Fox

In Study I, a balance-training side stepping exergame called *The Fox* (Silverfit3D, SilverfitBV, Woerden, NL) was used. A screenshot of the exergame can be seen in Figure 4.1. The fox avatar in this exergame mirrored the lateral movements of the players within a predefined exergaming area. The aim of the game was to catch falling grapes by moving under their trajectory and catch roasted chickens by raising at least one arm over the head whilst the avatar is placed under the prey. In addition, participants had to avoid being hit by (optional) falling branches that covered approximately 35 % of the screen width. No steps in either anterior or posterior direction are required to play the exergame. The point scores for all exergame items can be seen in Figure 4.2.

Figure 4.1: *Screenshot including all game items and the avatar used in the exergame The Fox (Silverfit3D, SilverfitBV, Woerden, NL).*

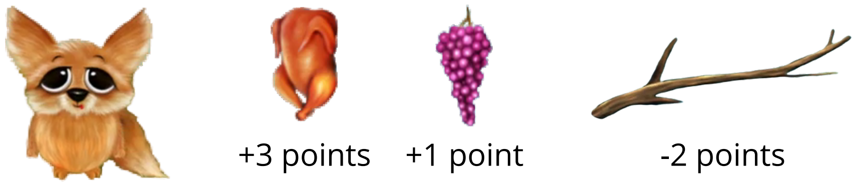
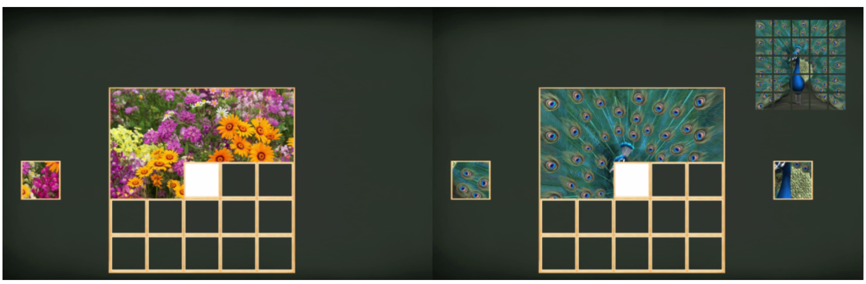


Figure 4.2: *Avatar and game items with their respective effects on the player's game score in the exergame The Fox (Silverfit3D, SilverfitBV, Woerden, NL). From left to right: fox avatar, chicken, grapes and branch.*

Puzzle

In Study II, a balance-training weight shifting exergame called *Puzzle* (Silverfit3D, SilverfitBV, Woerden, NL) was used. The tasks in this exergame consisted of completing a puzzle that was displayed on a screen. Puzzle pieces were selected by leaning the upper body sideways towards them. The exergame could be played in two different conditions as shown in Figure 4.3. Exergame players were either presented with only the one correct puzzle piece or had to choose the correct piece between two puzzle pieces presented on either side of the screen for the current position. Furthermore, participants played the exergame with two target pictures as shown in Figure 4.3.



(a) (b)

Figure 4.3: *Screenshot of the exergame Puzzle (Silverfit3D, SilverfitBV, Woerden, NL). (a) condition with only one puzzle piece at a time, (b) condition with choice option between two puzzle pieces.*

4.2.2 3D motion capture

In Study I a 3D motion capturing system (Oqus, Qualisys AB, Gothenburg, SE) with 22 reflective markers was used to record the position of anatomical landmarks throughout playing the exergame. The position of the markers can be seen in Figure 4.4. Double-sided tape and velcro bands were used to keep the markers in place. Eight cameras recorded the participant's movement throughout data collection at a frequency of 120 Hz. The software suite Qualisys Track Manager (Qualisys AB, Gothenburg, SE) was used to prepare the recorded raw position data of the 22 markers for export and further analyses in Matlab (The Mathworks Inc., Natick, MA). The marker on the center of the right thigh was used to make the distinction between the participant's left and right body side easier.

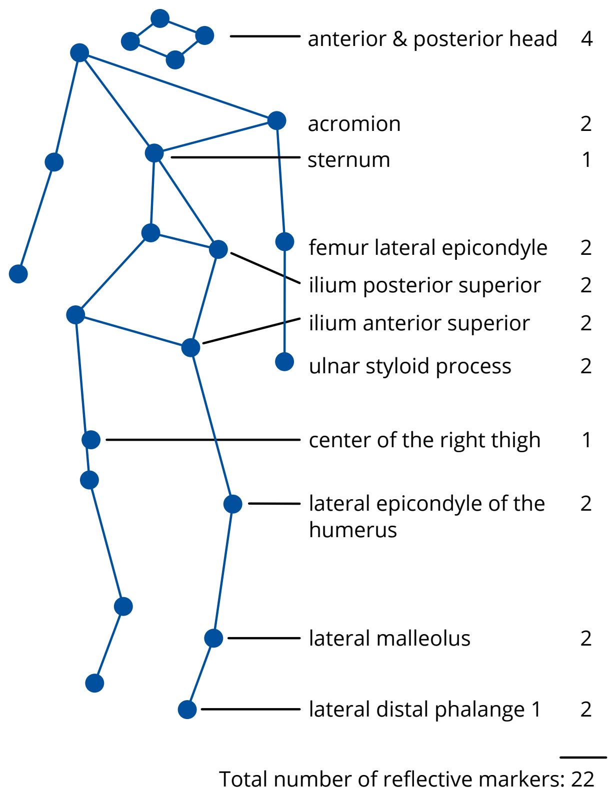


Figure 4.4: *Skeleton model of a participant in Study I, based on the recorded position of 22 reflective markers placed on anatomical landmarks digitized using a 3D motion capture system (Oqus, Qualisys, Gothenburg, SE). The lines in-between markers are for illustration purposes only and do not represent the actual skeletal structure.*

4.2.3 Electroencephalogram

In Studies II and III, EEG systems were used to record the participant's brain activity. In both studies 64 channels arranged according to the international 10-20 system (Klem et al., 1999, see Figure 2.6) were recorded using silver / silver chloride electrodes (Ag / AgCl electrodes).

In Study II, passive electrodes and an elastic cap (QuikCap, Compumedics Neuroscan, Charlotte, NC) were used. The reference electrode was positioned between CZ and CPZ. Electrode impedance was reduced to < 10 kΩ to ensure an appropriate signal-to-noise ratio. EEG data was amplified with an analog amplifier (SynAmps RT, Compumedics Neuroscan, Charlotte, NC). The analog EEG signal was digitized using a 24 bit analog-to-digital converter (SynAmps RT, Compumedics Neuroscan, Charlotte, NC) and subsequently recorded using Scan 4.5 (Compumedics Neuroscan, Charlotte, NC) with a sample frequency of 1 kHz.

In Study III active electrodes in an elastic cap (Easycap, Herrsching, DE) and a wireless amplifier (LiveAmp, Brain Products GmbH, Gilching, DE) were used. The impedance was kept below 25 kΩ, in accordance with the manufacturer's recommendations.

The amplifiers in both studies were placed in a backpack in order to relieve mechanical stress from the cables. This measure reduces the likelihood for artifacts due to lifting of the electrode.

4.2.4 Other equipment

In addition to the measurement of brain activity in Study II, ground reaction forces were recorded using force plates (Type 9286A, Kistler, Winterthur, CH) placed under each foot. Data was recorded at a frequency of 100 Hz.

Furthermore, in Study III the Witty SEM (Microgate Slr, Bolzano, IT) system was used. The system consisted of five combined RGB-LED matrices with a proximity sensor mounted on tripods.

4.3 Procedures

4.3.1 Study I: Movement characteristics during exergaming

All participants in Study I played eight exergame trials at two speed settings, either with or without branches present in counter balanced order using the exergame *The Fox* (Silverfit3D, Silverfit BV, Woerden, NL). Each trial had a duration of 2 min. The exergaming area was set to 2 by 2 m. Increasing the exergame speed led to an increased number of grapes and branches falling simultaneously on the screen (from 1 — 3 to 3 — 5 grapes, and from 1 — 2 to 1 — 3 branches) and reducing their time on the screen from 8 — 10 s to 6 — 9 s (measured from top to bottom of the screen for missed grapes and avoided branches). The number of chickens, as well as their time on the screen, remained unchanged regardless of the chosen game speed. In addition, functional reach test was performed to ensure that all participants were able to perform all required movements in order to play the exergame.

4.3.2 Study II: Brain activity during exergaming

Continuous EEG was recorded throughout the entire experiment. Three minutes of seated baseline data was recorded followed by self-paced sideways leaning with feet hip-wide apart on force plates to record both cortical activity and ground reaction forces. After a 2 min break, participants played the exergame *Puzzle* (Silverfit3D, Silverfit BV, Woerden, NL). Each participant played the exergame with and without choice option and with two different target pictures as shown in Figure 4.3, counterbalanced across participants. Each participant played 10 sets of two exergames for a total of 20 exergames. After completing all exergames, another seated baseline recording followed by self-paced sideways leaning was acquired.

4.3.3 Study III: Assessment of an automatic EEG artifact cleaning algorithm

Participants in Study III performed three tasks with increasing likelihood for causing EEG movement artifacts. All participants started with a seated working memory n-back task, with 10 sets of 30 stimuli of 2 s each. The n-back task consisted of a 3 by 3 dot matrix was presented on a computer screen. Participants were asked to press a button with their right thumb if the current pattern was the same as the pattern shown three pictures prior. Otherwise participants were asked to press a button with their left thumb. After completing the first task, participants were asked to perform 20 alternating single-leg stance phases held for 30 s each, with a break of 10 s between consecutive stance phases. Lastly, participants were asked to do two repetitions of a fast forward and backward walking task for 5.5 min each, using the Witty SEM (Microgate Slr, Bolzano, IT). Five LED lamps were mounted on tripods and placed at 0°, $\pm$ 22.5°, and $\pm$ 45° from the participant's point of view at a distance of 2.5 m. The task was to go swiftly (not run) to the lit LED lamp and cover it with their right hand before walking backwards to the starting position. This procedure continued until the end of the task.

4.4 Data analyses

Data collected throughout all studies was analyzed using Matlab (The Mathworks Inc., Natick, MA). A custom script was developed to analyze 3D motion capture data acquired during Study I. All processing of EEG in Studies I and II was performed using the EEGLAB toolbox (Delorme and Makeig, 2004).

4.4.1 Study I: Movement characteristics during exergaming

The motion capture data was analyzed using a custom Matlab (The Mathworks Inc., Natick, MA) script. In order to detect steps, the position of the markers on the velocity of the marker placed on the lateral malleolus was used. A step was defined as a ≥ 0.03 m displacement of the toe marker lasting for ≥ 0.05 s. A marker velocity of 0 ± 0.1 ms^{-1} was used for the identification of step initiation and termination. Arm lifts were detected by comparing the height of the marker on the wrist with the average height of the four head-mounted markers. The position of the exergamer within the exergaming area was determined by the position of the marker on the participant's sternum.

Step size, the ratio and mean duration of single-leg support, cadence, and arm lift frequency, as well as the position of the exergamer on the exergaming area, were calculated from the 3D motion capture data. Optical character recognition was used to record the game score, caught chickens and avoided branches (if present) using the screen captures. Furthermore, the number and duration of error messages was recorded using the same method.

4.4.2 Study II: Brain activity during exergaming

The recorded continuous EEG was band limited to 1 — 100 Hz before downsampling to 250 Hz. The CleanLine plugin for EEGLAB was used to remove line noise. A band-pass between 2 — 30 Hz (Winkler et al., 2015) was used to remove EMG and signal drift. Channels contaminated by excessive noise or major non-stereotypical artifacts were deleted after visual inspection before the EEG was re-referenced to common average. Non-stereotypical artifacts were removed manually by visual inspection. Data from two participants was excluded due to extensive artifact and noise contamination. To reveal the sources of brain activity, an adaptive mixture independent component analysis (Palmer et al., 2006, 2008) was used with subsequent manual selection of functional independent components (fICs). A four-shell spherical head model (Kavanagk et al., 1978) included in the DIPFIT function (Oostenveld and Oostendorp, 2002) was used to locate the equivalent dipoles. A k-means algorithm with a preset for five clusters was used to cluster the dipoles. Dipoles were assigned to a cluster if they were within two standard deviations of the respective cluster and showed a residual variance of less than 16 %. The absolute power of the EEG signal for each condition and cluster (Pivik et al., 1993) in the a priori defined frequency bands: theta (4 — 7 Hz) for the frontal cluster, as well as alpha-2 (10 — 12 Hz) for both central and parietal clusters was calculated as area under the curve.

Force plate data was used to calculate the mean of the medio-lateral center of pressure amplitude peaks for each sideways lean, as well as the overall center of pressure velocity.

4.4.3 Study III: Assessment of an automatic EEG artifact cleaning algorithm

The CleanLine plugin for EEGLAB was used to remove line noise before using a band pass with limiting frequencies at 3 and 30 Hz (Winkler et al., 2015). All EEG data sets were copied to obtain 11 identical versions, which were subsequently processed separately.

One data set was processed manually using the same workflow as in Study II. ASR was used to process the remaining 10 data sets. Channels were removed when poorly correlated ($r < 0.85$) to neighboring channels, or when non-transient noise exceeded 4 SDs. The cut-off parameter k was set to 1, 2, 5, 10, 20, 50, 100, 200, 500, and 1000, respectively. EEG data was downsampled to 250 Hz after cleaning.

Channels removed during either cleaning process were interpolated to avoid bias towards a hemisphere. Spatio-temporal sources of brain activity were calculated by using an adaptive mixture independent component analysis (Palmer et al., 2006, 2008). Their location was determined by using the dipfit-plugin (Oostenveld and Oostendorp, 2002) using a boundary element model (Akalin-Acar and Gençer, 2004; Gençer and Akalin-Acar, 2005). The fitTwoDipoles plug-in (Piazza et al., 2016) was used to account for bilaterally symmetrical ICs.

The IClabel plug-in (Pion-Tonachini et al., 2017) was used to classify ICs into seven categories (brain, muscle, eye, heart, line noise, channel noise, and other).

To assess the reliability and quality of the discovered fICs, RELICA plug-in (Artoni et al., 2014) was used.

4.5 Statistical analyses

All statistical analyzes were performed in R (R Core Team, 2019). Statistical significance was set at $p < 0.05$ in all studies.

4.5.1 Study I: Movement characteristics during exergaming

Movement characteristics derived from 3D motion capture data was statistically analyzed using a linear mixed effect analysis in R using the lme4 package (Bates et al., 2015). Fixed effects of the model were game speed, the presence or absence of obstacles, gender, and trial repetition. Random effects included intercepts for participants as well as by-participant random slope for the effect of body side (right or left arm or foot). Normality or homoscedasticity was assessed by visual inspection of the residual plots, with no derivations revealed. P-values were based on conditional F-tests with Kenward-Roger approximation for the degrees of freedom (Halekoh and Højsgaard, 2014).

4.5.2 Study II: Brain activity during exergaming

One-way repeated measures ANOVAs on the absolute EEG power of predefined frequency bands and the performance measures were used to statistically analyze differences between the conditions. Significant main effects were followed up by paired-sample t-tests. Friedman's test followed up by Wilcoxon's paired signed-ranks tests in case of detected significance was used for measures that were non normally distributed measures as indicated by a Shapiro-Wilk test.

4.5.3 Study III: Assessment of an automatic EEG artifact cleaning algorithm

Due to the data being non-normally distributed, Kruskal-Wallis tests by ranks were used in R (R Core Team, 2019) to assess the effects of task and cut-off parameter on the quality indices and dipolarity, the number of ICs classified as brain related, and the certainty of the classification as brain-related ICs. Wilcoxon's signed-rank tests were used as follow-up in case of significance. The resulting p-values after the Wilcoxon's signed-rank tests were corrected for multiple comparisons using Benjamini and Hochberg's (Benjamini and Hochberg, 1995) method.

Results 5

This chapter provides a summary of the results of the three papers this thesis is based on. Figure 5.1 to 5.3 present the main results of Papers I to III. In Figure 5.1 and 5.2 yellow is used to represent tasks with higher cognitive demands, whereas blue is used to represent less cognitively demanding tasks.

5.1 Paper I: Movement characteristics during exergaming

Paper I aimed to assess the changes in movement characteristics of older adults who played a side-stepping exergame caused by a change in game speed and the presence or absence of additional cognitive elements in the form of obstacles to avoid.

A summary of the main results of Paper I are shown in Figure 5.1. The calculated movement characteristics are shown in subfigures (A) to (E). The mean step size shown in Figure 5.1 (A) decreased significantly with increasing the exergame speed ($p = 0.038$) and if no obstacles were present ($p = 0.001$). Furthermore, the mean step size increased significantly with trial repetition (not shown in Figure 5.1, $p < 0.001$). The participant's cadence is shown in Figure 5.1 (B). It increased significantly with exergame speed ($p < 0.001$) and decreased if obstacles were present in the exergame ($p < 0.001$). Similarly, the frequency of arm lifts, shown in Figure 5.1 (C), significantly decreased if obstacles were present in the exergame ($p < 0.001$). However, with increased exergame speed the frequency of arm lifts decreased significantly ($p < 0.001$). The mean duration of single-support decreased significantly with an increase in exergame speed ($p < 0.001$), as shown in Figure 5.1 (D). The absence of obstacles led to a significant increase in the ratio of single-support ($p < 0.001$), as shown in Figure 5.1 (E).

The exergamers' position within the exergaming area was recorded using the chest mounted reflective marker. A heat map of the resulting observations is shown in Figure 5.1 (F). Warmer colors indicate more observations, whereas dark blue squares represent areas in which no observations were made. Participants drifted forward and towards the screen throughout playing the exergame as indicated by the warmer colored squares approximately 0.5 m in front of the starting position.

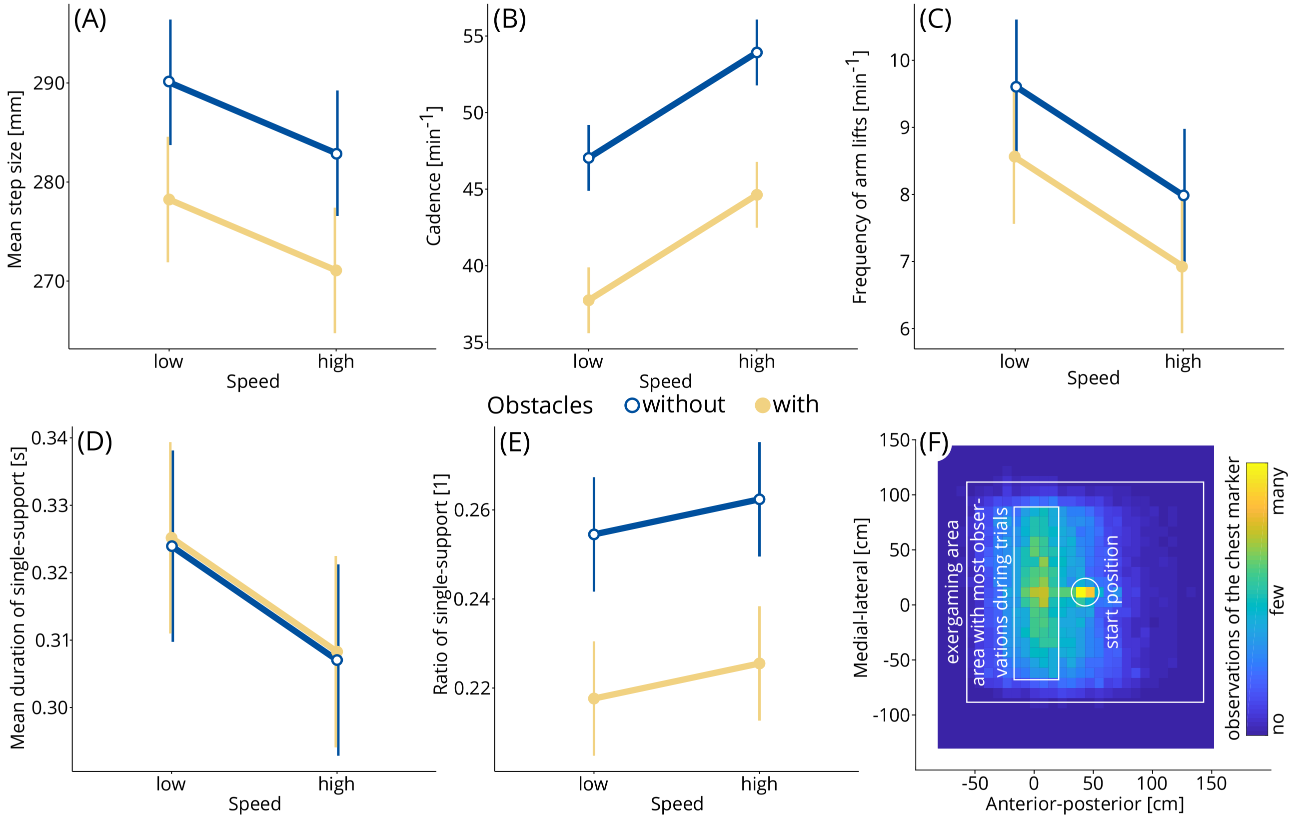


Figure 5.1: *Main results of Paper I at a glance. Movement characteristics in (A) to (E) of older exergames who played the exergame The Fox (Silverfit3D, SilverfitBV, Woerden, NL) using both speed settings and either with or without obstacles present. (F): Heatmap of the player's position in the exergaming area throughout the exergame.*

5.2 Paper II: Brain activity during exergaming

The aim of Paper II was to assess both feasibility of concurrent EEG measurements during exergaming, as well as to assess changes due to variations of cognitive demands in the exergame.

Results indicated that it is feasible to record brain activity in young adults while playing a simple exergame. Furthermore, five spatially different clusters were identified that were located frontal, bilateral central, and bilateral parietal as shown in Figure 5.2 (A). With increasing cognitive demands from the self-paced sideways movements (SP) to exergaming without choice option (NC) to exergaming with choice option (C), the frontal cluster showed a significant increase of absolute theta power as shown in Figure 5.2 (B), while both central clusters (D) showed a significant increase in absolute alpha-2 power from the self-paced condition to both exergaming conditions.

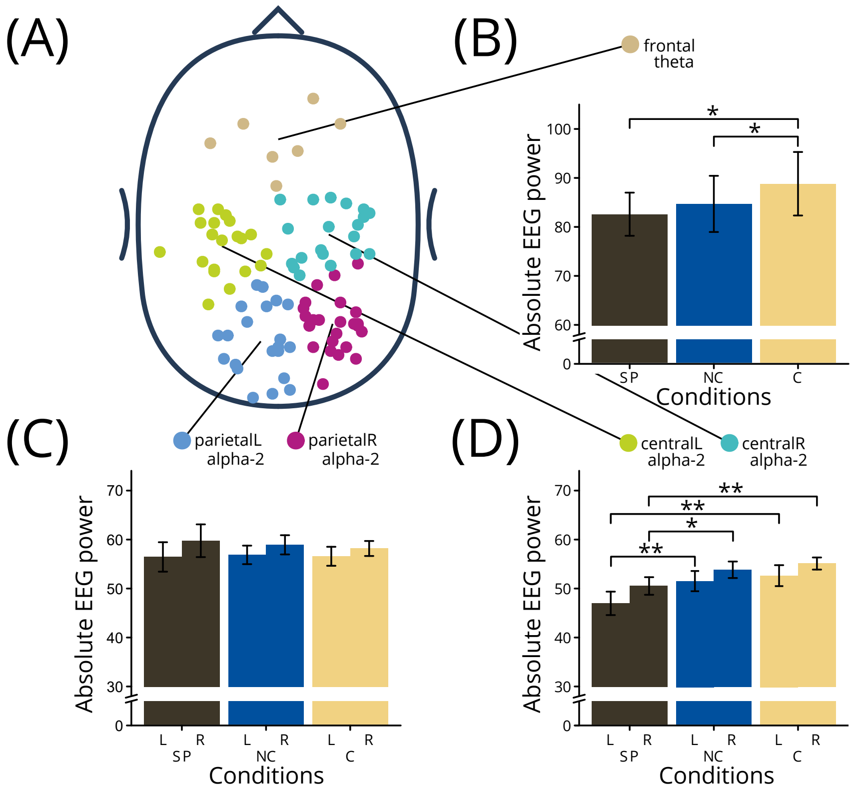


Figure 5.2: *Main results of Paper II at a glance. (A): five dipole clusters, (B): frontal absolute theta power, (C): parietal absolute alpha-2 power, and (D): central alpha-2 power during self-paced sideways leaning (SP, brown), no choice condition (NC, blue), and the choice condition (C, yellow).*

5.3 Paper III: Assessment of an automatic EEG artifact cleaning algorithm

In Paper III, the influence of task and cut-off parameter on ASR cleaned EEG data was assessed.

