Measuring Electrical Activity in the Brain During Exercise:

A Review of Methods, Challenges, and Opportunities

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Abstract

Background: During the last decade, the use of mobile electroencephalography (EEG) devices has furthered understanding of the mechanisms that underlie psychophysical and affective responses during the execution of gross movements (e.g., walking and cycling). Such devices can also be used to shed new light on the mechanisms that underlie attention allocation, fatigue-related symptoms, emotional reactions, and behavioural outcomes to physical activity programmes. This advancement could, potentially, herald a new era for the field of sport and exercise psychology, wherein researchers will be able to investigate athletic performance and exercise behaviour from a different perspective. *Objective:* In this review, we explore some of the most recent approaches used to measure electrical activity in the brain during exercise. *Practical Recommendations:* We provide an overview of the practical issues that researchers face in this field, such as dealing with artefacts elicited by body and cable movements and how to process the biological signal. We also review methods that researchers can employ to prevent electrical artefacts from compromising the fidelity of data. We make a case for assessing psychological and psychobiological parameters in tandem with EEG in order to arrive at a fuller understanding of exercise-related phenomena.

Keywords: cerebral cortex, electroencephalography, neuropsychology, physical activity, psychophysiology

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In recent years, researchers in the field of sport and exercise sciences have begun to assess brain function as a means by which to understand the mechanisms that underlie complex psychophysiological phenomena during the execution of movements (Broelz et al., 2019). This is due to the widely-held notion that the brain holds the answers to some of the most intriguing questions that pervade the realm of sport and exercise sciences (e.g., de Morree, Klein, & Marcora, 2012). What causes volitional exhaustion? What are the implications of fatigue-related symptoms? How does one's motivational state influence perceptions of physical exertion? Why do most people disengage from physical activity programmes? This is but a small selection of pertinent questions and despite recent advances in psychology and physiology, we lack neurophysiological explanations that enable us to "connect the dots". This is the reason why brain assessment techniques have attracted a great deal of interest in the last two decades (e.g., Jain, Gourab, Schindler-Ivens, & Schmit, 2013; Scanlon, Sieben, Holyk, & Mathewson, 2017).

There are numerous techniques available that facilitate assessment of the brain (e.g., functional magnetic resonance imaging [*f*MRI]); nonetheless, head movements that commonly occur during the execution of gross movements tend to compromise the quality of the biological signal. Accordingly, mobile technology has recently been developed to enable assessment of the brain during real-life situations. Functional near-infrared spectroscopy (*f*NIRS) and electroencephalography (EEG) are the techniques that currently show the most promise in relation to sport- and exercise-related tasks. In this short review article, we will discuss some of the most recent approaches used to measure electrical activity in the brain during exercise. We begin with a brief review of the main parameters and origins of the EEG signal. Thereafter, we address the general strengths and limitations of EEG as a technique.

We then proceed to expound the special considerations that pertain to the application of EEG in the realm of exercise psychophysiology. In addition, we provide guidance on dealing with artefacts elicited by body and cable movements, and on how to process the biological signal.

Measuring Electrical Activity in the Brain

The selection of techniques to assess the brain is based primarily on considerations that pertain to the level of temporal and spatial resolution (Liu, Ding, & He, 2006). EEG and electrocorticography (ECoG; i.e., invasive EEG) present a high level of temporal resolution (i.e., it captures the synchronised activity of neurons); however, such techniques provide a low degree of spatial resolution. EEG is often applied as a means by which to detect temporal events such as attention allocation; when an individual shifts her or his attention from one source of information to another (e.g., Luck, Woodman, & Vogel, 2000). Cognitive mechanisms such as attention allocation occur over brief epochs. Identifying this rapid response represents a significant challenge when employing techniques with poor temporal resolution such as positron emission tomography (PET). Along similar lines, EEG is not recommended as a tool with which to localise activity arising from deep areas of the brain such as the anterior cingulate cortex or the superior colliculus; rather signals that emanate from superficial areas are stronger and more spatially distinguishable (e.g., prefrontal cortex; Dickter & Kieffaber, 2013). Given that EEG activity is recorded using a two-dimensional array of electrodes, the three-dimensional location of deep sources of electrical activity cannot be accurately determined. This is a mathematical phenomenon known as the *inverse problem* that concerns inference of the precise location of brain activity through use of surface electrodes positioned on the scalp (Lopez Rincon & Shimoda, 2016). Nonetheless, source reconstruction analysis can be used to estimate the sources of brain activation and provide researchers with greater detail in terms of spatial location (see Luck, 2014).