The cut-off parameters equivalent to the ratio of EEG data removed in manual cleaning were 7 to 14 for the walking task, 5 to 40 for the single-leg stance task and 10 to 45 for the n-back task. Figure 5.3 (A) shows the accumulative mean ratios of removed and reconstructed EEG data for each task across participants and their respective ranges. No EEG data was reconstructed in datasets preprocessed using ASR with a cut-off value of 100 or above, as indicated by the flat lines.

The quality indexes calculated using RELICA (Artoni et al., 2014) increased up to plateau at a cut-off parameter of 10. Dipolarity was largely unaffected by the choice of cut-off parameters. Figure 5.3 (B) shows the mean quality indexes across participants for cut-off parameters between 1 and 100.

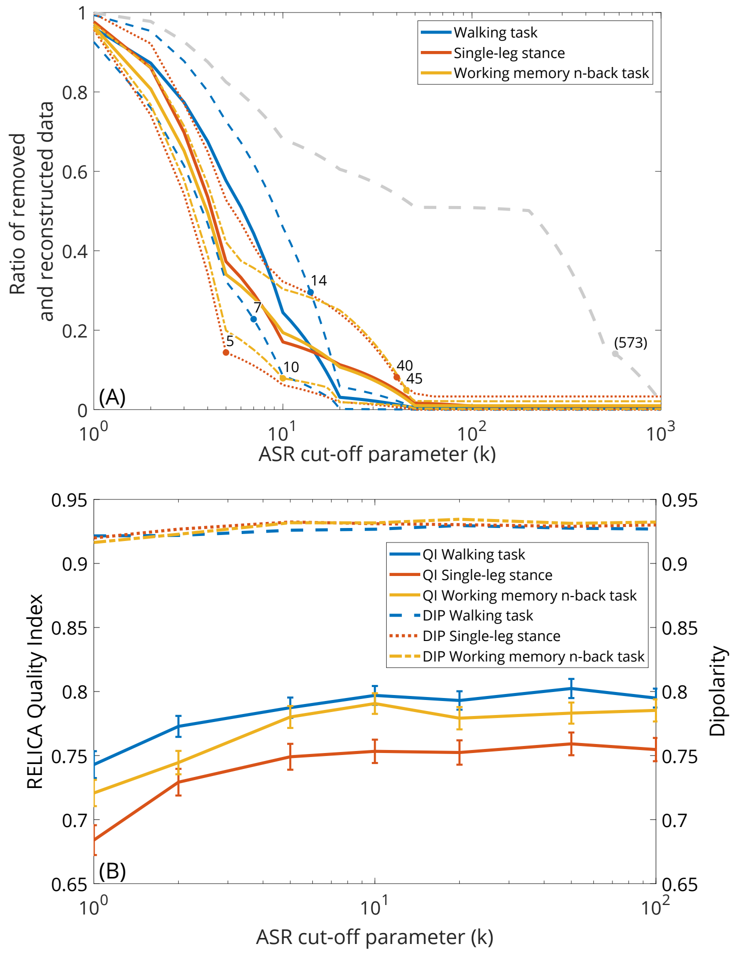


Figure 5.3: *Main results of Paper III at a glance. (A): Mean ratio and range of removed and recovered data using ASR for cut-off parameters (k) between 1 — 1000 for each of the three tasks. The dots indicate the intersection of the ratio of removed data after manual cleaning using visual inspection of the preprocessed EEG. The dashed grey line represents EEG of a participant during the n-back task. (B): mean quality index and mean dipolarity of independent components for all tasks preprocessed using ASR as calculated by RELICA for cut-off parameters of 1 — 100 only, using ICs with a dipolarity greater than 0.85. The error bars indicate the standard error of the measurements.*

Discussion 6

The aim of this dissertation is to contribute to the development of exergames as a tool for training and rehabilitation by studying movement characteristics and cortical activity concurrently during exergame play while using variations in game speed and cognitive demands. Furthermore, to enable the analysis of high-density EEG data recorded during movement intensive task, such as movements during exergaming, an automated EEG preprocessing algorithm was assessed for the effect of various movement tasks on its cleaning performance.

Exergames have been shown to have positive effects in several areas, such as in the adherence to exercise programs and in balance training. However, little is known about the effects of exergame settings, such as game speed, additional obstacles or the difficulty level of a task, on movement characteristics of older exergame players and directly measured cortical activity in general. Despite the lack of knowledge about their effects, variations in game settings are often used to adjust the difficulty of an exergame to the player's abilities in order to keep the player in a state of flow (Csikszentmihalyi, 1975). In the flow-zone a player is neither overly challenged, nor bored by the tasks or in this case the exergame. However, contrary to the goals of the entertainment industry, enjoyment is not the most important goal to achieve if an exergame is intended for rehabilitation and training purposes.

In summary, the first two papers of this thesis contribute towards building a more solid foundation of evidence on which further development of exergames can be based. By assessing and highlighting the effects of exergame settings, the papers emphasize the need for an informed approach in exergame design. Paper I provided insight into the movement characteristics of older adults while playing a side-stepping exergame and the effects of game speed and the presence of additional cognitive objects in the form of obstacles to be avoided. Paper II showed that usable EEG data can be measured concurrently during exergaming and that even a simple exergame contains cognitive elements as indicated by task-specific cortical representation.

Paper III aimed to contribute to a better understanding of a commonly used, but little understood, EEG preprocessing algorithm that originated from the field of BCIs. Applications such as the concurrent measurement of cortical activity during exergaming particularly benefit from EEG preprocessing methods that can remove prominent artifact contamination in otherwise unusable EEG data, whilst at large not removing significant portions of the recorded EEG data. Paper III is the first publication to assess the effect of several cut-off parameters which are used to control the rigor of the algorithm and the effect of movement intensity during the task on the cleaning performance of the algorithm assessed by results in source-space.

Beyond the results reported in each of the three papers, this thesis provides additional insights gained during the data collections, analyses and interpretation of the results of Studies I through III, which are described in detail in section 6.4. Furthermore, an interdisciplinary endeavor, such as the project this thesis is based on, comes with several challenges that need to be solved along the way. Some of the solutions found to overcome those hurdles did not find their way into the peer-reviewed journal articles but are nevertheless worth describing as they might help avoid unnecessary dead-ends and detours in future research.

6.1 Influencing movement characteristics of older exergamers

As this thesis illustrated, game characteristics affect how older adults play exergames designed to train their balance, but the effects can go in different directions and be beneficial or detrimental for balance training. Both game speed and the presence of obstacles were shown to influence players' movement characteristics. In Paper I, higher exergame speed led to higher step frequency and thereby more frequent weight shifts, which may benefit balance training. At the same time, the mean duration of single-support and step size decreased, which might not be beneficial for balance training. Therefore, an informed approach when designing exergames is necessary for eliciting the desired movements for balance training, while not losing sight of the enjoyment factor. An informed approach for the development of future exergames should include all elements of an exergame, such as the game design and the required movement speed, since those elements influence the elicited movements and cognitive activity in exergame players. Similar to the methods used in drug development, a method for quality assurance should be in place for newly developed exergames to ensure their effectiveness, and the actual elicited movements that result from the chosen exergame and its settings. This would also contribute to the acceptance of exergames as viable options for treatment for diseases and rehabilitation to restore and maintain physical functioning.

Both exergame designers and healthcare workers choosing exergames for their clinical practice can make smart choices in enticing players to make the most beneficial movements for training effects, or they can miss the trick. However, the variety of exergames on the market that are not certified medical products with documented effectiveness makes it difficult to select a suited exergame that elicits the required movements for effective training.

Besides the specific settings of an exergame, the exergame itself plays a major role in eliciting movements. An exergame can elicit movements unwanted for the intended training or rehabilitation purpose. This can be due to multiple reasons. Players can find out that a system can be tricked into thinking that a correct movement was performed using a e.g. less strenuous gesture. Furthermore, players could use unwanted and potentially dangerous strategies to play an exegergame, such as crossover steps in balance training. Besides the aforementioned movements, players can also drift towards unintended positions throughout playing an exergame. This slow and gradual movement, e.g. towards the screen, can result in unwanted disruptions of the exergame and should therefore be avoided by design. If an exergame is played using only movements along a single plane such as sideways movements in *The Fox* (Silverfit3D, Silverfit, Woerden, NL), corrective measures to nudge the player back into the intended position should be incorporated into the design of the exergame. Exergames played on a two dimensional playing field do not lead to players drifting into unwanted positions (e.g. *The Mole*, Silverfit3D, Silverfit, Woerden, NL; Skjæret-Maroni et al., 2016).

Elicited movements and brain activation can vary vastly between exergames and even between different exergame settings. This implies a need for a categorization of the evoked movement characteristics and brain response to specific exergames including the effects of changing its settings. The current findings in this thesis can serve as the first entries in a future catalogue or look-up table for evoked movement characteristics depending on either the exergame or the exergame setting used. This would enable physiotherapists or other health professionals to make an informed decision about the selection of the appropriate exergame interventions that offer the maximum benefit for the patient by choosing exergames that elicit the specific and desired movements required for training or rehabilitation. Moreover, such a database containing the required and elicited movements for playing the exergame would make the selection of an exergame that fits the functional abilities of a patient functioning easier.

National initiatives for the categorizing of exergames such as the *Spill deg bedre* (EN: Play to get better) project who published the user manual *Veileder for bruk av dataspill i opptrening etter sykdom eller skade* (EN: Guide for the use of computer games in training after illness or injury; Johansen, 2017) are useful for physiotherapists and occupational therapist who would like to use exergames in their rehabilitation and training programs. However, the guide lacks a thorough description of the movements elicited in exergames, including the effects of exergame settings, which were shown to affect the elicited movements. Adding this granularity to the categorization of exergames would enable healthcare professionals to choose the optimal exergame that suits the abilities of a patient and elicits the optimal movements for training or rehabilitation.

6.2 Concurrent measurement of cortical activity

With increasing capabilities of EEG recording hardware such as active electrodes (Laszlo et al., 2014) and high impedance amplifiers, and processing algorithms (Bigdely-Shamlo et al., 2015; Mullen et al., 2015), it has become possible to concurrently measure EEG during the execution of movement tasks. Furthermore, due to the advantages in temporal resolution of EEG compared to methods such as fNIRS, it is now possible to immediately measure which brain areas are active in specific exergame situations. This would potentially enable the use of exergames as neurorehabilitation tools, with documented cortical effects, or lack thereof, in specific regions of the brain.

The results of Paper II showed that it is possible to record usable EEG data during a simple exergame. However, for more movement intensive exergames, the preprocessing approach used in Paper II might not provide sufficiently clean EEG data for further processing to reveal the sources of cortical activity using an ICA. Fortunately, relatively recent developments in EEG data processing such as ASR might enable the use of EEG data recorded during more movement intensive exergames. As a consequence of the need for a method to remove artifacts from EEG recordings in high intensity movement tasks, the performance of ASR (Kothe and Jung, 2016; Mullen et al., 2015) in terms of quality and repeatability for different cut-off parameters was assessed in

Paper III. An informed cut-off parameter selection for ASR is crucial, since it controls the rigor of the artifact removal. If the chosen cut-off parameter is too low for the EEG dataset at hand, ASR can potentially remove cortical activity. On the other hand, if the cut-off parameter is too lax, ASR would likely leave artifacts uncleaned. Previous research (Chang et al., 2019) only assessed ASR using a single, low-intensity movement task. Paper III provides the first assessment of the effects on quality and repeatability of the resulting ICs based on EEG data recorded during different cognitive and movement tasks.

Advanced EEG cleaning methods, such as those assessed in Paper III, are necessary for the analysis of more movement intensive exergames, especially in datasets that consist of many channels as the likelihood for movement artifacts, such as electrode pops that increases with the number of channels. Manual cleaning of EEG data results in a significant loss of data, since contaminated parts in one channel have to be removed from the recording across all channels. Consequently, an EEG data collection would have to be substantially longer in order to account for the expected loss in data due to manual cleaning. Furthermore, a human rater might not be able to distinguish noise and artifacts from cortical activity in highly contaminated EEG datasets, making the use of automated EEG cleaning the only feasible option.

6.3 Methodological considerations

Within the scope of a PhD thesis, there are many choices to be made along the way, turns to be taken and hurdles to be overcome. Furthermore, external factors, such as time and availability of equipment, played an important role in those decisions. In this section, some of the decisions will be explained in further detail.

Two overall strengths of the current work are the use of state-of-the art motion capture technology to record the participants' movements in Study I and direct measurements of cortical activity in Study II. There were additional considerations regarding the study designs and execution that benefitted the quality and feasibility of the studies. The different strengths and limitations of the thesis will be addressed below.

The exergame used in Study II (*Puzzle*; Silverfit3D, SilverfitBV, Woerden, NL) was not as movement intensive as the exergame in Study I (*The Fox*; Silverfit3D, SilverfitBV, Woerden, NL). This decision was based on the expectation that a less movement intensive exergame would cause fewer movement artifacts. However, with more modern active EEG electrodes, the concurrent recording of cortical activity during more movement intensive exergames might be possible. Nevertheless, even an exergame simple in terms of movements required was able to elicit measurable changes in cortical activity. This shows that it is possible to record usable EEG data during the execution of movement tasks in an exergame and that the cognitive demands can be different depending on the settings of an exergame.

Although one of the aims of the project was to contribute to a better knowledge about exergaming that can benefit its application in older adults, younger adults participated in Study II and III. One of the aims of Study II was to assess the feasibility of concurrent EEG measurements during exergaming. Therefore, younger adults were recruited as participants for pragmatic reasons, since there was no focus on potential differences of the EEG activity due to age. EEG data collected in Study III was used for a methodological assessment of an EEG processing algorithm. We did not expect any differences in movement artifact patterns due to age. Furthermore, Study III only included female young adults as participants, since the EEG data was recorded after their participation in a different, unrelated study using the same EEG equipment, thereby avoiding the time-consuming participant preparation. We did not aim to assess any gender or age differences in cortical activity. Furthermore, we suspected movement artifacts to be the main contributor of non-stationary, non-stereotypical and high-variance signals ASR claims to remove from recorded EEG.

Taken together, the studies might provide some additional insights if repeated with older participants in the course of a study that follows the principles of MoBI in the future. Furthermore, since all participants in studies conducted in the scope of this thesis were convenience samples and free from self-reported injuries, it might be of interest to repeat the studies in more frail populations. In addition, exergame events could be measured concurrently in order to enable the analysis of event-related potentials (ERPs). This would enable linking exergame events to their immediate reaction in the brain.

6.4 Lessons learned along the way — side-quests and glitches

Scientists use peer-reviewed journal publications as the main channel to communicate their findings to other scientists. Although they offer a good way to communicate the results of research in a quality assured form, they do not cater themselves for the communication of smaller lessons learned throughout the conduction of a project - or honesty about bigger missteps. Despite not being substantial enough to become a manuscript on their own, communicating through a different channel such as this thesis might help other researchers to make better informed decisions for the conduction of their research projects.

6.4.1 Expect the unexpected

Although it might seem completely clear to the researchers what an exergame expects you to do, participants sometimes come up with alternative playing styles. An example of this was shown by participants in Study I, who either disregarded catching the chickens completely or only used one hand to trigger the avatar to jump. Depending on the research question, this could lead to complications down the statistical road and problems interpreting and generalizing the results. Extensive testing before the start of a study, ideally with people not familiar with the exergame, can help to anticipate such unanticipated playing tactics.

Another observation from Study I was that nearly all participants drifted closer to the screen as they were playing the exergame. This triggered an error message in the exergame. This observation bears important ramifications for the development of future exergames, in which artificial disruptions caused by error messages might be avoided by designing game elements that nudge players back to the center of the exergaming area instead of disrupting their flow by displaying an error message. This shows that extensive pilot testing is important to record usable data before conducting a large-scale study.

6.4.2 Application programming interfaces — or the lack thereof

Synchronized measurements of brain activity and movement data with events in an exergame would enable researchers to assess the immediate effects of events in an exergame. In EEG research ERPs, which are the mean value of EEG activity milliseconds before and after a trigger event, are often used to assess an underlying behavior pattern that would otherwise be obscured by random noise. By overlaying hundreds of ERPs a regression to the mean can be achieved. This would potentially help with movement artifact contamination. However, commercially available exergames often lack a method to record exergame events directly through an API.

If an exergame lacks a well-documented and accessible API, such as was the case for the exergames used in Studies I and II, it is more difficult to obtain usable events from the exergame. If exergame events are crucial for answering the research question, an exergame can be developed in-house. However, exergame development is time intensive and a different profession than being a researcher, which can potentially lead to boring and barely working exergame prototypes. If a commercially available exergame without an API is used, trigger signals can be obtained using optodes fixed to the screen if certain events in the exergame show a repeating pattern on the screen. However, this solution might necessitate the use of a second screen, ideally of the same size and latency, if the optode obscures the player's view. Furthermore, optodes and a second screen might not be readily available in the laboratory and need to be bought for an experiment which can add significant costs to a project.

6.4.3 Participant preparation time

Both the measurement of movements using a 3D motion capture system and the recording of cortical activity using an EEG system require time intensive preparation steps and highly trained professionals with practical experience. With some participants it might not be possible to ask them to sit still for an hour (e.g. children or people with diseases or cognitive decline) to ensure the proper placement of markers and electrodes as well as sufficiently low levels of impedances. Furthermore, depending on the research question, the simultaneous use of certain measurement systems might be mutually exclusive, such as reflective markers on the participant's back for 3D motion capture and an EEG amplifier in a backpack.

In this case, a lower fidelity measurement setup such as using a RGB-D camera instead of a marker based 3D motion capture system might be sufficiently accurate to answer the research question at hand. However, using EEG systems with faster preparation time such as dry EEG electrodes might not offer the necessary robustness towards movement artifacts and electrical noise. This might change with future innovations in the field of neuroscientific hardware.

6.5 Implications — taking exergames to the next level

Exergames offer a possibility to be active for people who have reduced or constrained opportunities to get sufficient movement and exercise, such as sedentary older adults. Below, perspectives for different stakeholder groups are presented on what is needed to be able to implement exergames in practice, and where future research could or should be going.

6.5.1 Perspectives on using exergames for serious business

From a patient's perspective, exergames offer a potentially fun way to do the recommended exercises prescribed by a healthcare professional for training or rehabilitation. Furthermore, exergames offer a more structured approach to exercising, with the possibility to track both frequency of training sessions and improvements in functioning. This can potentially help patients to recognize the effect of training or rehabilitation in a quantifiable way. Instead of just feeling better in general, patients could track their progress and therefore recognize the importance of adhering to a prescribed training program. Various movement characteristics were described in this thesis that could be used as feedback to the player. Furthermore, the meta-analysis by Sherrington et al. (2011) identified important movements for balance training. Depending on the cognitive abilities of the player, those metrics might need to be combined to an easier understandable score instead of presenting the user with the raw data. Besides presenting the player with either movement characteristics, or a summary thereof, it would be of great benefit for an exergame player to get immediate feedback on the quality of the performed movement tasks directly after, or even during, an exergame session. (Vonstad et al., 2018). Moreover, a considerable number of participants across the studies asked about their performance in comparison to their peers. This indicated that there is a potential for motivating exergame players by competition, similar to the functionality of exercise tracking apps such as Strava (Strava Inc., San Francisco, CA).

From a healthcare perspective, exergames offer a method for the administration of unsupervised training, while simultaneously offering a possibility to track the progress of a user. Instead of asking the patient whether they followed the prescribed training or rehabilitation plan, a physiotherapist can get a report from an exergaming system, containing frequency, duration and length of the training or rehabilitation sessions performed between e.g. weekly visits to the healthcare provider. A major advantage of exergames as a form of treatment is that patients after an introduction to the exergames, and depending on their abilities, can train unsupervised or under less supervision compared to traditional on-site rehabilitation.

From a technological perspective, exergames need to be usable and safe to use in a home setting, in order to be used as a method for administering training or rehabilitation in a widespread manner. Current systems are difficult to set up in people's homes due to the space required for an RGB-D camera and the required space for playing an exergame. If e.g. a living room is used for playing an exergame, it is important to set up the system in a way that no fall hazards are present. This either needs to be assured through video instructions or by a trained person installing and introducing the user to the exergaming system.

Furthermore, future exergame systems need to be easier to use for a non-technologically savvy person. This would require a commitment to designing a system that is “plug and play”.

The observed drift towards the screen of the participants indicated that older adults focus more on the exergame or screen, instead of being aware about their position in the real world. This is by itself a sign for immersion into the exergame which is desirable for achieving a state of flow, but in the context of safety, it becomes an issue to be aware of. Furthermore, a slow change of the player’s position within the exergaming area could lead to problems detecting the player if e.g. a RGB-D camera is used. If the player drifts too far to the edges of the area, some form of corrective measure needs to be triggered such as error messages. The issue of drifting can be resolved by designing an exergame that takes the movement in anterior-posterior direction into account. If an exergame is solely controlled by parallel movements to the screen and there is no exergame mechanics to control the drift of a player, an unwanted situation in terms of a disruption of the flow, such as through e.g. an error message or even worse, a fall could occur caused by e.g. a collision with an obstacle outside the exergaming area.

Both game designers and healthcare professionals installing and introducing the exergame system to a future user need to pay attention on how to mitigate tripping hazards. Given the rapid development in the field of computer vision and artificial intelligence, the process of identifying tripping hazards might be built into an exergame. The RGB-D camera system of an exergame could collect data for a 3D visualization of the room. The acquired data can then be assessed for potential hazards in the exergaming area.

From a regulatory perspective, clear evidence about the effectiveness of exergames as a rehabilitation tool is needed to elevate exergames from a useful toy to a classified medical product. A better understanding of the elicited movements both due to the exergame and its selected settings is needed for a better assessment of the effectiveness, or lack thereof, of exergame interventions. Furthermore, a classification as medical products might aid the acceptance in countries with strict policies on what is prescriptible by a medical doctor.

6.5.2 Future research

Concerning the implications for future research, the results presented in this thesis indicate that there are measurable differences in brain activity and movement characteristics that depend on settings in exergames. Future research can build upon and expand these findings presented in this thesis.

Firstly, future research can add to the catalogue of elicited movements in exergames for which this thesis provided the first entries. This would make the selection of the appropriate exergame for a patient or player for rehabilitation or training easier for healthcare providers. Furthermore, a methodical assessment of the elicited movements and the activation of certain brain areas for each exergame and its settings would aid the acceptance of exergaming as a serious tool to train and regain physical and cognitive functioning.

Secondly, future research could measure brain activity and 3D motion capture data simultaneously. The brain and the musculoskeletal system are physically connected and perform a constant interaction to maintain balance while performing tasks and reacting to game elements. Deepening our knowledge about this connected system could be valuable for the creation of more targeted neurorehabilitation exergames (Makeig et al., 2009). Assessing which areas of the brain are active during exergaming through concurrent measurement of brain activity during exergaming and capturing 3D motion capture data would be of great interest for the future development of exergames that can affect and thereby potentially regain neurological functions. Knowledge about which brain areas are activated while playing different kinds of exergames under different play settings can be used to design custom-made exergames that can activate specific areas of the brain affected by a disease. For example, an exergame could be used to activate areas of the brain affected by a stroke and thereby help the players to regain their lost abilities.

Thirdly, future research should aim to provide evidence for the effectiveness of exergaming as a medical or rehabilitation tool. A starting point for the assessment of the effectiveness of exergaming interventions for a specific treatment application could be the previously mentioned catalogue of elicited movements.

6.6 Conclusion

The characteristics of an exergame, such as game speed and difficulty level influence both movement characteristics and cortical activity in players. This implies that there is a need for a database or catalogue of elicited movements depending on both the exergame itself and the chosen settings in order to ensure that a patient plays the most beneficial exergame available. Furthermore, this thesis serves as a steppingstone for future mobile brain and body imaging research in exergaming. The results of the three papers pave the way for future research on movement characteristics and cortical activity during exergaming combined. Furthermore, the results of the papers by themselves may aid future development of exergames by providing empirical evidence for the effect of game settings, such as game speed and cognitive elements on cortical activity and movement characteristics. This knowledge can contribute to the design of more targeted exergames that potentially achieve better effectiveness.

References

Akalin-Acar, Z. and Gençer, N. G. (2004). An advanced boundary element method (bem) implementation for the forward problem of electromagnetic source imaging. *Physics in Medicine & Biology*, 49(21):5011.

Anders, P., Bengtson, E. I., Grønvik, K. B., Skjæret-Maroni, N., and Vereijken, B. (2020a). Balance training in older adults using exergames: Game speed and cognitive elements affect how seniors play. *Frontiers in Sports and Active Living*, 2:54.

Anders, P., Lehmann, T., Müller, H., Grønvik, K. B., Skjæret-Maroni, N., Baumeister, J., and Vereijken, B. (2018). Exergames inherently contain cognitive elements as indicated by cortical processing. *Frontiers in Behavioral Neuroscience*, 12:102.

Anders, P., Müller, H., Skjæret-Maroni, N., Vereijken, B., and Baumeister, J. (2020b). The influence of motor tasks and cut-off parameter selection on artifact subspace reconstruction in eeg recordings. *Medical & Biological Engineering & Computing*, 58:2673–2683.

Anderson-Hanley, C., Arciero, P. J., Brickman, A. M., Nimon, J. P., Okuma, N., Westen, S. C., Merz, M. E., Pence, B. D., Woods, J. A., Kramer, A. F., et al. (2012). Exergaming and older adult cognition: a cluster randomized clinical trial. *American journal of preventive medicine*, 42(2):109–119.

Anguera, J. A., Boccanfuso, J., Rintoul, J. L., Al-Hashimi, O., Faraji, F., Janowich, J., Kong, E., Larraburo, Y., Rolle, C., Johnston, E., et al. (2013). Video game training enhances cognitive control in older adults. *Nature*, 501(7465):97–101.

Artoni, F., Menicucci, D., Delorme, A., Makeig, S., and Micera, S. (2014). Relica: a method for estimating the reliability of independent components. *NeuroImage*, 103:391–400.

Bailey, H. and the OBS Project Contributors (2017). *Open Broadcaster Software Studio*. Open Broadcaster Software.

Baltaci, G., Harput, G., Haksever, B., Ulusoy, B., and Ozer, H. (2013). Comparison between nintendo wii fit and conventional rehabilitation on functional performance outcomes after hamstring anterior cruciate ligament reconstruction: prospective, randomized, controlled, double-blind clinical trial. *Knee surgery, sports traumatology, arthroscopy*, 21(4):880–887.

Basak, C., Boot, W. R., Voss, M. W., and Kramer, A. F. (2008). Can training in a real-time strategy video game attenuate cognitive decline in older adults? *Psychology and aging*, 23(4):765.

Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1):1–48.

Baumeister, J., Reinecke, K., Cordes, M., Lerch, C., and Weiß, M. (2010). Brain activity in goal-directed movements in a real compared to a virtual environment using the nintendo wii. *Neuroscience letters*, 481(1):47–50.

Beer, A. and Beer, P. (1852). Determination of the absorption of red light in colored liquids.

Bell, A. J. and Sejnowski, T. J. (1995). An information-maximization approach to blind separation and blind deconvolution. *Neural computation*, 7(6):1129–1159.

Benjamini, Y. and Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal statistical society: series B (Methodological)*, 57(1):289–300.

Berger, H. (1929). Über das elektroenkephalogramm des menschen. *Archiv für psychiatrie und nervenkrankheiten*, 87(1):527–570.

Bigdely-Shamlo, N., Mullen, T., Kothe, C., Su, K.-M., and Robbins, K. A. (2015). The prep pipeline: standardized preprocessing for large-scale eeg analysis. *Frontiers in neuroinformatics*, 9:16.

Bouguer, P. (1922). Essai d'optique sur la gradation de la lumière.

Brown, P. (2000). The piper rhythm and related activities in man. *Prog Neurobiol*, 60:97–108.

Caetano, M. J. D., Lord, S. R., Brodie, M. A., Schoene, D., Pelicioni, P. H., Sturnieks, D. L., and Menant, J. C. (2018). Executive functioning, concern about falling and quadriceps strength mediate the relationship between impaired gait adaptability and fall risk in older people. *Gait & posture*, 59:188–192.

Caetano, M. J. D., Lord, S. R., Schoene, D., Pelicioni, P. H., Sturnieks, D. L., and Menant, J. C. (2016). Age-related changes in gait adaptability in response to unpredictable obstacles and stepping targets. *Gait & posture*, 46:35–41.

Chang, C., Hsu, S., Pion-Tonachini, L., and Jung, T. (2019). Evaluation of artifact subspace reconstruction for automatic artifact components removal in multi-channel eeg recordings. *IEEE Transactions on Biomedical Engineering*, pages 1–1.

Cherry, C. (1953). Cocktail party problem. *Journal of the Acoustical Society of America*, 25:975–979.

Chou, I.-h. (2008). Read my mind. *Nature Physics*, 4(1):S17–S17.

Csikszentmihalyi, M. (1975). *Beyond Boredom and Anxiety*. The Jossey-Bass behavioral science series. Jossey-Bass Publishers.

Delorme, A. and Makeig, S. (2004). Eeglab: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis. *Journal of neuroscience methods*, 134(1):9–21.

Eggenberger, P., Wolf, M., Schumann, M., and de Bruin, E. D. (2016). Exergame and balance training modulate prefrontal brain activity during walking and enhance executive function in older adults. *Frontiers in aging neuroscience*, 8:66.

Fang, Q., Ghanouni, P., Anderson, S. E., Touchett, H., Shirley, R., Fang, F., and Fang, C. (2019). Effects of exergaming on balance of healthy older adults: a systematic review and meta-analysis of randomized controlled trials. *Games for health journal*.

Gençer, N. G. and Akalin-Acar, Z. (2005). Use of the isolated problem approach for multi-compartment bem models of electro-magnetic source imaging. *Physics in Medicine & Biology*, 50(13):3007.

Gwin, J. T., Gramann, K., Makeig, S., and Ferris, D. P. (2011). Electrocortical activity is coupled to gait cycle phase during treadmill walking. *Neuroimage*, 54(2):1289–1296.

Halekoh, U. and Højsgaard, S. (2014). A kenward-roger approximation and parametric bootstrap methods for tests in linear mixed models – the R package pbkrtest. *Journal of Statistical Software*, 59(9):1–30.

Hämäläinen, M., Hari, R., Ilmoniemi, R. J., Knuutila, J., and Lounasmaa, O. V. (1993). Magnetoencephalography—theory, instrumentation, and applications to noninvasive studies of the working human brain. *Reviews of modern Physics*, 65(2):413.

Hamari, J., Koivisto, J., and Sarsa, H. (2014). Does gamification work?–a literature review of empirical studies on gamification. In *2014 47th Hawaii international conference on system sciences*, pages 3025–3034. Ieee.

Heinrich, S., Rapp, K., Rissmann, U., Becker, C., and König, H.-H. (2010). Cost of falls in old age: a systematic review. *Osteoporosis international*, 21(6):891–902.

Höchsmann, C., Schüpbach, M., and Schmidt-Trucksäss, A. (2016). Effects of exergaming on physical activity in overweight individuals. *Sports Medicine*, 46(6):845–860.

Hornyak, V., Brach, J. S., Wert, D. M., Hile, E., Studenski, S., and VanSwearingen, J. M. (2013). What is the relation between fear of falling and physical activity in older adults? *Archives of physical medicine and rehabilitation*, 94(12):2529–2534.

Hyvärinen, A. and Oja, E. (2000). Independent component analysis: algorithms and applications. *Neural networks*, 13(4-5):411–430.

Johansen, T. (2017). *Spill deg bedre*. Sunnaas Sykehus HF, Bjørnemyrveien 11, 1450 Nesoddtangen, Norway.

Kannus, P., Niemi, S., Palvanen, M., and Parkkari, J. (2005). Rising incidence of fall-induced injuries among elderly adults. *Journal of Public Health*, 13(4):212–215.

Kavanagk, R. N., Darcey, T. M., Lehmann, D., and Fender, D. H. (1978). Evaluation of methods for three-dimensional localization of electrical sources in the human brain. *IEEE Transactions on Biomedical Engineering*, (5):421–429.

Klem, G. H., Lüders, H. O., Jasper, H., Elger, C., et al. (1999). The ten-twenty electrode system of the international federation. *Electroencephalogr Clin Neurophysiol*, 52(3):3–6.

Kothe, C. A. E. and Jung, T.-P. (2016). Artifact removal techniques with signal reconstruction. US Patent App. 14/895,440.

Kraft, E. (2012). Cognitive function, physical activity, and aging: possible biological links and implications for multimodal interventions. *Aging, Neuropsychology, and Cognition*, 19(1-2):248–263.

Lambert, J. H. (1892). *Photometrie: Photometria, sive De mensura et gradibus luminis, colorum et umbrae (1760)*, volume 31. W. Engelmann.

Laszlo, S., Ruiz-Blondet, M., Khalifian, N., Chu, F., and Jin, Z. (2014). A direct comparison of active and passive amplification electrodes in the same amplifier system. *Journal of neuroscience methods*, 235:298–307.

Laver, K., George, S., Ratcliffe, J., Quinn, S., Whitehead, C., Davies, O., and Crotty, M. (2012). Use of an interactive video gaming program compared with conventional physiotherapy for hospitalised older adults: a feasibility trial. *Disability and rehabilitation*, 34(21):1802–1808.

Makeig, S., Bell, A. J., Jung, T.-P., and Sejnowski, T. J. (1996). Independent component analysis of electroencephalographic data. In *Advances in neural information processing systems*, pages 145–151.

Makeig, S., Gramann, K., Jung, T.-P., Sejnowski, T. J., and Poizner, H. (2009). Linking brain, mind and behavior. *International Journal of Psychophysiology*, 73(2):95–100.

Mehta, R. and Parasuraman, R. (2013). Neuroergonomics: a review of applications to physical and cognitive work. *Frontiers in Human Neuroscience*, 7:889.

Mellecker, R., Lyons, E. J., and Baranowski, T. (2013). Disentangling fun and enjoyment in exergames using an expanded design, play, experience framework: a narrative review. *GAMES FOR HEALTH: Research, Development, and Clinical Applications*, 2(3):142–149.

Mullen, T. R., Kothe, C. A., Chi, Y. M., Ojeda, A., Kerth, T., Makeig, S., Jung, T.-P., and Cauwenberghs, G. (2015). Real-time neuroimaging and cognitive monitoring using wearable dry eeg. *IEEE Transactions on Biomedical Engineering*, 62(11):2553–2567.

Onton, J. A. and Makeig, S. (2009). High-frequency broadband modulation of electroencephalographic spectra. *Frontiers in human neuroscience*, 3:61.

Oostenveld, R. and Oostendorp, T. F. (2002). Validating the boundary element method for forward and inverse eeg computations in the presence of a hole in the skull. *Human brain mapping*, 17(3):179–192.

Palmer, J. A., Kreutz-Delgado, K., and Makeig, S. (2006). Super-gaussian mixture source model for ica. In Rosca, J., Erdogmus, D., Príncipe, J. C., and Haykin, S., editors, *Independent Component Analysis and Blind Signal Separation*, pages 854–861, Berlin, Heidelberg. Springer Berlin Heidelberg.

Palmer, J. A., Makeig, S., Kreutz-Delgado, K., and Rao, B. D. (2008). Newton method for the ica mixture model. In *2008 IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 1805–1808.

Piazza, C., Miyakoshi, M., Akalin-Acar, Z., Cantiani, C., Reni, G., Bianchi, A. M., and Makeig, S. (2016). An automated function for identifying eeg independent components representing bilateral source activity. In *XIV Mediterranean Conference on Medical and Biological Engineering and Computing 2016*, pages 105–109. Springer.

Pion-Tonachini, L., Makeig, S., and Kreutz-Delgado, K. (2017). Crowd labeling latent dirichlet allocation. *Knowledge and information systems*, 53(3):749–765.

Pivik, R. T., Broughton, R. J., Coppola, R., Davidson, R. J., Fox, N., and Nuwer, M. R. (1993). Guidelines for the recording and quantitative analysis of electroencephalographic activity in research contexts. *Psychophysiology*, 30(6):547–558.

R Core Team (2019). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Regulation (EU) (2017). 2017/745 of the european parliament and of the council of 5 april 2017 on medical devices, amending directive 2001/83/ec, regulation (ec) no 178/2002 and regulation (ec) no 1223/2009 and repealing council directives 90/385/eec and 93/42/eec.

Rhodes, R. E., Blanchard, C. M., Bredin, S. S., Beauchamp, M. R., Maddison, R., and Warburton, D. E. (2017). Stationary cycling exergame use among inactive children in the family home: a randomized trial. *Journal of behavioral medicine*, 40(6):978–988.

Sazgar, M. and Young, M. G. (2019). *Overview of EEG, Electrode Placement, and Montages*, pages 117–125. Springer International Publishing, Cham.

Schoene, D., Lord, S. R., Verhoef, P., and Smith, S. T. (2011). A novel video game–based device for measuring stepping performance and fall risk in older people. *Archives of physical medicine and rehabilitation*, 92(6):947–953.

Sherrington, C., Tiedemann, A., Fairhall, N., Close, J. C., and Lord, S. R. (2011). Exercise to prevent falls in older adults: an updated meta-analysis and best practice recommendations. *New South Wales public health bulletin*, 22(4):78–83.

Skjæret, N., Nawaz, A., Morat, T., Schoene, D., Helbostad, J. L., and Vereijken, B. (2016). Exercise and rehabilitation delivered through exergames in older adults: An integrative review of technologies, safety and efficacy. *International journal of medical informatics*, 85(1):1–16.

Skjæret-Maroni, N., Vonstad, E. K., Ihlen, E. A., Tan, X.-C., Helbostad, J. L., and Vereijken, B. (2016). Exergaming in older adults: movement characteristics while playing stepping games. *Frontiers in psychology*, 7:964.

Smith, S. T., Sherrington, C., Studenski, S., Schoene, D., and Lord, S. R. (2011). A novel dance dance revolution (ddr) system for in-home training of stepping ability: basic parameters of system use by older adults. *British journal of sports medicine*, 45(5):441–445.

Stanmore, E. K., Mavroeidi, A., de Jong, L. D., Skelton, D. A., Sutton, C. J., Benedetto, V., Munford, L. A., Meekes, W., Bell, V., and Todd, C. (2019). The effectiveness and cost-effectiveness of strength and balance exergames to reduce falls risk for people aged 55 years and older in uk assisted living facilities: a multi-centre, cluster randomised controlled trial. *BMC medicine*, 17(1):49.

Thompson, T., Steffert, T., Ros, T., Leach, J., and Gruzelier, J. (2008). Eeg applications for sport and performance. *Methods*, 45(4):279–288.

Troy M, L., Joseph T, G., and Daniel P, F. (2012). How many electrodes are really needed for eeg-based mobile brain imaging? *Journal of Behavioral and Brain Science*, 2012.

Van Diest, M., Lamoth, C. J., Stegenga, J., Verkerke, G. J., and Postema, K. (2013). Exergaming for balance training of elderly: state of the art and future developments. *Journal of neuroengineering and rehabilitation*, 10(1):101.

Vonstad, E. K., Su, X., Vereijken, B., Nilsen, J. H., and Bach, K. (2018). Classification of movement quality in a weight-shifting exercise. CEUR Workshop Proceedings.

Winkler, I., Debener, S., Müller, K., and Tangermann, M. (2015). On the influence of high-pass filtering on ica-based artifact reduction in eeg-erp. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 4101–4105.

World Health Organization (2015). *World report on ageing and health*. World Health Organization.

Yan, J. H. and Zhou, C. L. (2009). Effects of motor practice on cognitive disorders in older adults. *European review of aging and physical activity*, 6(2):67.

Yardley, L. and Smith, H. (2002). A prospective study of the relationship between feared consequences of falling and avoidance of activity in community-living older people. *The Gerontologist*, 42(1):17–23.

Zelinski, E. M. and Reyes, R. (2009). Cognitive benefits of computer games for older adults. *Gerontechnology: international journal on the fundamental aspects of technology to serve the ageing society*, 8(4):220.

Zijlstra, A., Ufkes, T., Skelton, D., Lundin-Olsson, L., and Zijlstra, W. (2008). Do dual tasks have an added value over single tasks for balance assessment in fall prevention programs? a mini-review. *Gerontology*, 54(1):40–49.

Paper I

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Balance Training in Older Adults Using Exergames: Game Speed and Cognitive Elements Affect How Seniors Play

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Falls in older adults are a serious threat to their health and independence, and a prominent reason for institutionalization. Incorrect weight shifts and poor executive functioning have been identified as important causes for falling. Exergames are increasingly used to train both balance and executive functions in older adults, but it is unknown how game characteristics affect the movements of older adults during exergaming. The aim of this study was to investigate how two key game elements, game speed, and the presence of obstacles, influence movement characteristics in older adults playing a balance training exergame. Fifteen older adults (74 ± 4.4 years) played a step-based balance training exergame, designed specifically for seniors to elicit weight shifts and arm stretches. The task consisted of moving sideways to catch falling grapes and avoid obstacles (falling branches), and of raising the arms to catch stationary chickens that appeared above the avatar. No steps in anterior-posterior direction were required in the game. Participants played the game for eight 2 min trials in total, at two speed settings and with or without obstacles, in a counterbalanced order across participants. A 3D motion capture system was used to capture position data of 22 markers fixed to upper and lower body. Calculated variables included step size, step frequency, single leg support, arm lift frequency, and horizontal trunk displacement. Increased game speed resulted in a decrease in mean single support time, step size, and arm lift frequency, and an increase in cadence, game score, and number of error messages. The presence of obstacles resulted in a decrease in single support ratio, step size, cadence, frequency of arm lifts, and game score. In addition, step size increased from the first to the second trial repetition. These results show that both game speed and the presence of obstacles influence players' movement characteristics, but only some of these effects are considered beneficial for balance training whereas others are detrimental. These findings underscore that an informed approach is necessary when designing exergames so that game settings contribute to rather than hinder eliciting the required movements for effective balance training.

Keywords: balance training, older adults, exergaming, movement characteristics, game settings

INTRODUCTION

The rapidly aging population in industrialized countries and concurrent strains on the health care system necessitate more cost-effective treatment and prevention options to counteract age-related decline in functioning. Falls in older adults are among the main causes for hospitalization and institutionalization (Kannus et al., 2005) and significantly impact the cost burden on health care budgets worldwide (Heinrich et al., 2010). Furthermore, both actual falls and fear of falling are associated with reduced activity (Yardley and Smith, 2002; Hornyak et al., 2013), which in turn increases the risk for developing chronic conditions.

There is good evidence that balance training reduces fall risk (e.g., Buchner et al., 1997) and can counteract inactivity caused by fear of falling (Gusi et al., 2012). A cost-effective way to administer additional balance training with good adherence rates is exergaming (Burke et al., 2009; Skjæret et al., 2016). Exergames are videogames that require bodily movements as input to play the game (Brox et al., 2011). The term is used both for vigorous exercises and for less intensive exercises such as balance training or seated upper body exercises. Furthermore, exergames allow for home-based training in elderly, as demonstrated in early studies using force-sensitive matbased stepping exergames (Schoene et al., 2011; Smith et al., 2011). In recent years, exergames have gained popularity both as a complementary tool or as a replacement for traditional exercise and rehabilitation (e.g., Mellecker et al., 2013), with the same or better effectiveness compared to usual care (Skjæret et al., 2016). In addition, exergames have been shown to have positive effects on physical activity in general (e.g., Höchsmann et al., 2016; Rhodes et al., 2017), as well as in specific rehabilitation settings (e.g., Laver et al., 2012; Baltaci et al., 2013). Ongoing developments in game technology, such as videobased motion detection of the player, allow for exergames with more variation in movements compared to mat-based exergame systems.

Correctly executed steps are important to maintain balance and to avoid falls (Robinovitch et al., 2013). In daily life, one is often required to make quick, unanticipated steps to react to changing circumstances in order to avoid a fall (Lord and Fitzpatrick, 2001). This requires both the mental and physical capacity to react to an unknown situation. Caetano et al. (2016) showed that the ability to adapt gait is an important factor in predicting fall risk. Furthermore, they showed that concurrent cognitive tasks resulted in older adults reducing their walking speed and shortening their steps during the stepping and avoidance paradigm used in their studies (Caetano et al., 2017, 2018).

Stepping exergames are well suited for creating artificial situations in which unplanned steps are needed and have been shown to reliably assess fall risk in community-dwelling older adults (Schoene et al., 2011). Furthermore, a recent systematic review of randomized control trials about the effect of balance exergames in older adults (Fang et al., 2020) found improvements in functional performance and balance confidence with respect to dynamic balance, perceived balance, chair stand test, and balance test batteries. Non-significant improvements in static balance and proactive balance were speculated to be caused by ceiling effects in the tests used.

Despite the good evidence for the use of stepping exergames to train balance, there is an overall lack of knowledge on the actual movement characteristics that are elicited by exergames, both in elderly players and in other populations. This knowledge is crucial for the development of evidence-based, targeted exergames if the intention is to provide effective training and rehabilitation in the aging population. This is even more critical when exergames are to be used unsupervised in home-based training. To date, most of the research has focused on the effectiveness of, and adherence to, training programs using exergames compared to usual care, not on whether the intended movements are actually elicited. Without knowledge about the movement characteristics elicited during gameplay, it is difficult to design effective balance training exergames or interpret the effects, or lack thereof, of exergaming interventions in clinical trials.

In order to design effective exergames that achieve high adherence rates over longer periods of time, expertise from multiple disciplines is necessary. On the one hand, health care professionals need to contribute with their knowledge about which exercises and movements are required to train specific functions. On the other hand, the expertise of programmers and video game designers is crucial, both for the technical aspects and to ensure that the exergames are enticing and inherently motivating over longer periods of time. Furthermore, to assess whether the intended movements are indeed elicited during gameplay, the expertise of human movement scientists is required. Such multidisciplinary effort at the intersection of health, movement science, and computer science becomes even more crucial given the lack of knowledge about movement characteristics of elderly exergame users that are elicited by different settings and potential additional cognitive challenges within the exergame.

A critical element for training and rehabilitation programs to be effective is adherence to the program. A common strategy to achieve high adherence during exergaming is to try to keep the player in a so-called flow-zone (Csikszentmihalyi, 1975). In the flow-zone, a player is neither overchallenged nor bored by the exergame. One way to achieve this is by dynamically adjusting the game settings during the game to match the performance of the player. For example, game speed can be changed to adjust the difficulty level of the exergame, thereby personalizing the exergame to the player's abilities and enabling progression (e.g., van Diest et al., 2013). However, very little is known about how a change in game speed affects the movement characteristics of the player, and whether these effects are beneficial or detrimental for the desired training or rehabilitation effect. For example, if a higher game speed would lead to less carefully executed movements, as in a speed-accuracy trade-off (cf. Heitz, 2014), this might not be beneficial to achieve the desired training effects. A better understanding of the effects of game speed on elicited movement characteristics is thus necessary to inform the development of targeted exergames for balance training and prevention of functional decline.

Similarly, additional challenges in the form of cognitive elements are used often in exergames to keep the player in the flow-zone or to add cognitive training to the physical exercise (Anders et al., 2018). These additional cognitive elements can be in the form of extra tasks in the exergame such as counting, matching objects, or avoiding obstacles. Cognitive elements in exergames can create a dual task situation in which the player needs to focus on two or more things simultaneously, thereby training cognitive function as well as physical function. Evidence suggests that dual task training can improve walking performance of older adults (Wollesen et al., 2017). However, the effect of additional cognitive elements on the player's movement characteristics in exergames is rarely explored. In a rare exception, Skjæret-Maroni et al. (2016) found a decrease in the quality of movement characteristics needed to train balance when cognitive tasks were present during exergaming, underscoring the need for better knowledge about how game settings influence elicited movements during exergaming.

The objective of the current study is to address these gaps in our knowledge by investigating the effect of game speed and obstacles on movement characteristics in older adults playing a balance training exergame. As there is good evidence that step-based balance training reduces the risk of falls in older adults (e.g., Okubo et al., 2017), we chose a stepping exergame for balance training and assessed the movement characteristics of older adults playing at two different speed settings and either with or without obstacles to avoid. To the best of our knowledge, there is no previous study that assessed the effects of game speed and obstacles in exergames on movement characteristics in older adults. This knowledge is crucial for both health care professionals and developers of exergames in order to choose between existing or design new exergames that are most beneficial for balance training.

We expected that both game speed and the presence of obstacles would influence movement characteristics, and that some of these effects would be beneficial for balance training but others detrimental. Furthermore, in exergames with higher cognitive load, we expected the participants to make smaller steps.

METHODS

Participants

Fifteen older adults between 65 and 83 years of age participated in an experimental laboratory study at the Norwegian University of Science and Technology (see **Table 1** for participant characteristics). To be included, participants had to be 65 years or older and live independently. Participants were excluded if they had an injury or had undergone surgery of the back or the lower extremities during the last 6 months, or if they were unable to follow instructions given by the researchers.

The protocol was approved by the Regional Committees for Medical and Health Research Ethics, Norway. All participants gave written informed consent before data collection in accordance with the Declaration of Helsinki.

TABLE 1 | Participant characteristics.

	Mean	SD	Range
Age (years)			
Female ($N = 7$)	72.6	4.7	65–79
Male ($N = 8$)	74.8	4.0	70–83
Total ($N = 15$)	73.7	4.4	65–83
Height (cm)			
Female	166.8	3.5	162.8–172.2
Male	175.2	6.1	165.8–183.5
Total	171.3	4.1	162.8–183.5
Weight (kg)			
Female	65.4	4.9	60–74.4
Male	76	4.1	70.2–82.8
Total	71	7	60–82.2

Procedure

All participants played a step-based balance training exergame ("The Fox," SilverfitBV, the Netherlands). The aim of the exergame was to feed a fox-avatar by moving it sideways into the trajectory of falling grapes. The avatar mirrored the lateral movements of the participants, so when the participants placed themselves to the far right of the exergaming area, the avatar would be on the far-right side of the screen. The exergaming area was set to 2 by 2 m as shown in **Figure 1**. Thus, the movement of the avatar from one side of the screen to the opposite side corresponded to a 2 m distance in the physical playing area. The game itself did not determine any required step size, as participants can take several smaller or fewer larger steps to move the avatar the desired distance. Occasionally appearing stationary chickens above the fox-avatar were caught by raising at least one arm, which triggered the fox to jump. Only arm movements that resulted in at least one hand being lifted higher than the head were accepted by the exergame as a trigger for a jump. Other arm movements, e.g. to maintain balance, were ignored by the game. Participants had a time window of 7 s to place themselves under a chicken and raise at least one arm to trigger a jump, before the prey disappeared again.

No movement in the anterior-posterior direction was required to play the exergame. The exergame system used a Microsoft Kinect v2 camera (Microsoft Corporation, Redmond, WA, USA) to capture the movements of the participants. The Kinect v2 was used as input for the exergame only and not for data capturing.

Each participant played eight 2-min exergame trials at two speed settings and either with or without additional obstacles, falling branches, that had to be avoided. The width of a falling branch can be seen in **Figure 1**. The distance between the grapevines on either side corresponded to a physical distance of 2 m, a branch covered approximately 57 cm (35%). Increasing the exergame speed led to an increased number of grapes and branches falling simultaneously on the screen (from 1–3 to 3–5 grapes, and from 1–2 to 1–3 branches) and reducing their time on the screen from 8–10 s to 6–9 s (measured from top to bottom of the screen for missed grapes and branches). Neither the number

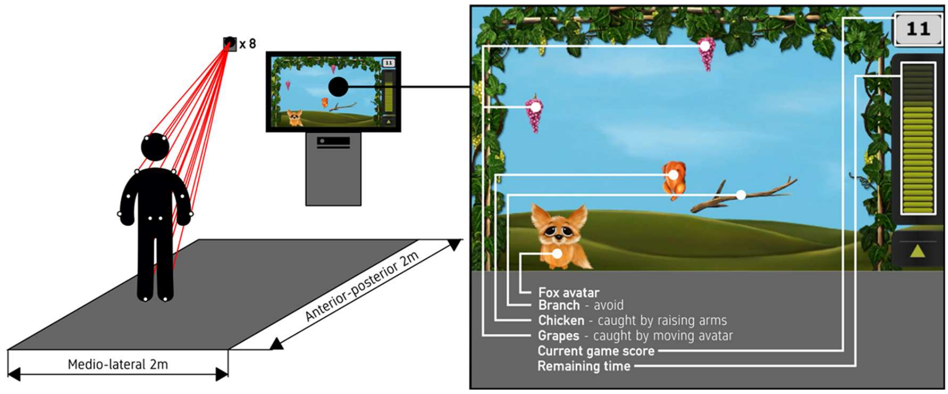

FIGURE 1 | Graphical image of the exergame area (left panel) and a screenshot of "The Fox" exergame (right panel) showing all exergame elements (Fox-avatar, grapes, chickens, branches, game score, and remaining game time).

of chickens nor their time on the screen were affected by changes of the game speed. The four conditions were played twice in counterbalanced order across participants. Participants had a 2-min break between exergame trials. Before the first trial, each participant tested the game at a lower speed setting to ensure that they understood the task and that they were able to perform all required movements. After the participants completed all eight trials, they performed a range-of-motion test to quantify that they were able to perform all required movements such as arm lifts and forward and sideways steps.

To record the participant's movements throughout the trials, 22 retroreflective markers were placed on anatomical landmarks using double-sided tape and a headband. Markers were placed bilaterally on the posterior and anterior side of the head, ulna styloid process, lateral epicondyle of the humerus, acromion, ilium posterior superior, ilium anterior superior, femur lateral epicondyle, lateral malleolus, and lateral distal phalange 1 (big toe), as well as one marker on the sternum and one on the center of the right thigh. A 3D motion capture system (OQUS, Qualisys, Gothenburg, Sweden) consisting of eight cameras was used to record the spatial positions of the markers throughout all exergame trials, with a measurement frequency of 120 Hz. The cameras were wall-mounted to minimize blockage by the TV screen or the Kinect v2 camera. Markers that fell off during a trial were replaced before the start of the next trial.

The output of the exergame on the 55" (139.7 cm) TV screen was captured using Open Broadcaster Software Studio (version 21.0; Open Broadcaster Software Studio, 2018). **Figure 1** shows an exemplary frame including all game elements. The game score displayed on the top right of the screen was explained to the participants, but they were not specifically encouraged to achieve the highest possible score.

If the participant moved outside the predefined exergaming area of 2 by 2 m, the game stopped and an error message appeared on the screen containing information on how to resolve the issue, e.g., "You are too far in the back. Please move closer to the screen." The exergame continued as soon as the participant returned to the exergaming area. The size of the exergaming area was not indicated on the floor in order to mimic a home-based setting.

Data Analysis

A custom Matlab script (version: 9.3.0, Mathworks Inc., Nantick, MA) was used to analyze the movement of the extremities as well as the position of the trunk based on the 3D motion capture data. The start and stop of each step was identified using the same method as in Skjæret-Maroni et al. (2016), which used the position of the markers on the lateral malleolus. A step was defined as a $\geq$ 0.03 m displacement of the toe marker lasting for $\geq$ 0.05 s. A marker velocity of 0 $\pm$ 0.1 ms^{-1} was used for the identification of step initiation and termination. From these, mean duration of single leg support, mean step size, and cadence were calculated for each foot. We chose the term step size rather than step length or step width to capture both sideways and forward aspects of steps, as some participants partly rotated their upper body whereas others remained parallel to the screen while taking steps. Furthermore, the ratio of the total duration of single-leg support (total accumulated single-leg support time divided by trial time) was calculated. Movement data for the arms was used to calculate the number of arm lifts per minute. The start and end of an arm lift was determined by the relationship between the vertical positions of the average height of all head markers compared to the left and right markers on the ulna styloid processes (wrists). The player's position on the playing field was determined by the position of the marker on the sternum. Displacements of the sternum marker were used to create heatmaps that reflected upper body positions of the participants in relation to the screen.

There were slight variations in the duration of each exergame across trials and participants due to error messages that appeared on the screen when a participant left the exergaming area, which temporarily stopped the game but not the 3D motion capture recording. Therefore, we report the ratio for single-leg support and the frequency of arm lifts rather than the total duration of single-leg support and the total number of arm lifts.

Finally, optical character recognition was used on the captured screen frames to identify error messages during each trial, as well as the total game score and the number of chickens caught and branches hit (if present) at the end of each trial.

Statistics

A linear mixed effect analysis in R (R Core Team, 2019) was used to analyze the effects of game speed, the presence or absence of obstacles, gender, and trial repetition, which served as fixed effects on the investigated movement characteristics, using the lme4 package (Bates et al., 2015). Random effects included intercepts for participants as well as by-participant random slope for the effect of body side (right or left arm or foot). Visual inspection of residual plots did not reveal deviations from normality or homoscedasticity. The computation of p-values was based on conditional F-tests with Kenward-Roger approximation for the degrees of freedom (Halekoh and Højsgaard, 2014). Statistical significance was set at $p < 0.05$. The linear mixed effect analysis was chosen to remove individual differences between participants (Schoene et al., 2011) and to account for the slight gender imbalance without losing statistical power.

RESULTS

Game Score

The game score that appeared on the screen after each trial was a combination of grapes and chickens caught and branches avoided (+ 1 point for each grape caught, + 3 points for each chicken caught, and −2 points for each branch hit). The number of grapes presented varied across trials, depending on the chosen game speed, thereby resulting in more opportunities for catching grapes in games with high game speed. In contrast, the number of chickens did not vary with game speed but was constant at 11 chickens per trial. The game score results are shown in **Table 2**. Not surprisingly, the mean game score was higher in the trials at high game speed without obstacles. The presence of obstacles reduced the game score by approximately 20 points for either game speed setting, while the game score was about 20 points higher in games at high speed compared to games at low speed. The percentage of grapes caught was ∼20% higher in low-speed compared to high-speed games. Interestingly, the percentage of grapes caught with or without obstacles was similar, with a small trend to increase when obstacles were present. In contrast, a clear decrease was seen in the percentage of chickens caught in games with obstacles present. Percentage of branches unsuccessfully avoided was very low and slightly higher in games with low speed settings.

TABLE 2 | Mean game score and mean percentage of caught grapes, caught chickens, and unsuccessfully avoided branches for all combinations of game speeds and obstacles.

	Obstacles	Speed: *low*	Speed: *high*	Overall
Game score	*without*	69.8	86	**78.5**
	with	48.7	67.4	**58.3**
	Overall	**59**	**77.1**	**68.5**
Grapes caught	*without*	77.6%	53.7%	**64.8%**
	with	79.8%	59.1%	**69.3%**
	Overall	**78.7%**	**56.3%**	**67%**
Chickens caught	*without*	91.3%	93.1%	**92.3%**
	with	74.8%	76.1%	**75.5%**
	Overall	**82.9%**	**84.9%**	**83.9%**
Branches hit	*with*	5%	3.8%	**4.4%**

The values in bold font represent the average across game speed, presence of obstacles and overall.

Movement Characteristics

Single Leg Support

As standing on one leg is an important strategy to train balance, we investigated both the mean duration of single support events per foot (in seconds) and the ratio of single leg support (accumulated single support time during a trial divided by trial time). The mixed effects model indicated that the mean duration of single support events decreased significantly ($p < 0.001$) with an increase in game speed, whereas the ratio of single support increased slightly but not significantly ($p = 0.189$) (see **Figure 2** and **Table 3**). This indicates that participants stood slightly more often but significantly shorter on one foot when playing at higher speed. Furthermore, the ratio of single support decreased when obstacles were present, indicating that participants accumulated less single support time during a trial when having to avoid obstacles. Neither ratio nor duration of single support were significantly affected by trial repetition, gender, or body side (all p's > 0.10).

Mean Step Size and Cadence

Step size and cadence where both affected significantly by the game speed (mean step size: $p < 0.05$; cadence: $p < 0.001$) and the presence of obstacles (mean step size: $p = 0.001$; cadence: $p < 0.001$). As can be seen in **Figure 3**, higher game speed and the presence of obstacles led to a decrease in mean step size (panel A). Cadence decreased as well when additional obstacles were present but increased with an increase in game speed (panel B). In addition, trial repetition had a significant effect on mean step size ($p < 0.001$), with larger steps when participants played the same condition for the second time. See **Table 3** for all statistical results for mean step size and cadence.

Frequency of Arm Lifts

The frequency of arm lifts decreased with high game speed ($p < 0.001$) and when additional obstacles were present ($p = 0.001$), as shown in **Figure 4**. Trial repetition, gender, and body side had no significant effects on the frequency of arm lifts (all p's > 0.08). See **Table 3** for all statistical results.

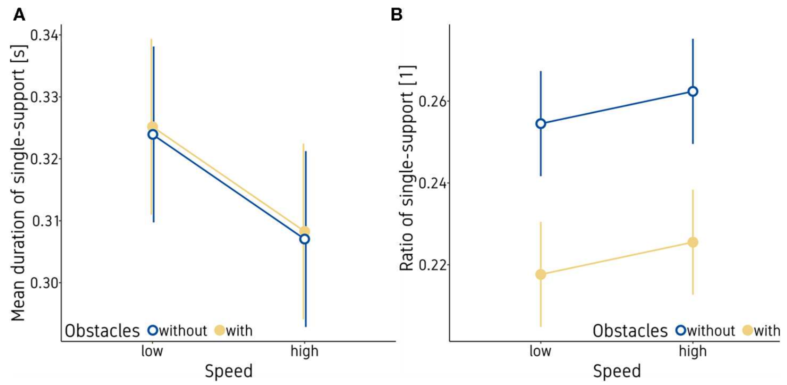

FIGURE 2 | Mean duration of single support events **(A)** and ratio of single support **(B)**. Vertical bars indicate the standard error of the model.

Player's Position

Heatmaps

As described above, the active area in which the exergame could be played was ∼2 by 2 m. The heatmap (see **Figure 5**) shows the number of observations of the sternum marker in the exergaming area (white square) across all participants and all trials, on a 30 by 30 grid. Warmer colors indicate more observations. The starting position was centered in front of the screen, 0 mm in medial-lateral and 500 mm in posterior direction (white circle in **Figure 5**). On average, participants drifted ∼0.5 m closer to the screen throughout an exergame trial, as indicated by the green and yellow squares, indicating more observations of the sternum marker parallel to the screen (white rectangle). There were no systematic differences in the heatmaps between the different conditions.

Moving Outside the Exergaming Area

When a participant moved outside the active exergame area of 2 by 2 m in any direction while playing, an error message would appear on the screen to inform the participant to correct their position in the playing area. We used a custom Matlab script including optical character recognition to detect error messages in the screen recording. Out of 15 participants, only two participants never drifted outside the active exergame area while playing the exergames. The remaining participants moved outside the area between one and nine times across all conditions. On average, 0.38 error messages per exergame trial were observed across all exergame trials that had valid screen captures (113 out of 120 trials). The majority of error messages were triggered by participants who drifted too close to the screen while playing (36 out of 43 error messages in total). The average time to resolve this was 2.44 s. The remaining error messages were divided between being too far to the left (4 times, on average 1.34 s to resolve), too far to the right (once, 0.67 s), and too far back (twice, 1.70 s).

More error messages were triggered in trials at high game speed compared to those at low game speed (see **Table 4**). However, a chi-square test indicated that the presence or absence of obstacles showed no consistent effect on the number of error messages triggered, nor was there a significant interaction between game speed and the presence of obstacles, $\chi^2_{(1)} = 1.203$, $p > 0.05$.

DISCUSSION

The purpose of this study was to investigate the effect of game speed and obstacles on movement characteristics of older adults who played a step-based balance training exergame. According to a meta-analysis by Sherrington et al. (2011), effective balance exercises should include displacement of the center of gravity and reduced base of support. Therefore, we assessed mean step size and cadence, the ratio and duration of single-leg support, as well as the frequency of arm lifts as arm lifts and stretches influence the center of gravity. Both changes in game speed and additional cognitive elements are used regularly in exergames to keep the player in the flow-zone and/or train cognitive and physical functions simultaneously. However, as the results of the current study show, changing the settings of an exergame can have both positive and negative effects on the player's movement characteristics with respect to training balance. Below, we discuss our main findings regarding the effects of game speed, the presence of obstacles, and trial repetition on movement characteristics, the consequences of these effects for balance training, and their relevance for choosing existing or developing new exergames for balance training in older adults.

Game Speed

Higher game speed led to shorter single support events, shorter steps, fewer arm lifts, and increased cadence. Higher cadence is associated with more frequent weight shifts, which are considered beneficial for effective balance training (Sherrington et al., 2011). Furthermore, eliciting faster steps during gaming at higher speed may benefit the training of a quick step to avoid, or recover from, a balance disturbance and imminent fall. On the other hand, participants were more likely to move outside

TABLE 3 | The degrees of freedom (df), confidence intervals (CI), and significance level (p) for the mean duration of single support events, ratio of single support, mean step length, cadence, and the frequency of arm lifts.

	Mean duration of single support (s)			Ratio of single support (1)			Mean step size (mm)			Cadence (min^{-1})			Frequency of arm lifts (min^{-1})		
	df	CI	*p*	df	CI	*p*	df	CI	*p*	df	CI	*p*	df	CI	*p*
Speed	229.07	−0.03 to −0.01	**<0.001**	229.09	−0.00 to 0.02	0.189	293.14	−13.87 to −0.45	**0.038**	229.07	5.22 to 8.56	**<0.001**	229.07	−2.27 to −0.99	**<0.001**
Obstacles	229.07	−0.01 to 0.01	0.774	229.09	−0.05 to −0.03	**<0.001**	−7.16	−18.54 to −5.12	**0.001**	229.07	−10.97 to −7.63	**<0.001**	229.07	−1.70 to −0.42	**0.001**
Trial	229.07	−0.01 to 0.01	0.582	229.09	−0.01 to 0.02	0.318	−11.83	5.78 to 19.20	**<0.001**	229.07	−0.80 to 2.55	0.306	229.07	−0.97 to 0.32	0.321
Gender	17.31	−0.05 to 0.06	0.909	17.29	−0.02 to 0.07	0.280	12.49	−42.63 to 3.39	0.113	17.31	−2.12 to 14.10	0.166	17.31	−5.64 to 1.94	0.352
Side	229.07	−0.00 to 0.02	0.102	229.09	−0.01 to 0.01	0.982	−19.62	−7.02 to 6.40	0.928	229.07	−0.64 to 2.70	0.229	229.07	−1.20 to 0.08	0.086

The values in bold font represent significant p values.

the active exergaming area when playing at higher speed, as indicated by more than twice as many error messages. This would cause the exergame to stop, thereby potentially interrupting the participant's flow. Further research is necessary to find an optimal balance between these contrasting effects of game speed when designing or choosing the most beneficial game and game settings for balance training. This is further attested to by our results regarding game score. As higher game speed led to higher scores, this may have important ramifications for exergames where achieving a high score is the focus for the player, as game speed affects the movement characteristics as well.

Obstacles

The presence of obstacles led to shorter steps, reduced cadence, fewer arm lifts, and a decrease in the ratio of single-support time. A likely explanation for these changes in movement characteristics is increased cognitive load caused by the presence of additional exergame elements and potentially conflicting demands on the player. These results indicate that although cognitive elements are often added to the game to increase enjoyment and/or simultaneously train cognitive functions, they can lead to unwanted side effects on elicited movement characteristics that are less favorable for balance training (see also Skjæret-Maroni et al., 2016).

Furthermore, we observed that when participants moved their avatar toward the edge of the screen, the avatar was occasionally trapped there by falling branches that blocked the path back to the middle or the other side of the screen. This resulted in participants waiting for the obstacle to pass before continuing to play the game and try to catch grapes and chickens. The waiting period in which the participants stood still could take up to several seconds. The low percentage of collisions with branches indicates that participants indeed tried to avoid being hit by branches as much as possible, even when that meant having to wait for the branch to pass before continuing to catch chickens and grapes. Although having to avoid obstacles may be positive in terms of adding cognitive training and enjoyment to the exergame, this may also lead to strategies and movements that are considered less beneficial for the training of balance. Waiting for a situation to resolve should be avoided by the game design, for example by allowing the avatar to move forward or backward around the obstacle. An alternative solution could be to introduce e.g., an extra bracing position to protect the avatar from falling branches which could simultaneously challenge balance. Our results underscore that the effects of additional cognitive elements on intended movement characteristics need to be taken into account when designing or using exergames for balance training.

Trial Repetition

Participants played each condition twice, but we did not expect to find learning or fatigue effects with such short exposure. Although most movement characteristics were indeed unaffected by the repetition, we did find larger steps on the second trial compared to the first. A possible explanation for this might be that in the second trial, participants were more familiar and comfortable with playing the exergame in general and

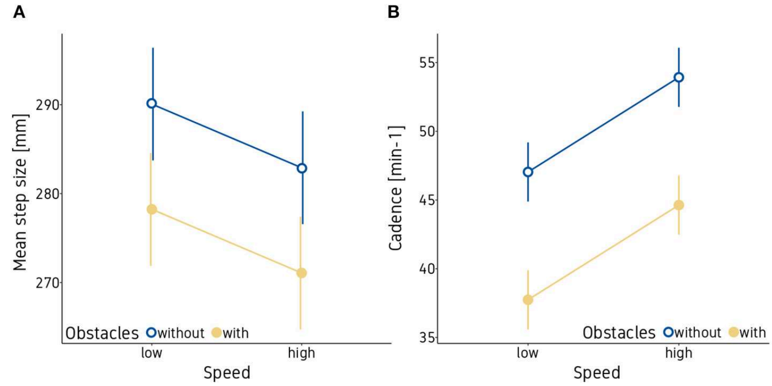

FIGURE 3 | Mean step length **(A)** and cadence **(B)**. Vertical bars indicate the standard error of the model.

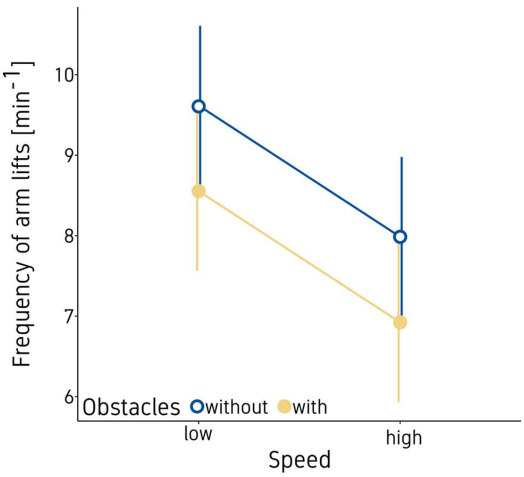

FIGURE 4 | Mean frequency of arm lifts. Vertical bars indicate the standard error of the model.

the movements required to play the exergame in particular. Pure sideways stepping without a forward component to the movement is less common in everyday life. Therefore, it may be speculated whether participants needed a short adaption phase in order to perform this movement with enough confidence to perform larger steps. In that respect, the observed increase in mean step size from trial one to trial two is a positive result, as stepping sideways can be an important strategy to recover postural control after a balance disturbance (Hsiao-Wecksler and Robinovitch, 2007). Furthermore, this result indicates also that exergames might have an immediate short-term learning effect.

Other Observations and Lessons Learned

Although the exergame itself did not distinguish between different ways of raising arms to catch chickens, we observed several distinct playing styles. Some participants raised both arms to catch chickens, whereas others raised one arm only. One participant did not raise the arms at all during the game and did not catch any chickens. These differences did not result from physical limitations, as we checked that all participants were able to perform the required movements with both arms. Some participants also used the jump of the avatar to catch falling grapes faster instead of waiting underneath the trajectory of the falling grapes. These observations indicate that exergame players may perform or play in many different ways that can benefit or hinder the intended balance training. Ideally, the game technology used should be able to distinguish correct vs. incorrect movements in these situations and provide feedback in order for the exergame to function as an effective balance training and rehabilitation tool (cf. Vonstad et al., 2018). Thus, the knowledge gained by investigating different movement characteristics displayed by the players when exergaming should be used in the design and development of new exergames for health benefits.

Throughout each trial, participants moved ∼0.5 m closer to the screen on average. There was no incentive in the exergame to do so as the game was played on a two-dimensional plane parallel to the screen. This gradual forward movement was observed across all conditions and participants. The implemented elements in the game such as the falling branches did not affect this behavior. A possible explanation for the drift toward the screen might be that a pure sideways movement is difficult to achieve and less common in activities of daily living compared to side steps with an additional forwards component to them, as in avoiding an obstacle in the path of progression. Alternatively, it can be speculated that the older adults who served as participants in this study struggled to learn to use the system quickly enough to avoid drifting outside the exergaming area. Younger adults and children, the main customer-base of video game technology, grew

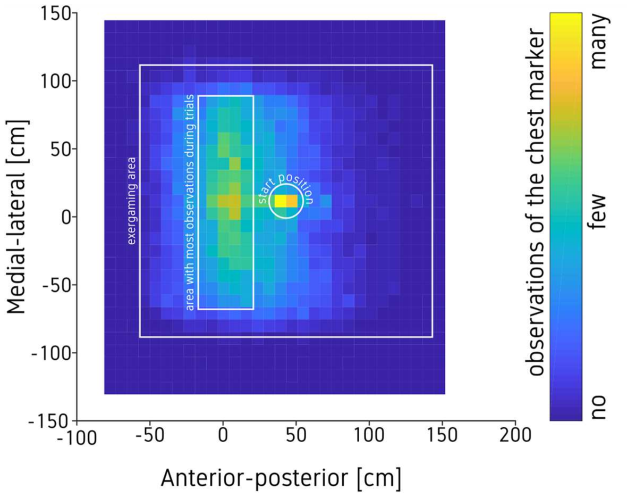

FIGURE 5 | Heatmap of the players' positions in the exergaming area based on the marker on the chest across all conditions and participants. The white square indicates the 2 by 2m active exergaming area. All participants started each trial in the white circle. The white rectangle indicates the area with most observations. The game screen was positioned to the left of the playing area.

TABLE 4 | Error messages triggered by the players moving outside the active exergaming area for each combination of settings.

Error messages		Obstacles		
		without	*with*	**Total**
Speed	*low*	5	8	13
	high	17	13	30
	Total	22	21	43

up using technology such as Microsoft's Kinect or Sony's EyeToy and are therefore more familiar with digital avatars mirroring movements, as well as with the inherent limitations caused by the limited field-of-view of the infrared cameras. Thus, they may be more likely to reposition themselves when they drift away from the center of the observable area. Although we did not mark the exergaming area with tape in order to mimic a more natural home-based setting, proper delimitation might help to reduce the ambiguity concerning one's position within the exergaming area.

Over time, the accumulation of the drift forward resulted in error messages and breaks in the game until participants stepped back into the active exergame area. Though usually of short duration and easily corrected by the player, those error messages and game breaks likely result in a disruption of the flow-zone (Csikszentmihalyi, 1975), with associated potential negative consequences for enjoyment and adherence. However, as we did not collect data on enjoyment of the exergame, this remains an assumption that needs corroboration in further studies. Yet, future development of exergames could take our findings into account by letting the game stimulate the player to move back toward the center of the play area without disrupting the exergame experience by error messages and game breaks.

The current study was designed to observe immediate effects of game settings on movement characteristics in a single exergaming session. But even across only two trial repetitions, steps became significantly larger. In order to achieve lasting improvements in the ability to maintain balance, multiple sessions over a longer period of time are needed. With more repetitions, people who routinely use exergames for balance training might show additional changes in movement characteristics in reaction to changes in game speed or additional challenges. Further research is needed with longer follow-up time to study potential effects over extended playing time.

Limitations

The current study offers several insights into how game settings in exergames influence the movement characteristics of older adults, allowing to provide recommendations for the development and usage of exergames to elicit the movements necessary to train balance in older adults. However, a few limitations should be highlighted as well. First, this study was conducted using a screen-based exergame. Newly developed exergames might use newer technologies such as immersive virtual reality or gamified objects in the environment rather than TV screens. However, we believe that many of the lessons learned may be transferrable to virtual reality exergames, since the basic concepts for eliciting the desired vs. less desirable movements may largely be the same. Furthermore, older adults are a specific subgroup of users who, at the moment, might be less familiar with modern game and simulation technologies than younger generations. However, continued developments in non-immersive virtual reality and increasing tech-savviness of new generations of older adults may contribute to the accessibility of exergame technology for a wider audience. Finally, although no formal tests of the participants' physical and mental capacity were performed in this study, all participants were healthy for their age and living independently. Further research should broaden out to participants with a wider range of functional capacities to investigate how they would react to changes in game speed and additional challenges.

Next Steps

Methods to deliver safe, home-based, low-cost balance training to older adults in order to prevent falls and to maintain independence are an important issue for future research, and the availability of a control system implemented in an exergame that maximizes the likelihood of eliciting the most beneficial balance-training movements is of great interest. There are still several unanswered questions, such as potential changes in movement characteristics when playing over extended periods of time and to what extent comparable findings would be produced using different game settings or different exergames. Furthermore, personalizing the delivery of exergame training to the abilities and preferences of older adults, including providing feedback about the correctness of performance, might help accommodate differences in functioning in this heterogenous age group and potentially lead to additional improvements in balance training outcomes.

CONCLUSION

Together, the results of the current study provide important insights into how the settings of an exergame influence the movement characteristics of older adults when playing a step-based balance training exergame. Higher game speed led to faster-paced movements with shorter duration of single support, whereas additional cognitive elements in the form of obstacles to avoid led to slower movements and smaller steps. Some of these effects on movement characteristics are beneficial for balance training, whereas others likely make the exergame less efficient. Therefore, informed decisions are necessary when designing new, or choosing between existing, balance training exergames if they are to be effective tools for balance training in older adults.

DATA AVAILABILITY STATEMENT

The datasets generated for this study will not be made publicly available. Due to Norwegian legislation, the dataset for this article is not open access. Questions regarding the dataset can be sent to Beatrix Vereijken, beatrix.vereijken@ntnu.no.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Regional Committees for Medical and Health Research Ethics. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

All authors contributed to the conception and design of the study. PA, EB, and KG collected the data. PA and EB processed the data. PA performed statistical analyses. PA and BV drafted the manuscript. All authors contributed to manuscript revision, read, and approved the final version.

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REFERENCES

Anders, P., Lehmann, T., Müller, H., Grønvik, K. B., Skjæret-Maroni, N., Baumeister, J., et al. (2018). Exergames inherently contain cognitive elements as indicated by cortical processing. *Front. Behav. Neurosci.* 12:102. doi: 10.3389/fnbeh.2018.00102

Baltaci, G., Harput, G., Haksever, B., Ulusoy, B., and Ozer, H. (2013). Comparison between nintendo wii fit and conventional rehabilitation on functional performance outcomes after hamstring anterior cruciate ligament reconstruction: prospective, randomized, controlled, double-blind clinical trial. *Knee Surg. Sports Traumatol. Arthrosc.* 21, 880–887. doi: 10.1007/s00167-012-2034-2

Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015). Fitting linear mixed-effects models using lme4. *J. Stat. Softw.* 67, 1–48. doi: 10.18637/jss.v067.i01

Brox, E., Luque, L. F., Evertsen, G. J., and Hernández, J. E. G. (2011). "Exergames forelderly: social exergames to persuade seniors to increase physical activity, in *2011 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops* (Dublin), 546–549. doi: 10.4108/icst.pervasivehealth.2011.246049

Buchner, D. M., Cress, M. E., de Lateur, B. J., Esselman, P. C., Margherita, A. J., Price, R., et al. (1997). The effect of strength and endurance training on gait, balance, fall risk, and health services use in community-living older adults. *J. Gerontol. A Biol. Sci. Med. Sci.* 52, M218–M224. doi: 10.1093/gerona/52A.4.M218

Burke, J. W., McNeill, M., Charles, D. K., Morrow, P. J., Crosbie, J. H., and McDonough, S. M. (2009). Optimising engagement for stroke rehabilitation using seriousgames. *Vis. Comput.* 25, 1085–1099. doi: 10.1007/s00371-009-0387-4

Caetano, M. J. D., Lord, S. R., Brodie, M. A., Schoene, D., Pelicioni, P. H., Sturnieks, D. L., et al. (2018). Executive functioning, concern about falling and quadriceps strength mediate the relationship between impaired gait adaptability and fall risk in older people. *Gait Posture* 59, 188–192. doi: 10.1016/j.gaitpost.2017.10.017

Caetano, M. J. D., Lord, S. R., Schoene, D., Pelicioni, P. H., Sturnieks, D. L., and Menant, J. C. (2016). Age-related changes in gait adaptability in response to unpredictable obstacles and stepping targets. *Gait Posture* 46, 35–41. doi: 10.1016/j.gaitpost.2016.02.003

Caetano, M. J. D., Menant, J. C., Schoene, D., Pelicioni, P. H. S., Sturnieks, D. L., and Lord, S. R. (2017). Sensorimotor and cognitive predictors of impaired gait adaptability in older people. *J Gerontol. A Biol. Sci. Med. Sci.* 72, 1257–1263. doi: 10.1093/gerona/glw171

Csikszentmihalyi, M. (1975). *Beyond Boredom and Anxiety. The Jossey-Bass Behavioral Science Series.* San Francisco, CA: Jossey-Bass Publishers.

Fang, Q., Ghanouni, P., Anderson, S. E., Touchett, H., Shirley, R., Fang, F., et al. (2020). Effects of exergaming on balance of healthy older adults: a systematic review and meta-analysis of randomized controlled trials. *Games Health J.* 9, 11–23. doi: 10.1089/g4h.2019.0016

Gusi, N., Adsuar, J. C., Corzo, H., del Pozo-Cruz, B., Olivares, P. R., and Parraca, J. A. (2012). Balance training reduces fear of falling and improves dynamic balance and isometric strength in institutionalised older people: a randomised trial. *J. Physiother.* 58, 97–104. doi: 10.1016/S1836-9553(12)70089-9

Halekoh, U., and Højsgaard, S. (2014). A kenward-roger approximation and parametric bootstrap methods for tests in linear mixed models – the R package pbkrtest. *J. Stat. Softw.* 59:i09. doi: 10.18637/jss.v059.i09

Heinrich, S., Rapp, K., Rissmann, U., Becker, C., and König, H.-H. (2010). Cost of falls in old age: a systematic review. *Osteoporos. Int.* 21, 891–902. doi: 10.1007/s00198-009-1100-1

Heitz, R. P. (2014). The speed-accuracy tradeoff: history, physiology, methodology, and behavior. *Front. Neurosci.* 8:150. doi: 10.3389/fnins.2014.00150

Höchsmann, C., Schüpbach, M., and Schmidt-Trucksäss, A. (2016). Effects of exergaming on physical activity in overweight individuals. *Sports Med.* 46, 845–860. doi: 10.1007/s40279-015-0455-z

Hornyak, V., Brach, J. S., Wert, D. M., Hile, E., Studenski, S., and vanSwearingen, J. M. (2013). What is the relation between fear of falling and physical activity in older adults? *Arch. Phys. Med. Rehabil.* 94, 2529–2534. doi: 10.1016/j.apmr.2013.06.013

Hsiao-Wecksler, E. T., and Robinovitch, S. N. (2007). The effect of step length on young and elderly women's ability to recover balance. *Clin. Biomech.* 22, 574–580. doi: 10.1016/j.clinbiomech.2007.01.013

Kannus, P., Niemi, S., Palvanen, M., and Parkkari, J. (2005). Rising incidence of fall-induced injuries among elderly adults. *J. Public Health* 13, 212–215. doi: 10.1007/s10389-005-0115-0

Laver, K., George, S., Ratcliffe, J., Quinn, S., Whitehead, C., Davies, O., et al. (2012). Use of an interactive video gaming program compared with conventional physiotherapy for hospitalised older adults: a feasibility trial. *Disabil. Rehabil.* 34, 1802–1808. doi: 10.3109/09638288.2012.662570

Lord, S. R., and Fitzpatrick, R. C. (2001). Choice stepping reaction time: a composite measure of falls risk in older people. *J. Gerontol. A Biol. Sci. Med. Sci.* 56, M627–M632. doi: 10.1093/gerona/56.10.M627

Mellecker, R., Lyons, E. J., and Baranowski, T. (2013). Disentangling fun and enjoyment in exergames using an expanded design, play, experience framework: a narrative review. *Games Health J.* 2, 142–149. doi: 10.1089/g4h.2013.0022

Okubo, Y., Schoene, D., and Lord, S. R. (2017). Step training improves reaction time, gait and balance and reduces falls in older people: a systematic review and metaanalysis. *Br. J. Sports Med.* 51, 586–593. doi: 10.1136/bjsports-2015-095452

Open Broadcaster Software Studio (2018). Retrieved from: https://github.com/obsproject/obs-studio (accessed April 29, 2020).

R Core Team (2019). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Rhodes, R. E., Blanchard, C. M., Bredin, S. S., Beauchamp, M. R., Maddison, R., and Warburton, D. E. (2017). Stationary cycling exergame use among inactive children in the family home: a randomized trial. *J. Behav. Med.* 40, 978–988. doi: 10.1007/s10865-017-9866-7

Robinovitch, S. N., Feldman, F., Yang, Y., Schonnop, R., Leung, P. M., Sarraf, T., et al. (2013). Video capture of the circumstances of falls in elderly people residing in long-term care: an observational study. *Lancet* 381, 47–54. doi: 10.1016/S0140-6736(12)61263-X

Schoene, D., Lord, S. R., Verhoef, P., and Smith, S. T. (2011). A novel video game–based device for measuring stepping performance and fall risk in older people. *Arch. Phys. Med. Rehabil.* 92, 947–953. doi: 10.1016/j.apmr.2011.01.012

Sherrington, C., Tiedemann, A., Fairhall, N., Close, J. C., and Lord, S. R. (2011). Exercise to prevent falls in older adults: an updated meta-analysis and best practice recommendations. *N. S. W. Public Health Bull.* 22, 78–83. doi: 10.1071/NB10056

Skjæret, N., Nawaz, A., Morat, T., Schoene, D., Helbostad, J. L., and Vereijken, B. (2016). Exercise and rehabilitation delivered through exergames in older adults: an integrative review of technologies, safety and efficacy. *Int. J. Med. Inform.* 85, 1–16. doi: 10.1016/j.ijmedinf.2015.10.008

Skjæret-Maroni, N., Vonstad, E. K., Ihlen, E. A., Tan, X.-C., Helbostad, J. L., and Vereijken, B. (2016). Exergaming in older adults: movement characteristics while playing stepping games. *Front. Psychol.* 7:964. doi: 10.3389/fpsyg.2016.00964

Smith, S. T., Sherrington, C., Studenski, S., Schoene, D., and Lord, S. R. (2011). A novel dance revolution (ddr) system for in-home training of stepping ability: basic parameters of system use by older adults. *Br. J. Sports Med.* 45, 441–445. doi: 10.1136/bjsm.2009.066845

van Diest, M., Lamoth, C. J., Stegenga, J., Verkerke, G. J., and Postema, K. (2013). Exergaming for balance training of elderly: state of the art and future developments. *J. Neuroeng. Rehabil.* 10:101. doi: 10.1186/1743-0003-10-101

Vonstad, E. K., Su, X., Vereijken, B., Nilsen, J. H., and Bach, K. (2018). "Classification of movement quality in a weight-shifting exercise," in *CEUR Workshop Proceedings* (Stockholm).

Wollesen, B., Mattes, K., Schulz, S., Bischoff, L. L., Seydell, L., Bell, J. W., et al. (2017). Effects of dual-task management and resistance training on gait performance in older individuals: a randomized controlled trial. *Front. Aging Neurosci.* 9:415. doi: 10.3389/fnagi.2017.00415

Yardley, L., and Smith, H. (2002). A prospective study of the relationship between feared consequences of falling and avoidance of activity in community-living older people. *Gerontologist*, 42, 17–23. doi: 10.1093/geront/42.1.17

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Paper II

frontiers in Behavioral Neuroscience

ORIGINAL RESEARCH
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Exergames Inherently Contain Cognitive Elements as Indicated by Cortical Processing

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Exergames are increasingly used to train both physical and cognitive functioning, but direct evidence whether and how exergames affect cortical activity is lacking. Although portable electroencephalography (EEG) can be used while exergaming, it is unknown whether brain activity will be obscured by movement artifacts. The aims of this study were to assess whether electrophysiological measurements during exergaming are feasible and if so, whether cortical activity changes with additional cognitive elements. Twenty-four young adults performed self-paced sideways leaning movements, followed by two blocks of exergaming in which participants completed a puzzle by leaning left or right to select the correct piece. At the easy level, only the correct piece was shown, while two pieces were presented at the choice level. Brain activity was recorded using a 64-channel passive EEG system. After filtering, an adaptive mixture independent component analysis identified the spatio-temporal sources of brain activity. Results showed that it is feasible to record brain activity in young adults while playing exergames. Furthermore, five spatially different clusters were identified located frontal, bilateral central, and bilateral parietal. The frontal cluster had significantly higher theta power in the exergaming condition with choice compared to self-paced leaning movements and exergaming without choice, while both central clusters showed a significant increase in absolute alpha-2 power in the exergaming conditions compared to the self-paced movements. This is the first study to show that it is feasible to record brain activity while exergaming. Furthermore, results indicated that even a simple exergame without explicit cognitive demands inherently requires cognitive processing. These results pave the way for studying brain activity during various exergames in different populations to help improve their effective use in rehabilitation settings.

Keywords: exergaming, balance, EEG, theta, alpha, cognition

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INTRODUCTION

Exergames are videogames that require bodily movements by the user in order to play the game (Brox et al., 2011). Even though most commercial exergames are primarily developed for entertainment purposes (Zyda, 2005), exergames have in recent years been considered valuable to encourage participation in exercise, as well as to improve adherence to exercise and rehabilitation tasks (Burke et al., 2009; Skjæret et al., 2016). Exergames have rapidly gained popularity in all age groups the last decade (e.g., Mellecker et al., 2013), and have shown positive effects on increased physical activity in general (e.g., Höchsmann et al., 2016; Rhodes et al., 2017), as well as in specific rehabilitation settings (e.g., Laver et al., 2012; Baltaci et al., 2013). Several studies have concluded that exergames can be beneficial when used as an adjunct to, or even instead of, usual care, as exergames are generally found to be as effective as—or more effective than—traditional exercise programs, with generally no reported negative effects (Skjæret et al., 2016).

Exergames do not only address physical activity, but have the potential to influence players' cognitive abilities as well through dual tasks, decision making tasks and discrimination tasks (Zelinski and Reyes, 2009; Anguera et al., 2013). As many of these additional tasks require multiple cognitive processes, exergames may have advantages over separate physical or cognitive interventions, as simultaneous physical activities with decision-making opportunities may be essential to maximize synergistic benefits (Basak et al., 2008; Yan and Zhou, 2009; Anderson-Hanley et al., 2012; Kraft, 2012). However, most of these positions have not yet been substantiated with direct empirical support. Most studies either used cognitive tests as proxy measures for cognitive processing rather than directly measuring brain activity during exergaming, or demonstrated changes in cortical activation in pre-post exergame intervention designs. For example, Eggenberger et al. (2016) found significantly reduced oxygenation in the prefrontal cortex after 8 weeks of interactive cognitive-motor exergame training, as examined with functional near infrared spectroscopy. Furthermore, Anguera et al. (2013) used electroencephalography (EEG) to quantify cortical processing before and after video game training, and demonstrated enhanced frontal theta power and fronto-parietal theta coherence as indicators for improved cognitive processes. While these studies indirectly addressed cognitive processing related to exergaming, only Baumeister et al. (2010) directly assessed brain activity during exergaming in a virtual golf-putting environment. Their EEG results revealed increased frontal theta and decreased parietal alpha-2 power during virtual putting compared to a resting period. Collectively, these electrophysiological approaches to cognitive elements of exergaming indicate alterations of cortical activation, suggesting changes in cognitive control during and after gameplay, but there is still a lack of knowledge regarding cortical processing during exergaming. Furthermore, no study has investigated whether exergames inherently require different cortical processing compared to performing similar movements without exergame guidance, and whether additional cognitive elements in an exergame further increase demands on executive functioning. Gaining more knowledge about whether and how cognitive tasks in exergames influence cortical activity could elucidate underlying neurobiological mechanisms (Stanmore et al., 2017), thereby allowing more effective use of exergames in exercise and rehabilitation settings. Therefore, the aims of the current study were to investigate whether it is feasible to measure brain activity during gameplay using EEG and if so, whether exergames inherently require cortical processing, and whether increased cognitive demand in the exergame further changes brain activity.

To address these aims, we measured cortical activity using a portable EEG system in young, healthy participants. In order to reduce movement artifacts in the EEG signals as much as possible, we chose a puzzle exergame that is played by performing simple sideways leaning movements. Furthermore, the puzzle exergame could be played with and without an additional cognitive choice task. We hypothesized that even this simple exergame would require increased cortical processing compared to performing similar movements without exergame guidance, as indicated by increased frontal theta with concomitant changes in alpha-2 activity (Sauseng et al., 2005). Similar to their experiment on visuospatial working memory tasks, participants in the current study would need to mentally manipulate a picture in order to make a correct choice. Furthermore, we hypothesized that the addition of a simple choice task would further increase cortical processing, as reflected by increasing frontal theta and decreasing parieto-central alpha-2 (Gevins et al., 1997). Activity in the alpha band was shown to be inversely related to task difficulty in order to allocate more resources to the task performance. Both Gevins et al. (1997) and Sauseng et al. (2005) described theta and alpha as neurophysiological indicators of cognitive processing related to working memory demands, with increased cortical processing related to increased frontal theta power and inversely related to alpha power in parietal areas of the cortex.

MATERIALS AND METHODS

Participants

As this study addressed the feasibility of recording EEG while exergaming, a convenience sample of young participants was chosen. Twenty-four injury-free young adults (12 of each gender; age: 24.6 ± 2.1 years, height: 175 ± 10 cm, weight: 74.8 ± 11.8 kg) provided written consent to participate in this experimental study at the Norwegian University of Science and Technology in Trondheim, Norway. To be included, participants had to be between 20 years and 30 years old with no history of injuries or surgeries to the lower extremity and/or back within the last 6 months, no balance problems, and no neurological disorders that could affect postural control.

All participants indicated that they were physically active for at least 2–3 times a week. The majority (18 participants) described their physical activity as "quite strenuous," with a duration of 30–90 min per session (20 participants).

This study was carried out in accordance with the recommendations of the Regional Committees for Medical and Health Research Ethics, Norway. The protocol was approved by the Regional Committees for Medical and Health Research Ethics, Norway. All subjects gave written informed consent in accordance with the Declaration of Helsinki.

Procedure

We recorded EEG continuously throughout the entire protocol, starting with participants seated for 3 min, followed by 3 min of self-paced leaning sideways (SP) with feet hip-wide apart. Participants were instructed on how to perform SP before the start of the trial, without guidance or feedback during the

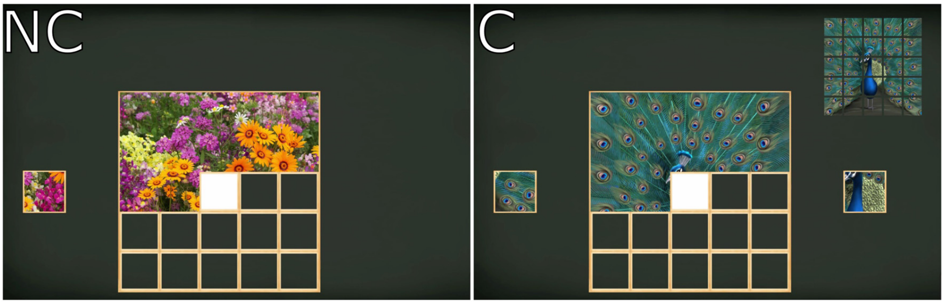

FIGURE 1 | Screen images of the "Puzzle" exergame. Left panel: no-choice condition (NC) presents only the correct puzzle piece to the left or right; Right panel: choice condition (C) presents two puzzle pieces simultaneously.

trial. After a 2-min break, participants played a commercially available exergame («Puzzle», SilverFit, Netherlands). The aim of the exergame was to complete a screen-based 5-by-5-puzzle in sequential order. Puzzle pieces were selected by leaning sideways in the direction of the desired puzzle piece. This simple exergame was chosen as it can be played without vigorous movements, so as to mitigate the risk for movement artifacts in the EEG signal. Each participant played the exergame in two conditions ("no-choice condition" NC and "choice condition" C) and with two different target pictures as shown in **Figure 1**, counterbalanced across participants. In NC, participants were presented with one puzzle piece, which was selected by leaning in the corresponding direction. In C, participants had to choose between two puzzle pieces and lean in the direction corresponding to the correct piece. Each participant played two sets, each consisting of ten exergames for NC or C. After playing all 20 exergames, another seated EEG baseline was recorded for 2 min followed by 1 min of self-paced leaning. In a preliminary examination the day before data collection, participants were familiarized with the laboratory environment and the EEG equipment. Furthermore, head circumferences were measured in order to choose the proper EEG cap size.

Performance Measures

To check whether participants made similar leaning movements in the different conditions, two force platforms (Kistler, type 9286A, Winterthur, CH) with a measurement frequency of 100 Hz were used to record ground reaction forces. The force platforms were located 2.5 m in front of the exergame screen. The mean of the medio-lateral center of pressure (COP) amplitude peaks for each sideways lean as well as the overall COP velocity were calculated. Due to technical issues with the force platforms, COP trajectories could not be calculated for four trials.

EEG Recordings and Analysis

Cortical activity was recorded continuously from 64 Ag/AgCl passive electrodes, using an elastic cap (QuikCap, Compumedics Neuroscan, Charlotte, NC, USA), with electrodes placed according to the international 10–20 electrode placement standard (Klem et al., 1999) and a standard reference electrode positioned between CZ and CPZ. Electrode impedance was reduced to $<$10 kΩ to ensure an appropriate signal-to-noise ratio. EEG data was amplified with an analog amplifier (SynAmps RT, Compumedics Neuroscan, Charlotte, NC, USA), which was placed in a small backpack in order to reduce mechanical stress in the cables and to allow mobility during data collection. The analog EEG signal was digitized using a 24-bit analog-to-digital converter (SynAmps RT, Compumedics Neuroscan, Charlotte, NC, USA) and subsequently recorded using Scan 4.5 (Compumedics Neuroscan, Charlotte, NC, USA) with a sample frequency of 1 kHz.

The EEGLAB 14.0.0b (Delorme and Makeig, 2004) toolbox for MATLAB (Mathworks Inc., Natick, MA, USA) was used for processing the acquired EEG data. The digitized EEG signal was band limited between 1 Hz and 100 Hz. The resulting digital signal was down sampled to 250 Hz after filtering using the CleanLine plugin (Mullen, 2012) to remove line noise and applying a finite impulse response filter with a band-pass between 2 Hz and 30 Hz. Any channels contaminated by excessive noise or major non-stereotypical artifacts were identified and manually deleted. EEG data was then re-referenced to common average.

Non-stereotypical artifacts were removed by visual inspection of the continuous EEG signal. Due to extensive artifact contamination, EEG data from two participants was excluded from further analysis. For the remaining participants, 47%–55% of the EEG data remained in each of the three conditions for further processing. Given the number and length of the trials, this was sufficient data to decompose the spatial-temporal sources (Onton and Makeig, 2006). Spatio-temporal features of the remaining participants were extracted using an adaptive mixture independent component analysis (AMICA; Palmer et al., 2006, 2008) on the entire dataset, resulting in spatially static and maximally independent components (Makeig et al., 1996). A heuristic approach described by Onton and Makeig (2006) was used to distinguish between functional and stereotypical artifacts.

Based on the results of the AMICA decompositions, a four-shell spherical head model (Kavanagh et al., 1978) included in the DIPFIT function (Oostenveld and Oostendorp, 2002)

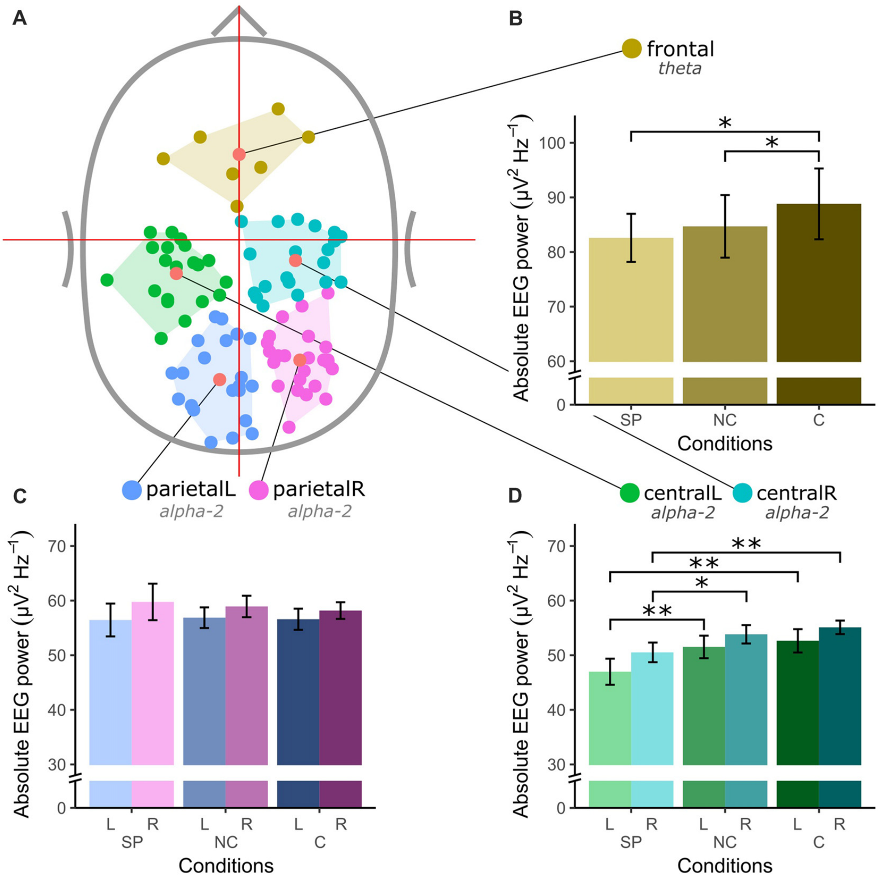

FIGURE 2 | Spatial location of electroencephalography (EEG) sources and absolute EEG power in $\mu V^2 Hz^{-1}$ for all clusters and conditions (SP, self-paced; NC, no-choice; C, choice) in *a priori* defined frequency bands theta (4–7 Hz) and alpha-2 (10–12 Hz). **(A)** Top-view of the identified EEG sources. **(B)** Absolute theta power in the frontal cluster. **(C)** Absolute alpha-2 power in left and right central clusters. **(D)** Absolute alpha-2 power in left and right parietal cluster. The asterisk (*) denotes a significance level of < 0.05 and the double asterisk (**) denotes a significance level of < 0.01. The error bars in **(B–D)** show the standard error.

of EEGLAB was used to locate equivalent dipole locations of independent components. The resulting dipoles across all participants were clustered using a k-means algorithm with a preset for five clusters. Dipoles were assigned to a cluster if they were within two standard deviations of the respective cluster. Dipoles with a residual variance larger than 16% were excluded.

The absolute power of the EEG signal was calculated as area under the curve for each condition and cluster (Pivik et al., 1993) in the *a priori* defined frequency bands: theta (4–7 Hz) for the frontal cluster, as well as alpha-2 (10–12 Hz) for both central and parietal clusters.

Statistics

All statistical analyses were performed using R 3.4.2 (R Development Core Team, 2017). Differences between SP, NC, and C were analyzed using one-way repeated measures ANOVAs on the absolute EEG power of predefined frequency bands and the performance measures, with *post hoc* paired-samples *t*-tests to follow up significant main effects. For those measures that were not normally distributed as indicated by Shapiro-Wilk's test, namely centralL and COP amplitude, Friedman's test was used to assess main effects, followed up by Wilcoxon's paired signed-ranks tests. Statistical level of significance was set at $p < 0.05$.

RESULTS

Performance Measures

Although the mean medio-lateral COP amplitudes were of comparable magnitude across the conditions (SP: $M = 33.41$ cm,

SD = 7.23 cm; NC: M = 38.7 cm, SD = 4.89 cm; C: M = 39.98 cm, SD = 5.32 cm), there was a main effect of condition, $\chi^2_{(2, N = 22)} = 11.47$, $p = 0.003$. *Post hoc* Wilcoxon's signed-ranks tests indicated that the leaning movements were significantly smaller in SP compared to C ($Z = 3.09$, $p = 0.002$) and NC ($Z = 3.04$, $p = 0.002$). COP velocity showed no significant main effect of condition ($F_{(2,36)} = 0.07$, $p = 0.933$).

Cortical Activity

Figure 2 shows the spatial location of EEG sources and the absolute EEG power in the respective frequency bands for all conditions and clusters. Clustering of included functional brain components revealed five robust clusters of dipoles located in the frontal ($n_{IC} = 7$), bilateral central (centralL $n_{IC} = 20$ and centralR $n_{IC} = 20$) and bilateral parietal (parietalL $n_{IC} = 21$ and parietalR $n_{IC} = 25$) areas. A significant main effect for condition was found in absolute frontal theta power ($F_{(2,12)} = 5.55$, $p = 0.02$). *Post hoc* paired t-tests showed a significant difference between SP and C ($t_{(6)} = 2.44$, $p = 0.05$), and between NC and C ($t_{(6)} = 2.84$, $p = 0.03$). Furthermore, both clusters in the central area showed significant differences in absolute alpha-2 power (centralL $\chi^2_{(2, N = 20)} = 9.1$, $p = 0.011$; centralR $F_{(2,38)} = 7.2$, $p = 0.003$). A *post hoc* paired Wilcoxon's signed-ranks test on centralL and a paired-samples t-test on centralR showed a significant difference between SP and both exergaming conditions in both clusters (centralL: SP-C $Z = 2.91$, $p = 0.004$, SP-NC $Z = 2.91$, $p = 0.004$; centralR: SP-C $t_{(19)} = 3.11$ $p = 0.006$, SP-NC $t_{(19)} = 2.58$, $p = 0.018$). No significant main effects were found for the parietal clusters.

DISCUSSION

The present study investigated the feasibility of measuring cortical activity in healthy young adults while playing an exergame, as well as the effect of different levels of cognitive demand on cortical activity. It was hypothesized that cortical activity in frontal, central and parietal areas of the brain would be affected differently by self-paced and exergame conditions with and without an additional choice task.

Cortical Activity During Exergaming

The first major finding of the present study was that it was feasible to collect good quality EEG signals of cortical activity during exergaming despite participants making bodily movements. Although approximately half of the EEG signal consisted of non-stereotypical artifacts that had to be removed, the remaining signal was both quantitatively and qualitatively sufficient for finding functional brain components. Furthermore, the amplitude and velocity of the sideways leaning movements were comparable across self-paced and exergaming conditions, despite a small but significant difference in amplitude, indicating that participants' movements were largely similar with or without exergame guidance. After cleaning and processing of the EEG data, clustering of independent components revealed five robust clusters, which were assigned to frontal, central and parietal brain areas, based on their equivalent dipole centroids. The frontal cluster was centrally located over the prefrontal cortex, while the estimated location of the equivalent mean dipoles of the central clusters was close to the lateral motor areas. In addition, the location of two lateral clusters was estimated to be in the left and right posterior-parietal cortex.

Another major finding of the present study was significantly higher absolute theta power in the frontal cluster during exergaming with choice. The task consisted of assembling a virtual puzzle by consecutively selecting matching puzzle pieces from two options displayed on the screen. This required the processing of visual information, extracting features of distinct choices, and subsequently generating a task appropriate response. The interface between these underlying perception and action circuits is responsible for temporally maintaining task relevant information and focused attention (Baddeley, 2012; Diamond, 2013). Moreover, evidence from electrophysiological studies implies that the control of cognitive processes may be indicated by theta oscillations (4–7 Hz) in the prefrontal cortex, which is known to be involved in processes of attentional control (Klimesch, 1999; Slobounov et al., 2005; Sauseng et al., 2010). Furthermore, theta activity was previously shown to be linked to rhythmic modulations of neuronal excitability in the cortex (Womelsdorf et al., 2010). As synchronized synaptic excitation is more likely to activate neuronal populations in terms of information processing, spatially and temporally dependent theta synchronization has been related to active neuronal processing for cognitive functions (Palva and Palva, 2011). Some studies previously reported increased theta synchronization with additional task requirements (Jensen and Tesche, 2002), as well as during specific selection processing of choice in goal-directed behavior (Womelsdorf et al., 2010). In line with these earlier findings, significantly higher frontal theta may indicate increased cognitive demands during exergaming with choice, compared to self-paced movement or no-choice exergaming. Since these latter conditions did not contain a choice task, higher demands on cognitive processing during exergaming with choice may explain the task-dependent increase of frontal theta in the present study.

Previous research has demonstrated that both theta and alpha-2 oscillations are involved in cognitive processes (Klimesch, 1999). While theta has been attributed to a general integrative function for the organization of cortical activity (Sauseng et al., 2005), alpha-2 has been associated with task-specific active processing or inhibition (Bazanova and Vernon, 2014), characterized by an inverse relationship between amplitude and number of neuronal populations activated (Niedermeyer and da Silva, 2005). In this regard, the present results support the notion that inhibition of task-irrelevant activity in non-essential cortical areas may facilitate cognitive processes and task performance (Klimesch et al., 2007; Palva and Palva, 2011). In particular, alpha-2 power in the central clusters demonstrated a significant increase from self-paced movement to exergaming, with no difference between the no-choice and choice exergames. The centrally located motor cortex, which contributes to movement initiation and complex motion coordination, has been reported to be involved in postural control as well (Slobounov et al., 2005, 2008). Additionally, suppressed activity within the alpha-2 frequency band in sensorimotor areas was shown to be associated with increased processing of sensory and movement-related information (Pfurtscheller and Berghold, 1989; Babiloni et al., 2014). However, the current study demonstrated alpha-2 synchronization during exergaming compared to self-paced movement. Based on reports of Jensen et al. (2002), the present results suggest that cortical activity of bilateral motor areas decreases with cognitive load. Moreover, context-dependent inhibition of the motor cortex may indicate that the generation of postural responses in exergames results from an interplay between various levels of the brain (Jacobs and Horak, 2007). Traditionally, subcortical structures like the cerebellum, basal ganglia, and brainstem have been linked to anticipatory or automatized regulation of postural control during upright stance (Nutt et al., 2011; Takakusaki, 2017). These neural structures are postulated to contribute to posture and voluntary movement through basic modifications of muscle amplitudes and patterns (Jacobs and Horak, 2007). As response latencies increase, cortical circuitries from either the prefrontal or motor cortex progressively influence subcortical pathways in order to optimize postural responses for the given environmental context (Jacobs and Horak, 2007). Thus, it may be proposed that self-paced movement with no external stimulus required active control through subcortical-cortical circuitries. Furthermore, since the dual-task conditions changed the distribution of attention resources between the cognitive and motor tasks (Fujita et al., 2016), exergaming may predominantly involve automatized subcortical processes of postural control in favor of cognitive performance.

Regarding the parietal clusters, no significant changes in alpha-2 power were found between self-paced and exergame conditions. The parietal lobe is part of a functionally interconnected sensorimotor network of motor, prefrontal and temporal cortical areas (De Waele et al., 2001). It has been suggested to play an essential role in the integration of multimodal sensory information related to voluntary movement and postural control (Varghese et al., 2015). However, consistent alpha-2 power in parietal areas may indicate that sensorimotor processing in the current postural task may not change with increased cognitive demand in a population of young adults. Furthermore, it may be hypothesized that inhibition of parieto-occipital areas may facilitate the maintenance of cognitive processes in frontal areas of the cortex (Jensen et al., 2002).

Methodological Considerations

Although the present investigation showed that EEG measurements during exergaming are possible and show relevant findings, some methodological considerations should be highlighted. First of all, participants in the current study were healthy young adults for whom the different conditions posed little challenge. Older or less healthy populations may show stronger effects of exergaming, or indeed different effects. Furthermore, it was not possible to provide guidance or feedback during the self-paced condition without simultaneously introducing cognitive processing, which would have rendered the control condition invalid. Nonetheless, the sideways movements were quite similar across the conditions. Although the amplitude was slightly smaller in the self-paced condition, movement velocity was the same across conditions, suggesting comparable physical effort. Another potential limitation of the current research protocol is the challenging nature of EEG measurements during human movement. Although several functional clusters were identified, the presence of movement-related artifacts may have limited the number of functional brain components being decomposed and may explain the relatively small number of independent components included in the frontal cluster. With recent advances in active EEG systems and individualized head models, future studies may further elucidate cortical processing changes during exergaming.

CONCLUSION

In conclusion, the present study demonstrated that even a simple exergame contains cognitive elements as indicated by task-specific cortical representation. Despite use of a passive EEG system that is sensitive to movement artifacts and the use of young adults as participants, frontal theta was found to significantly increase with increasing task demands that involve cognitive processes, such as in exergaming with a choice task. Furthermore, central alpha-2 power was significantly higher in exergame conditions compared to self-paced movement. Exergames may therefore require adjustment in the distribution of cortical resources between cognitive and motor elements in order to optimize task performance (Fujita et al., 2016). These results may provide further insight into why exergame training has been effective in improving sensorimotor processing (e.g., Gevins et al., 1997), and pave the way for follow-up research into how exergames can be used effectively to improve both cognitive and physical functions in specific populations.

AUTHOR CONTRIBUTIONS

PA, TL, NS-M, JB and BV contributed to the conception and design of the study. PA, HM and KG collected and processed data. PA and TL performed the statistical analyses. PA, TL, HM, KG, NS-M and BV wrote sections of the manuscript. All authors contributed to manuscript revision, and read and approved the final version.

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REFERENCES

Anderson-Hanley, C., Arciero, P. J., Brickman, A. M., Nimon, J. P., Okuma, N., Westen, S. C., et al. (2012). Exergaming and older adult cognition: a cluster randomized clinical trial. *Am. J. Prev. Med.* 42, 109–119. doi: 10.1016/j.amepre.2011.10.016

Anguera, J. A., Boccanfuso, J., Rintoul, J. L., Al-Hashimi, O., Faraji, F., Janowich, J., et al. (2013). Video game training enhances cognitive control in older adults. *Nature* 501, 97–101. doi: 10.1038/nature12486

Babiloni, C., Del Percio, C., Arendt-Nielsen, L., Soricelli, A., Romani, G. L., Rossini, P. M., et al. (2014). Cortical EEG α rhythms reflect task-specific somatosensory and motor interactions in humans. *Clin. Neurophysiol.* 125, 1936–1945. doi: 10.1016/j.clinph.2014.04.021

Baddeley, A. (2012). Working memory: theories, models, and controversies. *Annu. Rev. Psychol.* 63, 1–29. doi: 10.1146/annurev-psych-120710-100422

Baltaci, G., Harput, G., Haksever, B., Ulusoy, B., and Ozer, H. (2013). Comparison between Nintendo Wii Fit and conventional rehabilitation on functional performance outcomes after hamstring anterior cruciate ligament reconstruction: prospective, randomized, controlled, double-blind clinical trial. *Knee Surg. Sports Traumatol. Arthrosc.* 21, 880–887. doi: 10.1007/s00167-012-2034-2

Basak, C., Boot, W. R., Voss, M. W., and Kramer, A. F. (2008). Can training in a real-time strategy video game attenuate cognitive decline in older adults? *Psychol. Aging* 23, 765–777. doi: 10.1037/a0013494

Baumeister, J., Reinecke, K., Cordes, M., Lerch, C., and Weiß, M. (2010). Brain activity in goal-directed movements in a real compared to a virtual environment using the Nintendo Wii. *Neurosci. Lett.* 481, 47–50. doi: 10.1016/j.neulet.2010.06.051

Bazanova, O. M., and Vernon, D. (2014). Interpreting EEG α activity. *Neurosci. Biobehav. Rev.* 44, 94–110. doi: 10.1016/j.neubiorev.2013.05.007

Brox, E., Luque, L. F., Evertsen, G. J., and Hernández, J. E. G. (2011). "Exergames for elderly: social exergames to persuade seniors to increase physical activity," in *Proceedings of the 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, (Dublin: IEEE), 546–549.

Burke, J. W., McNeill, M. D. J., Charles, D. K., Morrow, P. J., Crosbie, J. H., and McDonough, S. M. (2009). Optimising engagement for stroke rehabilitation using serious games. *Vis. Comput.* 25, 1085–1099. doi: 10.1007/s00371-009-0387-4

De Waele, C., Baudonnière, P., Lepecq, J., Huy, P. T. B., and Vidal, P. (2001). Vestibular projections in the human cortex. *Exp. Brain Res.* 141, 541–551. doi: 10.1007/s00221-001-0894-7

Delorme, A., and Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J. Neurosci. Methods* 134, 9–21. doi: 10.1016/j.jneumeth.2003.10.009

Diamond, A. (2013). Executive functions. *Annu. Rev. Psychol.* 64, 135–168. doi: 10.1146/annurev-psych-113011-143750

Eggenberger, P., Wolf, M., Schumann, M., and de Bruin, E. D. (2016). Exergame and balance training modulate prefrontal brain activity during walking and enhance executive function in older adults. *Front. Aging Neurosci.* 8:66. doi: 10.3389/fnagi.2016.00066

Fujita, H., Kasubuchi, K., Wakata, S., Hiyamizu, M., and Morioka, S. (2016). Role of the frontal cortex in standing postural sway tasks while dual-tasking: a functional near-infrared spectroscopy study examining working memory capacity. *Biomed Res. Int.* 2016:7053867. doi: 10.1155/2016/7053867

Gevins, A., Smith, M. E., McEvoy, L., and Yu, D. (1997). High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing and practice. *Cereb. Cortex* 7, 374–385. doi: 10.1093/cercor/7.4.374

Höchsmann, C., Schüpbach, M., and Schmidt-Trucksäss, A. (2016). Effects of exergaming on physical activity in overweight individuals. *Sports Med.* 46, 845–860. doi: 10.1007/s40279-015-0455-z

Jacobs, J. V., and Horak, F. B. (2007). Cortical control of postural responses. *J. Neural Transm.* 114, 1339–1348. doi: 10.1007/s00702-007-0657-0

Jensen, O., Gelfand, J., Kounios, J., and Lisman, J. E. (2002). Oscillations in the α band (9–12 Hz) increase with memory load during retention in a short-term memory task. *Cereb. Cortex* 12, 877–882. doi: 10.1093/cercor/12.8.877

Jensen, O., and Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. *Eur. J. Neurosci.* 15, 1395–1399. doi: 10.1046/j.1460-9568.2002.01975.x

Kavanagh, R. N., Darcey, T. M., Lehmann, D., and Fender, D. H. (1978). Evaluation of methods for three-dimensional localization of electrical sources in the human brain. *IEEE Trans. Biomed. Eng.* 25, 421–429. doi: 10.1109/TBME.1978.326339

Klem, G. H., Lüders, H. O., Jasper, H., and Elger, C. (1999). The ten-twenty electrode system of the International Federation. The International federation of clinical neurophysiology. *Electroencephalogr. Clin. Neurophysiol.* 52, 3–6.

Klimesch, W. (1999). EEG α and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Res. Rev.* 29, 169–195. doi: 10.1016/s0165-0173(98)00056-3

Klimesch, W., Sauseng, P., and Hanslmayr, S. (2007). EEG α oscillations: the inhibition-timing hypothesis. *Brain Res. Rev.* 53, 63–88. doi: 10.1016/j.brainresrev.2006.06.003

Kraft, E. (2012). Cognitive function, physical activity, and aging: possible biological links and implications for multimodal interventions. *Neuropsychol. Dev. Cogn. B Aging Neuropsychol. Cogn.* 19, 248–263. doi: 10.1080/13825585.2011.645010

Laver, K., George, S., Ratcliffe, J., Quinn, S., Whitehead, C., Davies, O., et al. (2012). Use of an interactive video gaming program compared with conventional physiotherapy for hospitalised older adults: a feasibility trial. *Disabil. Rehabil.* 34, 1802–1808. doi: 10.3109/09638288.2012.662570

Makeig, S., Bell, A. J., Jung, T.-P., and Sejnowski, T. J. (1996). "Independent component analysis of electroencephalographic data," in *Advances in Neural Information Processing Systems*, eds D. Touretzky M. Mozer and M. Hasselmo (Cambridge MA: MIT Press), 145–151.

Mellecker, R., Lyons, E. J., and Baranowski, T. (2013). Disentangling fun and enjoyment in exergames using an expanded design, play, experience framework: a narrative review. *Games Health J.* 2, 142–149. doi: 10.1089/g4h.2013.0022

Mullen, T. (2012). *CleanLine EEGLAB Plugin.* San Diego, CA: Neuroimaging Informatics Toolsand Resources Clearinghouse (NITRC).

Niedermeyer, E., and da Silva, F. L. (2005). *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields.* Philadelphia: Lippincott Williams and Wilkins.

Nutt, J. G., Horak, F. B., and Bloem, B. R. (2011). Milestones in gait, balance, and falling. *Mov. Disord.* 26, 1166–1174. doi: 10.1002/mds.23588

Onton, J., and Makeig, S. (2006). Information-based modeling of event-related brain dynamics. *Prog. Brain Res.* 159, 99–120. doi: 10.1016/s0079-6123(06)59007-7

Oostenveld, R., and Oostendorp, T. F. (2002). Validating the boundary element method for forward and inverse EEG computations in the presence of a hole in the skull. *Hum. Brain Mapp.* 17, 179–192. doi: 10.1002/hbm.10061

Palmer, J. A., Kreutz-Delgado, K., and Makeig, S. (2006). "Super-gaussian mixture source model for ICA," in *Independent Component Analysis and Blind Signal Separation.* eds J. Rosca, D. Erdogmus, J. C. Principe and S. Haykin (Berlin, Heidelberg: Springer-Verlag), 854–861.

Palmer, J. A., Makeig, S., Kreutz-Delgado, K., and Rao, B. D. (2008). "Newton method for the ICA mixture model," in *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, (Las Vegas, Nevada), 1805–1808.

Palva, S., and Palva, J. M. (2011). Functional roles of α-band phase synchronization in local and large-scale cortical networks. *Front. Psychol.* 2:204. doi: 10.3389/fpsyg.2011.00204

Pfurtscheller, G., and Berghold, A. (1989). Patterns of cortical activation during planning of voluntary movement. *Electroencephalogr. Clin. Neurophysiol.* 72, 250–258. doi: 10.1016/0013-4694(89)90250-2

Pivik, R. T., Broughton, R. J., Coppola, R., Davidson, R. J., Fox, N., and Nuwer, M. R. (1993). Guidelines for the recording and quantitative analysis of electroencephalographic activity in research contexts. *Psychophysiology* 30, 547–558. doi: 10.1111/j.1469-8986.1993.tb02081.x

R Development Core Team. (2017). *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing. Available online at: https://www.R-project.org

Rhodes, R. E., Blanchard, C. M., Bredin, S. S., Beauchamp, M. R., Maddison, R., and Warburton, D. E. (2017). Stationary cycling exergame use among inactive children in the family home: a randomized trial. *J. Behav. Med.* 40, 978–988. doi: 10.1007/s10865-017-9866-7

Sauseng, P., Griesmayr, B., Freunberger, R., and Klimesch, W. (2010). Control mechanisms in working memory: a possible function of EEG theta oscillations. *Neurosci. Biobehav. Rev.* 34, 1015–1022. doi: 10.1016/j.neubiorev.2009.12.006

Sauseng, P., Klimesch, W., Schabus, M., and Doppelmayr, M. (2005). Fronto-parietal EEG coherence in theta and upper α reflect central executive functions of working memory. *Int. J. Psychophysiol.* 57, 97–103. doi: 10.1016/j.ijpsycho.2005.03.018

Skjæret, N., Nawaz, A., Morat, T., Schoene, D., Helbostad, J. L., and Vereijken, B. (2016). Exercise and rehabilitation delivered through exergames in older adults: an integrative review of technologies, safety and efficacy. *Int. J. Med. Inform.* 85, 1–16. doi: 10.1016/j.ijmedinf.2015.10.008

Slobounov, S., Hallett, M., Cao, C., and Newell, K. (2008). Modulation of cortical activity as a result of voluntary postural sway direction: an EEG study. *Neurosci. Lett.* 442, 309–313. doi: 10.1016/j.neulet.2008.07.021

Slobounov, S., Hallett, M., Stanhope, S., and Shibasaki, H. (2005). Role of cerebral cortex in human postural control: an EEG study. *Clin. Neurophysiol.* 116, 315–323. doi: 10.1016/j.clinph.2004.09.007

Stanmore, E., Stubbs, B., Vancampfort, D., de Bruin, E. D., and Firth, J. (2017). The effect of active video games on cognitive functioning in clinical and non-clinical populations: a meta-analysis of randomized controlled trials. *Neurosci. Biobehav. Rev.* 78, 34–43. doi: 10.1016/j.neubiorev.2017.04.011

Takakusaki, K. (2017). Functional neuroanatomy for posture and gait control. *J. Mov. Disord.* 10, 1–7. doi: 10.14802/jmd.16062

Varghese, J. P., Beyer, K. B., Williams, L., Miyasike-daSilva, V., and McIlroy, W. E. (2015). Standing still: is there a role for the cortex? *Neurosci. Lett.* 590, 18–23. doi: 10.1016/j.neulet.2015.01.055

Womelsdorf, T., Vinck, M., Leung, L. S., and Everling, S. (2010). Selective theta-synchronization of choice-relevant information subserves goal-directed behavior. *Front. Hum. Neurosci.* 4:210. doi: 10.3389/fnhum.2010.00210

Yan, J. H., and Zhou, C. L. (2009). Effects of motor practice on cognitive disorders in older adults. *Eur. Rev. Aging Phys. Act.* 6, 67–74. doi: 10.1007/s11556-009-0049-6

Zelinski, E. M., and Reyes, R. (2009). Cognitive benefits of computer games for older adults. *Gerontechnology* 8:220. doi: 10.4017/gt.2009.08.04.004.00

Zyda, M. (2005). From visual simulation to virtual reality to games. *Computer* 38, 25–32. doi: 10.1109/mc.2005.297

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Paper III

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ORIGINAL ARTICLE

The influence of motor tasks and cut-off parameter selection on artifact subspace reconstruction in EEG recordings

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Abstract
Advances in EEG filtering algorithms enable analysis of EEG recorded during motor tasks. Although methods such as artifact subspace reconstruction (ASR) can remove transient artifacts automatically, there is virtually no knowledge about how the vigor of bodily movements affects ASRs performance and optimal cut-off parameter selection process. We compared the ratios of removed and reconstructed EEG recorded during a cognitive task, single-leg stance, and fast walking using ASR with 10 cut-off parameters versus visual inspection. Furthermore, we used the repeatability and dipolarity of independent components to assess their quality and an automatic classification tool to assess the number of brain-related independent components. The cut-off parameter equivalent to the ratio of EEG removed in manual cleaning was strictest for the walking task. The quality index of independent components, calculated using RELICA, reached a maximum plateau for cut-off parameters of 10 and higher across all tasks while dipolarity was largely unaffected. The number of independent components within each task remained constant, regardless of the cut-off parameter used. Surprisingly, ASR performed better in motor tasks compared with non-movement tasks. The quality index seemed to be more sensitive to changes induced by ASR compared to dipolarity. There was no benefit of using cut-off parameters less than 10.

Keywords Artifact · Data processing · Electroencephalography

1 Introduction

Electroencephalogram (EEG) is one of the most used methods to record activity of the brain in both clinical and applied research (e.g. epilepsy and exergaming, e.g. Acharya et al. [1] and Anders et al. [2]). Recent developments in both hardware and software, such as active electrodes [3] and advanced filter algorithms [4] make it possible to record usable EEG, while participants perform tasks involving physical movements or even in real-world environments. This offers neuroscientists a plethora of novel research designs, such as the concurrent measurement of brain activity during the execution of motor tasks, instead of having to rely on pre-post EEG comparisons or minimal participant behavior, thereby enabling the development of more natural behavior models [5].

However, the analysis of brain activity measured while participants perform motor tasks remains challenging due to the lower signal-to-noise ratio compared with, e.g., resting state analyses. EEG recordings are typically contaminated with non-brain related signals such as eye blink artifacts, artifacts due to impedance changes caused by a relative shift between the electrode and the skull, and artifacts due to electrical activity produced by facial and skeletal muscles. In general, the likelihood of the occurrence of the latter two types of artifacts increases with the vigor of the motor task.

A commonly applied strategy to isolate stereotypical noise sources such as eye blinks or repetitive motion artifacts is the use of independent component analysis (ICA) [6]. In ICA, an inverse model is used to reveal the independent components (ICs), that is, the sources of the cortical activity. ICs can then be classified as functional, non-functional, or a mixture of both. In order to create the inverse model used for the calculation of ICs, the EEG data needs to be cleaned, i.e., long-term signal non-stationarities [7] and large transient and non-repetitive artifacts [8] need to be removed.

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Traditionally, EEG experts with experience in data cleaning remove transient artifacts and noise-contaminated channels through visual inspection [2, 9]. A major disadvantage of the current state-of-the-art manual artifact removal process is the loss of data. If an artifact is present in one channel, data from corresponding time series in all other channels has to be removed as well. This problem has become even more pronounced with the advent of high-density EEG systems (> 128 channels), since the likelihood for electrode shifts which cause the rejection of data increases with the number of EEG channels. Furthermore, manual cleaning of EEG data using visual inspection is not fully reproducible and time-consuming and requires extensive experience.

The recent advances in EEG processing algorithms [7] pave the way towards an automated and standardized method to remove artifacts. From a practical perspective, automatic preprocessing would speed up data processing as it would serve as a replacement, either in full or in part, of time-intensive manual artifact removal. This advantage becomes even more pronounced when EEG datasets are of long duration or are recorded using high-density EEG systems.

An important step towards automated and reproducible EEG preprocessing in research is the development of recent filter algorithms that originated in the field of brain-computer-interfaces (BCIs). One promising example is the artifact subspace reconstruction (ASR) [10]. ASR creates a robust covariance matrix based on the cleanest parts of an EEG recording. Subsequently, principal component analyses are performed in a sliding window of 1 second. A window is rejected if the standard deviation of a principal component exceeds the standard deviation of the automatically chosen cleanest part of the EEG recording multiplied by a tunable cut-off parameter (k). A rejected window is then reconstructed using the covariance matrix. A more detailed description of ASR can be found in [11–14].

The degree of reconstruction in ASR is influenced by the selected cut-off parameter k. However, selection of appropriate cut-off parameters is challenging as the literature background is sparse and studies typically underreport cut-off parameters used in their processing pipelines. A rare exception are the studies of Chang et al. [11, 14] on EEG data recorded while participants performed a simulated driving task. They found that cut-off parameters between 10 and 100 or 20–30, respectively, and delivered the best results in terms of eye artifact removal and conservation of brain activity. No studies are currently available in which participants performed more vigorous motor tasks during EEG recordings. It is therefore not known whether ASR can be used in such tasks and how they affect which ASR cut-off parameters are appropriate.

Following the identified gaps in our knowledge, the aim of the current study was to investigate how movement vigor and choice of cut-off parameters in ASR affect properties of the EEG data. To this end, we (1) assessed the ratio of EEG data removed or reconstructed in sensor-space for three tasks that required different amounts and vigor of movement when using an automated preprocessing pipeline including ASR using 10 different cut-off parameters, compared to manually cleaned EEG data using visual inspection, (2) evaluated the reproducibility and dipolarity of the resulting ICs, and (3) assessed whether either of these qualities were affected by the cut-off parameter or the task. Furthermore, we assessed the number and quality of functional ICs depending on the task and the cut-off parameter used.

2 Methods

2.1 Sample population

To assess the effect of task on the artifact removal performance of ASR, we used recorded EEG instead of simulated EEG in order to test the algorithms under conditions as close to reality as possible. A convenience sample of five healthy young participants (all female; age: 23.2 ± 2.58 years, height: 172.4 ± 3.13 cm, weight: 63.8 ± 4.38 kg) was recruited.

All procedures performed in this study were in accordance with the ethical standards of the institutional review board of the University of Paderborn and with the 1964 Helsinki declaration and its later amendments. All participants provided informed consent prior to data collection.

2.2 Procedure

We recorded continuous EEG data during three tasks that required different amounts of movement. All participants performed the tasks in the same order.

The first task was a seated working memory n-back task, with 10 sets of 30 stimuli of 2 s each. The participants looked at a computer display presenting a 3 by 3 dot matrix. If the current pattern was the same as the pattern three pictures before, they had to press a button with their right thumb. If not, the participant had to press a button with their left thumb.

The second task consisted of 20 alternating single-leg stance phases held for 30 s each, with a break of 10 s between consecutive stance phases.

The third task consisted of two repetitions of a fast forward and backward walking task of 5.5 min each, using the Witty SEM (Microgate Slr, Bolzano, Italy). Five LED lamps were mounted on tripods and placed at 0°, ± 22.5°, and ± 45° from the participant's point of view at a distance of 2.5 m. When one of the five LED lamps was switched on, the participants were asked to walk swiftly, not run, towards the lit LED lamp and to cover the light using their right hand before walking backwards to their starting position. This process was repeated until the end of the task. Both repetitions were combined into one EEG recording and treated as a single recording in further analyses.

2.3 Data acquisition

Brain activity was recorded at 500 Hz using an EEG system consisting of a 64 channel Ag/AgCl active wet electrode elastic cap (Easycap, Herrsching, Germany) in an extended 10–20 electrode layout [15] and a wireless amplifier (Live Amp, Brain Products GmbH, Gilching, Germany) placed in a backpack to relief stress from the cables. The impedance was kept below 25 kΩ, in accordance with the manufacturer's recommendations.

In order to ensure comparability of dipole locations between conditions, the electrode cap was not moved or manipulated between conditions. Furthermore, no gel was reapplied to the electrodes after participant preparation.

2.4 Preprocessing

Data processing was performed in EEGLAB 14.1.1b [16], a toolbox for Matlab (Mathworks Inc., Nantick, MA).

In order to remove sinusoidal noise at 50 Hz and their harmonics, the CleanLine plug-in [7] was used. A band-pass filter with limiting frequencies of 3 and 30 Hz [17] was used to remove disturbances caused by both direct current drift and higher frequency disturbances such as electrical activity caused by the innervation of skeletal muscles.

After the removal of line noise and band limitation, all EEG data was copied to obtain 11 identical datasets, which were subsequently processed separately.

In one dataset, after re-referencing to average and downsampling to 250 Hz, an EEG expert removed noise contaminated channels and transient, non-stereotypical artifacts using visual inspection.

The remaining 10 datasets were preprocessed using the artifact subspace reconstruction [10] implemented in the clean_rawdata plug-in [12] separately for each task and participant. Channels were removed when poorly correlated ($r < 0.85$) to neighboring channels or when non-transient noise exceeded 4 SDs. ASR then reconstructed time windows contaminated with transient artifacts that exceeded k SDs based on the automatically chosen reference data or removed time windows when more than 25% of the remaining channels exceeded the threshold cut-off parameter. The cut-off parameter k was set to 1, 2, 5, 10, 20, 50, 100, 200, 500, and 1000, respectively. The cut-off parameters were chosen to cover the same range as in [11, 14]. Due to the expected computation time, we opted to use cut-off parameters that would result in equal intervals between values on a logarithmic scale. The available random-access memory for ASR was limited to 8 GB on a 16 GB computer to ensure equal availability for all iterations of automatic preprocessing. The 10 automatically processed datasets were subsequently re-referenced to average and downsampled to 250 Hz.

Subsequently, the following processing steps were applied to all 11 datasets in preparation for source space analysis:

Data of removed channels was interpolated using the EEGLAB function pop_interp in order to avoid bias towards a hemisphere with more remaining channels. This does not change the number of resulting ICs, as the rank of the matrix remains unchanged.

Spatiotemporal sources of brain activity were calculated by using an adaptive mixture independent component analysis (AMICA) [18, 19]. The locations of the spatiotemporal sources were determined by the dipfit plug-in for EEGLAB [20] based on a boundary element model [21, 22]. The fitTwoDipoles plug-in [23] was used to account for bilaterally symmetrical ICs.

ICs were classified into seven categories, namely "brain," "muscle," "eye," "heart," "line noise," "channel noise," and "other," using the IClabel plug-in [24]. We chose this classification algorithm based on classification performance and computation time.

2.5 Quality assessment of the results in source-space

In order to assess reproducibility of ICs across participants, we used the EEGLAB plug-in RELICA [25]. In RELICA, BeamICA [26], a less computationally expensive ICA compared with AMICA, allows for bootstrap statistics, which provides a quality index for all discovered ICs. BeamICA was set to use "point-by-point" mode with 50 iterations. The quality index is a measure for the dispersion of resulting ICs and can thereby be used to assess the reproducibility of ICs in terms of their localization. Subsequently, source localization as described above was applied to calculate the dipolarity of the ICs, as brain-related ICs are dipolar [8]. Dipolarity is a measure for how well the estimated dipole explains the original data. It describes the percentage to which a scalp map of an independent component can be explained by the scalp projection of a single equivalent dipole [4, 27]. The resulting dipolarity and quality index coordinates were used to classify the ICs into four categories (I, II, III, and the "forbidden region"), as described in [25]. ICs in category I are highly dipolar and reproducible (dipolarity > 0.85 and a quality index $>$ 0.95). ICs in category II are a combination of brain signal and artifacts or a mixture of multiple cortical processes (dipolarity ≤ 0.85 and quality index > 0.95). ICs in category III are an inseparable mixture of artifacts and brain signals (quality index ≤ 0.95). ICs in the last category, the so-called "forbidden region," have high dipolarity but low-quality index (dipolarity > 0.75 and quality index of < 0.45).

2.6 Statistical analyses

Because the data was non-normally distributed, Kruskal-Wallis tests by ranks were used in R [28] to assess the effects of task and cut-off parameter on the quality indices and dipolarity, the number of ICs classified as brain related and the certainty of the classification as brain-related ICs. Wilcoxon's signed-rank tests were used as follow-up in case of significance. The resulting p-values after the Wilcoxon's signed-rank tests were corrected for multiple comparisons using Benjamini and Hochberg's [29] method. The level for significance was set to $p < 0.05$.

3 Results

Below, we first present the ratio of data removed and reconstructed for each task using ASR compared with the amount of data removed using visual inspection. Secondly, the dipolarity and reproducibility measured using the quality index calculated by RELICA for each task and cut-off parameter is presented. Thirdly, we present the classification results of ICs using IClabel.

3.1 Ratio of data removed and reconstructed using ASR

As to be expected, lower cut-off parameters led to higher removal and reconstruction ratios. The walking task showed the highest overall removal ratio after visual inspection compared with single-leg stance task and the working memory task.

Figure 1 shows the ratio of removed and reconstructed EEG data in sensor-space for ASR cut-off parameters ranging from 1 to 1000 for each of the three tasks. Each line represents one participant performing one task. The dots indicate the intersection of each line with the respective ratio of manually removed data after visual inspection by an EEG expert. Linear interpolation was used to estimate the ratio of removed and reconstructed data in between calculated data points.

All curves showed a similar shape, except the curve of one participant performing the n-back task (dashed line). This was likely caused by a sudden onset of excessive noise in channel CP4 after 311 s of 600 s, resulting in larger ratios of data reconstructed. Excluding this task for this participant, the resulting ranges of cut-off parameters across participants were 7–14 for the walking task, 5–40 for the single-leg stance task, and 10–45 for the working memory n-back task.

The intersection of the ratio of manually removed data after visual inspection and the ratio curve of automatically preprocessed data using ASR for the single-leg stance task was at a cut-off parameter equal to 5 for one participant. For the other participants, the intersections in this task were located in the range between 20 and 40.

As indicated, ASR removes and reconstructs EEG data based on the input parameters. As can be seen in Fig. 1, no EEG data was reconstructed when using cut-off parameters larger than 100. The flat lines parallel to the x-axis for the range above 100 show the amount of data removed without being reconstructed by ASR. Based on this, we present results for cut-off parameters between 5 and 100 only in Figs. 2 and 3, in order to enhance readability.

3.2 Dipolarity and quality of independent components

The quality indices calculated for each task and across all cut-off parameters using the RELICA plug-in for ICs with a dipolarity of > 0.85 increased until it reached a plateau at a cut-off parameter of 10 (solid lines in Fig.2). The total number of all ICs and the remaining ICs after removing ICs with a dipolarity of < 0.85 can be seen in Fig. 3. Quality index curves for all tasks showed roughly the same general behavior. The standard errors were comparable in size across all cut-off parameters and tasks. The highest quality indices were recorded for the walking task, followed by the n-back task, and the single-leg stance task. Dipolarity, on the other hand, only showed a slight increase towards higher cut-off parameters (dashed lines in Fig.2). The dipolarity and quality indices of the subset of ICs with a dipolarity of 0.85 or higher and preprocessed using ASR with cut-off parameters of one and two were significantly lower than the remaining ICs preprocessed with cut-off parameters of > 2 (all p's < 0.001, except for $k = 2$ versus 5 and 10: $p < 0.01$ and $p < 0.005$, respectively). Furthermore, the dipolarity of ICs discovered in the fast-walking task was significantly lower ($p < 0.05$) compared with the ICs in both other tasks. Furthermore, the quality indices of ICs discovered in EEG recorded during the walking task were significantly higher than the quality indices of ICs of the remaining tasks (both p's < 0.001, see Fig. 2). The resulting quality indices for ICs based on data processed using cut-off parameters of one or two were significantly lower compared with IC-based preprocessed using the remaining cut-off parameters (all p's < 0.001, except for $k = 2$ versus 5: $p < 0.005$).

The majority of ICs were sorted in category III [25], indicating that there is inseparable noise mixed into the ICs. Only a few ICs were sorted as category I (both quality index and dipolarity above retention threshold) or category II (either artifact or a mix of two or more processes). We found 21 ICs in the "forbidden region," where dipolarity is larger than 0.75 but the quality index below 0.45. As BeamICA did not deliver consistent results in any of the tasks for the manually cleaned data, resulting in quality indices of 0, these are not included in Fig. 2.

3.3 Classification of independent components

Compared with manual cleaning, using ASR to clean the data resulted in more ICs due to fewer removed channels, as can be seen in Fig. 4 (black dots).

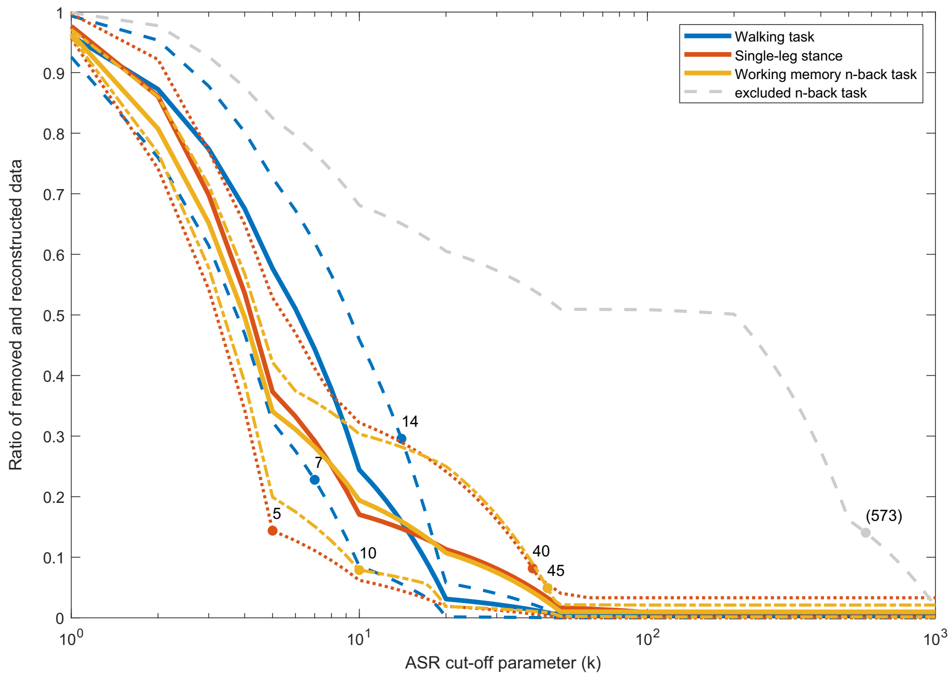

Fig. 1 Mean ratio and range of removed and recovered data using ASR for cut-off parameters (k) between 1 and 1000 for each of the three tasks. The dots indicate the intersection of the ratio of removed data after manual cleaning using visual inspection of the preprocessed EEG for each participant. The dashed gray line represents EEG of a single participant during the n-back task

The automatic classification of ICs into functional or brain-related ICs and non-functional ICs revealed no difference in the number of brain-related ICs for either cleaning method (red dots). As expected, the number of ICs classified as brain activity by the IClabel plug-in was significantly lower in the walking task compared with the other conditions (both p's < 0.001). There was no clear trend whether the cut-off parameter influenced the number of discovered brain-related ICs in this dataset, which was confirmed by the non-significant result of the Kruskal-Wallis test ($\chi^2 = 1.7163$, df = 10, $p = 0.9981$).

No ICs were classified as line noise since the CleanLine plug-in was used to remove line noise, as well as a bandpass filter with an upper edge frequency of 30 Hz.

IClabel classified more ICs as "other noise" when cut-off parameters of $k = 1, 2$, and 5 where used compared with higher ASR cut-off parameters or manual cleaning. This result seems to be due to fewer ICs being classified as "muscle" (orange dots). The number of ICs classified as "eye"-related (light green) seems to be largely unaffected by the cut-off parameter and cleaning method.

Furthermore, the certainty of the classification is based on the mean probability value that can be interpreted as a measure of classifier confidence in the discrete classification as brain-related IC [24, 30] seems to be unaffected by both the method of cleaning used and the cut-off parameter used in automatic cleaning (red crosses).

However, the certainty of the classification as brain-related IC was affected by the type of task, and significantly lower in the walking task than in the other two tasks (both p's < 0.001). Furthermore, the classification certainty of brain-related ICs in the n-back task was significantly lower compared with the single-leg stance ($p < 0.05$).

4 Discussion

The present study investigated the effect of ASR cut-off parameters on characteristics of EEG data recorded under three different tasks (n-back task, single-leg stance, and short bursts of fast walking). The effect of task and cut-off parameter was assessed using (1) the ratio of data removed or reconstructed using ASR in sensor-space, (2) the dipolarity and reproducibility of ICs as assessed by RELICA, and (3) the classification of ICs using IClabel. This knowledge is needed, particularly when motor tasks are employed with higher likelihood for causing movement artifacts such as in postural control or walking tasks.

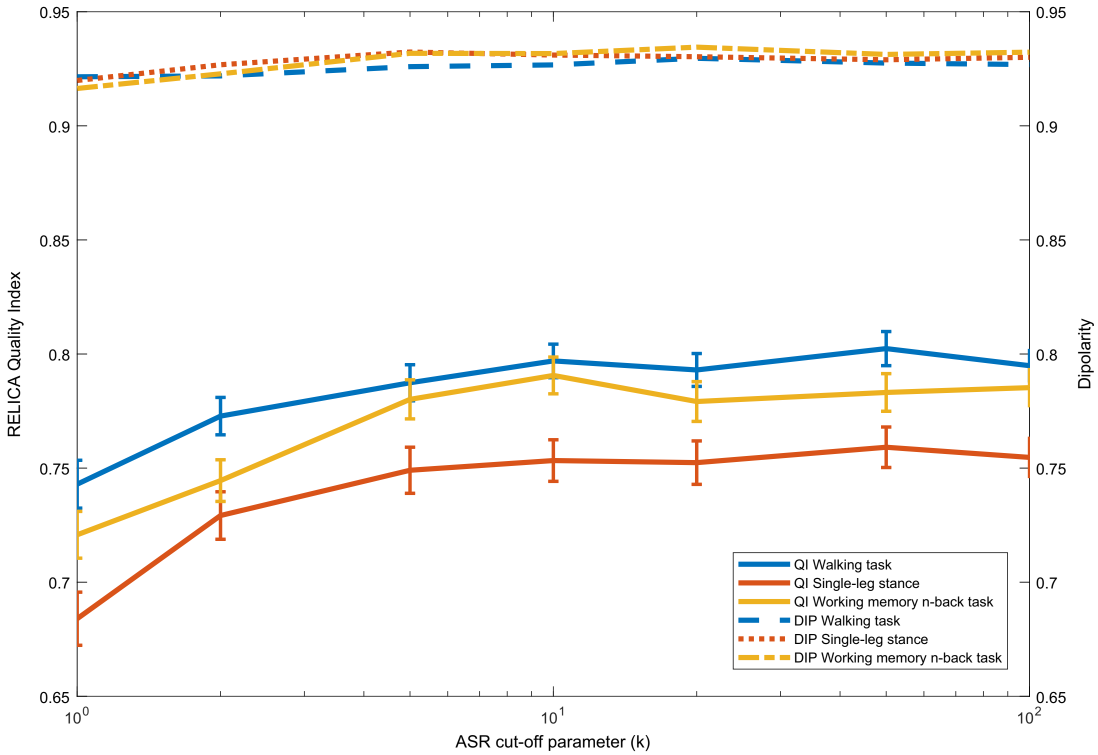

Fig. 2 Resulting mean quality index and mean dipolarity of independent components for all tasks preprocessed using ASR as calculated by RELICA for cut-off parameters of 1–100 only, using ICs with a dipolarity greater than 0.85. The error bars indicate the standard error of the measurements

ASR, as a preprocessing step before ICA, delivered the best results in terms of reproducibility and dipolarity in EEG recorded during bursts of fast walking compared with EEG recorded during a cognitive task and single-leg stance. The number and certainty of the classification as brain-related ICs were unaffected by the choice of cut-off parameter across all tasks. The cut-off parameters resulting in the same ratio of data removed and reconstructed as in manual cleaning using visual inspection revealed a lower range of equivalent cut-off parameters in the walking task compared with the cognitive and single-leg stance task.

4.1 Ratio of data removed and reconstructed using ASR

Tasks more likely to cause movement artifacts seem to require lower cut-off parameters for ASR, when compared with the ratio of removed data during manual cleaning, as shown in Fig. 1. The ranges of cut-off parameters determined by the comparison to manually cleaned data for the single-leg stance task and the *n*-back task (Fig. 1) show rough agreement with recent literature. Mullen et al. [12] used cut-off parameters between 5 and 7. However, their application of ASR was in a BCI system using dry electrodes. Chang et al. [11] recommended to use cut-off parameters between 10 and 100 which was later adjusted to cut-off parameters between 20 and 30 [14]. These results were based on EEG recorded while performing a simulated driving task. Our results show that a human rater would remove a similar percentage of EEG as ASR with previously recommended cut-off parameters in the single-leg stance task and the *n*-back task. The range of cut-off parameters in the walking task was lower than the recommendations in recent literature. A possible explanation could be differences in the level of movement artifact contamination compared with the EEG used in [11, 14]. The walking task in our study might show higher levels of contamination as walking is a more vigorous task compared to simulated driving.

4.2 Dipolarity and reproducibility of independent components

Surprisingly, significantly higher quality indices were observed for ICs in the walking task. This indicates the best reproducibility of ICs using EEG from this task. This finding

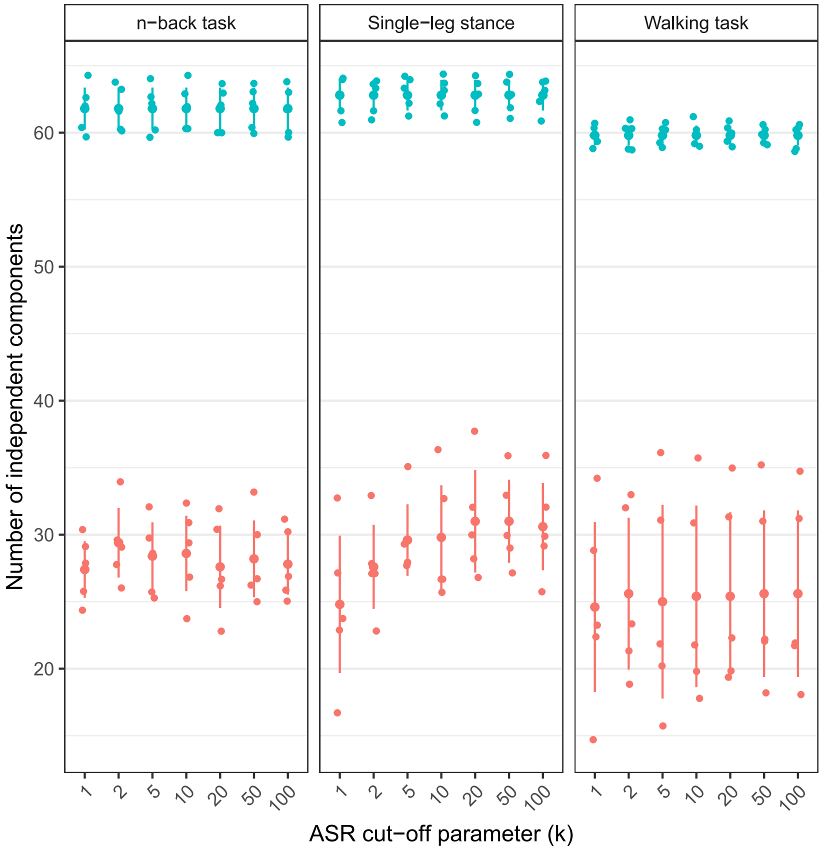

Fig. 3 The number of ICs for each task identified by BeamICA. Teal dots represent all ICs, and red dots represent ICs with a dipolarity of > 0.85. The vertical bars indicate the standard error of the measurements

was not anticipated since the walking task was the most contaminated with movement artifacts. The single-leg stance task showed the lowest quality indices, despite being the task with presumably the second lowest likelihood for causing artifacts. A possible explanation for this result might be that ASR partly removed brain-related activity in addition to removing noise and artifacts, since alpha waves were the most prominent feature in the EEG from this task.

The high plateau for all quality indices for cut-off parameters higher than 10 indicates that the quality of ICs is negatively affected by more aggressive cut-off parameters. This supports the findings of Chang et al. [14] that cut-off parameters of less than 20 are not advisable and resulted in significantly lower quality indices and dipolarity across tasks.

Interestingly, dipolarity was not affected as severely as the quality index by the choice of cut-off parameters. A consequence of this is that dipolarity alone might not be the optimal tool to determine whether an IC is brain-related and of high quality or not. Although computationally expensive, RELICA can potentially serve as a more dependable assessment tool for quality assurance of source-space results.

The overall quality of ICs was lower than those of Artoni et al. [25]. Our results are likely related to the amount of movement and the thereby induced artifacts. However, the cognitive task had no, or a very limited amount, movement. The reason for the difference in the quality index may be related to Artoni et al. using event-related potentials in their experiment whereas we used continuous EEG recordings.

Contrary to the findings of Artoni et al. [25], we found ICs in the "forbidden region." They hypothesized that highly dipolar ICs cannot have extremely low-quality indices. Most ICs in the "forbidden region" (17 out of 21) were calculated using EEG preprocessed with ASR with a cut-off parameter of 10 or less. Twelve of those ICs used a cut-off parameter of 1. This indicates that low cut-off parameters may reduce the quality indices but do not affect the dipolarity of ICs. The single-leg stance task was the most prominent task in the "forbidden region," with 15 of the 21 ICs. It seems possible that ASR, when used with cut-off parameters below the recommended range ($k < 20$) [14], can have a negative effect on the reproducibility of ICs. This assumption is supported by

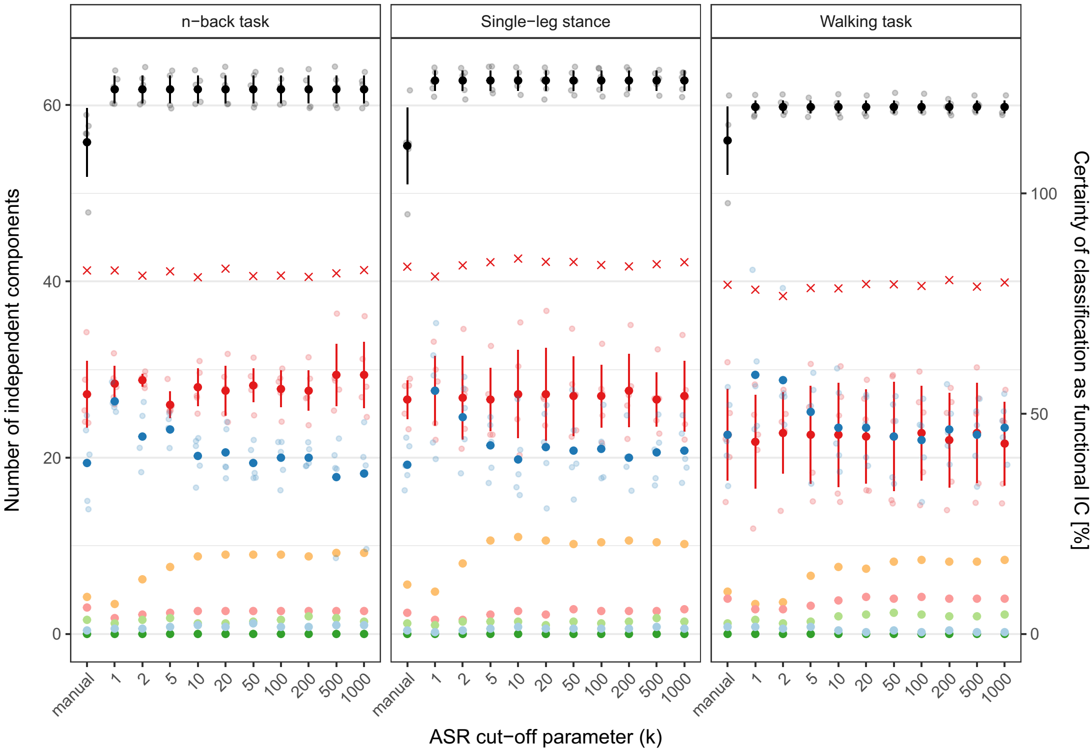

Fig. 4 Independent components for EEG data preprocessed using ASR with cut-off parameters ranging from 1 to 1000 and manually cleaned EEG data. Spatiotemporal features were calculated using an adaptive mixture-independent component analysis. Total number of independent components (black) and independent components classified into seven categories using IClabel (red, "brain"; blue, "other noise"; other colors, "muscle," "eye," "heart," "line noise," and "channel noise"). The bars indicate the standard error. The crosses indicate the certainty of the classification of independent components as brain-related

the significant difference between ICs preprocessed with cut-off parameters of one or two compared with the remaining cut-off parameters used.

Unfortunately, it was not possible to calculate quality indices of ICs that were based on manually cleaned data using RELICA. To further investigate whether this was related to eye blinks or remaining movement artifacts, we used the RELICA plug-in on manually cleaned and artifact-free seated, open-eyes baseline data from a previous study [6]. Despite this dataset not containing any movement contamination but only artifacts due to eyeblinks, we arrived at similar results. It was possible to obtain plausible resulting values from RELICA after removing the eyeblink artifacts from either EEG data set using ASR, ruling out the possibility that manual cleaning with resulting boundaries between the remaining EEG caused the issue. Although we cannot answer for sure what may have caused RELICA to perform unsatisfactory in manually cleaned EEG data, it seems reasonable to assume that the prominent eyeblink artifacts in both cases had an important role in its inability to deliver quality indices.

4.3 Classification of independent components

The number of functional ICs classified by IClabel in each task remained constant regardless of the cut-off parameter used. This indicates that ASR does not lead to an artificial increase of brain-related ICs. Significantly more ICs were classified as functional in the n-back task and the single-leg stance task compared to the walking task. This might be due to the level of movement artifact contamination that remained in the EEG after cleaning. For the walking task, more ICs were needed to model the remaining noise, hence leaving fewer ICs available for functional processes.

The classification of noise sources was influenced by cut-off parameters less than 10 across all three tasks. Hence, it can be assumed that ASR, when used with cut-off values below 10, alters the noise patterns in the EEG, so that they cannot be distinguished by the automatic IC classification tool IClabel. This led to more ICs being classified as "other noise" instead of being distinguished into specific classes of noise. This effect was most notable in the class of "muscle" ICs. Therefore, it seems reasonable to assume that strong high-frequency broadband activity used to classify ICs as "muscle"-related was affected by the reconstruction of the signal by ASR [24]. The number of functional ICs remained constant, suggesting that ASR preserves functional ICs across cut-off parameters. Further research is needed to further support this interpretation.

4.4 Next steps

Manual cleaning is likely to remove EEG linked to high intensity movements, whereas ASR reconstructs them. A potential implication of this is a bias either due to systematic removal of EEG or due to the reconstruction of EEG. Especially in mobile brain/body imaging applications [5], EEG recorded during movements is of high interest and an important topic for future research. There are still many unanswered questions such as which parameters can be used to automate the selection of cut-off parameters used in ASR and whether there is a bias introduced by the reconstruction of data.

Our results based on two motor tasks and one cognitive task indicate that it may not be possible to provide general recommendations for the choice of ASR cut-off parameters across different types of tasks performed while measuring brain activity. However, detecting the plateau in quality indices calculated using RELICA might be a good candidate for the parameterization of the selection of ASR cut-off parameters. Despite being computationally expensive, a data-driven approach for the selection process of cut-off parameters would be beneficial for the development of automatic processing pipelines.

4.5 Limitations

Using real-world data for analyzing filtering algorithms comes with the caveat that there is no gold standard for EEG preprocessing. However, it is important to compare the results of a common preprocessing practice with newly developed automatic preprocessing algorithms as in the current study, in order to get a better understanding of the behavior of the latter. In addition, quantifiable quality features of the EEG were used to assess the effect of the cut-off parameter used in ASR. A further limitation is that the list of tasks included in this study is not exhaustive and we only used one particular type of EEG system. Thus, the results may vary for other motor tasks with different compositions of noise or different EEG amplifiers and electrodes. Nevertheless, this is the first study to investigate the effect of movement tasks, showing differences in reproducibility and dipolarity depending on the cut-off parameter used. This knowledge is important for, and may inspire, future research.

5 Conclusion

Artifact subspace reconstruction appears a valuable tool for the automatic cleaning of EEG data recorded while performing motor tasks when used as a preprocessing step for an independent component analysis. We showed that the dipolarity and the reproducibility of independent components reached a combined maximum when cut-off parameters of 10 or higher were used in EEG data recorded from real participants. The number of functional ICs classified by an automatic tool remained constant, regardless of the cut-off parameter used. However, in EEG with low levels of movement induced artifacts, we observed lower combined reproducibility and dipolarity compared with more contaminated data, indicating that ASR might be less suitable for non-contaminated EEG datasets. Furthermore, ASR with cut-off parameters lower than 10 produced ICs with high dipolarity and low reproducibility.

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References

1. Acharya UR, Sree SV, Swapna G, Martis RJ, Suri JS (2013) Automated EEG analysis of epilepsy: a review. Knowl-Based Syst 45:147–165
2. Anders P, Lehmann T, Müller H, Grønvik KB, Skjæret-Maroni N, Baumeister J, Vereijken B (2018) Exergames inherently contain cognitive elements as indicated by cortical processing. Front Behav Neurosci 12
3. Laszlo S, Ruiz-Blondet M, Khalifian N, Chu F, Jin Z (2014) A direct comparison of active and passive amplification electrodes in the same amplifier system. J Neurosci Methods 235:298–307
4. Delorme A, Mullen T, Kothe C, Akalin Acar Z, Bigdely-Shamlo N, Vankov A, Makeig S (2011) EEGLAB, SIFT, NFT, BCILAB, and ERICA: new tools for advanced EEG processing. Comput Intell Neurosci 2011:1–12
5. Makeig S, Gramann K, Jung TP, Sejnowski TJ, Poizner H (2009) Linking brain, mind and behavior. Int J Psychophysiol 73(2):95–100 Neural Process Clin Psychophysiol

6. Makeig S, Bell AJ, Jung TP, Sejnowski TJ (1996) Independent component analysis of electroencephalographic data. In: Advances in neural information processing systems, pp 145–151
7. Bigdely-Shamlo N, Mullen T, Kothe C, Su KM, Robbins KA (2015) The PREP pipeline: standardized preprocessing for large-scale EEG analysis. Front Neuroinform 9:16
8. Delorme A, Palmer J, Onton J, Oostenveld R, Makeig S (2012) Independent EEG sources are dipolar. PLoS One 7(2):e30135
9. Jung TP, Makeig S, Westerfield M, Townsend J, Courchesne E, Sejnowski TJ (2000) Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects. Clin Neurophysiol 111(10):1745–1758
10. Kothe CAE, Jung TP (2016) Artifact removal techniques with signal reconstruction. Google Patents. US Patent App. 14/895,440
11. Chang CY, Hsu SH, Pion-Tonachini L, Jung TP. Evaluation of artifact subspace reconstruction for automatic EEG artifact removal. In: 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE; 2018. p. 1242–1245
12. Mullen TR, Kothe CA, Chi YM, Ojeda A, Kerth T, Makeig S et al (2015) Real-time neuroimaging and cognitive monitoring using wearable dry EEG. IEEE Trans Biomed Eng 62(11):2553–2567
13. Pion-Tonachini L, Hsu S, Chang C, Jung T, Makeig S. Online automatic artifact rejection using the Real-time EEG Source-mapping Toolbox (REST). In: 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2018. p. 106–109
14. Chang C, Hsu S, Pion-Tonachini L, Jung T. Evaluation of Artifact Subspace Reconstruction for Automatic Artifact Components Removal in Multi-channel EEG Recordings. IEEE Transactions on Biomedical Engineering. 2019;p. 1–1
15. Klem GH, Lüders HO, Jasper H, Elger C et al (1999) The ten-twenty electrode system of the international federation. Electroencephalogr Clin Neurophysiol 52(3):3–6
16. Delorme A, Makeig S (2004) EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. J Neurosci Methods 134(1):9–21
17. Winkler I, Debener S, Müller K, Tangermann M. On the influence of high-pass filtering on ICA-based artifact reduction in EEG-ERP. In: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2015. p. 4101–4105
18. Palmer JA, Kreutz-Delgado K, Makeig S (2006) Super-Gaussian Mixture Source Model for ICA. In: Rosca J, Erdogmus D, Príncipe JC, Haykin S (eds) Independent Component Analysis and Blind Signal Separation. Springer, Berlin, pp 854–861
19. Palmer JA, Makeig S, Kreutz-Delgado K, Rao BD (2008) Newton method for the ICA mixture model. In: 2008 IEEE International Conference on Acoustics, Speech and Signal Processing, pp 1805–1808
20. Oostenveld R, Oostendorp TF (2002) Validating the boundary element method for forward and inverse EEG computations in the presence of a hole in the skull. Hum Brain Mapp 17(3):179–192
21. Akalin-Acar Z, Gençer NG (2004) An advanced boundary element method (BEM) implementation for the forward problem of electromagnetic source imaging. Phys Med Biol 49(21):5011–5028
22. Gençer NG, Akalin-Acar Z (2005) Use of the isolated problem approach for multicompartment BEM models of electro-magnetic source imaging. Phys Med Biol 50(13):3007–3022
23. Piazza C, Miyakoshi M, Akalin-Acar Z, Cantiani C, Reni G, Bianchi AM, et al. An automated function for identifying eeg independent components representing bilateral source activity. In: XIV Mediterranean Conference onMedical and Biological Engineering and Computing 2016. Springer; 2016. p. 105–109
24. Pion-Tonachini L, Makeig S, Kreutz-Delgado K (2017) Crowd labeling latent Dirichlet allocation. Knowl Inf Syst 53(3):749–765
25. Artoni F, Menicucci D, Delorme A, Makeig S, Micera S (2014) RELICA: a method for estimating the reliability of independent components. NeuroImage. 103:391–400
26. Kothe CA, Makeig S (2013) BCILAB: a platform for brain–computer interface development. J Neural Eng 10(5):056014
27. Groppe DM, Makeig S, Kutas M (2009) Identifying reliable independent components via split-half comparisons. Neuroimage. 45(4):1199–1211
28. R Core Team (2019) R: a language and environment for statistical computing. R Foundation for statistical computing, Vienna, Austria. URL https://www.R-project.org/
29. Benjamini Y, Hochberg Y (1995) Controlling the false discovery rate: a practical and powerful approach to multiple testing. J R Stat Soc Ser B Methodol 57(1):289–300
30. Pion-Tonachini L, Kreutz-Delgado K, Makeig S (2019) ICLabel: an automated electroencephalographic independent component classifier, dataset, and website. NeuroImage. 198:181–197

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