EEG was first recorded non-invasively from the human scalp in 1924 by the German psychiatrist Hans Berger. The early EEG studies adopted the use of brain waves to identify a patient's arousal state and the delineation of sleep stages (e.g., Loomis, Harvey, & Hobart, 1936; Ray & Cole, 1985). Brain waves have also been investigated extensively in the fields of neurology and psychophysiology to further understanding of a range of disorders and traumas, such as epilepsy and cerebral injuries. The EEG signal derived from brain activity encompasses a range of frequencies. These frequencies are stratified according to different band waves by use of frequency-domain analyses such as Fast Fourier Transform (FFT). Delta (0.5–4 Hz), theta (4.5–8 Hz), alpha (8.5–13 Hz), beta (13.5–30 Hz), and gamma (30.5–100 Hz) are the most commonly designated brain wave bands. In this context, power is the square of the EEG magnitude, and magnitude is the integral average of the EEG signal (Keil et al., 2014). The power of brain frequencies in different wavebands as well as the amplitude (measured in microvolts) of the electrical signal at a particular timepoint can be influenced by sensory stimuli (e.g., Daly et al., 2014; Spring, Tomescu, & Barral, 2017), cognitive tasks (e.g., Bing-Canar, Pizzuto, & Compton, 2016; Twomey, Murphy, Kelly, & O'Connell, 2015), movement execution (e.g., Scanlon et al., 2017; Thompson, Steffert, Ros, Leach, & Gruzelier, 2008), and psychological responses (e.g., Jadhav, Manthalkar, & Joshi, 2017; Lee & Hsieh, 2014).

The Neural Origins of the EEG Signal

EEG is generated in neural tissue by flows of current in the extracellular space. This current may be influenced by the activity of many thousands of neurons, and can produce effects by volume conduction at a recording electrode distant from the source (Dickter & Kieffaber, 2013). In a wire, electrical current flows in one direction; however, in volume conduction, the current spreads in all directions. The generators of the extracellular current flows are intracellular postsynaptic potentials (Avitan, Teicher, & Abeles, 2009). Both excitatory and inhibitory postsynaptic potentials contribute to EEG, but there is no simple relationship between negative and positive EEG voltages and neural excitation and inhibition.

Electrodes placed on the scalp record EEG predominantly from the underlying cerebral cortex, and the largest contribution to the EEG signal comes from the summed synaptic potentials of pyramidal cells (Olejniczak, 2006). These are the largest cortical cells with their axons forming the main outputs to other cortical and subcortical areas. Their orientation is perpendicular to the cortical surface spanning most of the depth of the grey matter. The bodies of pyramidal cells are typically found in cortical layer 5, close to the base of the grey matter, and their apical dendrites (i.e., the apex of the branched extension of a nerve cell) stretch up to layer 1, close to the outer surface of the cortex. Furthermore, they receive their main synaptic inputs in two main regions: thalamic inputs in layer 4 (towards the base), and transcortical inputs in layers 2-3 (nearer the surface). The pyramidal cell tends to act as a switchable electrical dipole, meaning that the end of the cell that receives an excitatory input is negative, and the other end is positive. For example, consider a small patch of cortex such as 5 × 5 mm. All the pyramidal cells in that patch will be similarly oriented and receive related inputs, so it is likely that the dipoles will be similarly oriented and show some synchronisation, producing a strong EEG signal (Dickter & Kieffaber, 2013; Olejniczak, 2006). Conversely, other types of cortical cells have a weak effect on EEG. They are oriented more randomly, and their dipoles will thus point in many different directions, so that the net current flow for a cluster of active stellate neurons would probably tend to zero, even if they were stimulated synchronously. Thus, the cortical generator for an EEG signal may be modelled as a set of columns of cortical tissue, each acting as a single dipole source. From an exterior viewpoint, the most striking feature of the human cortex is that it is a continuous but much-folded surface, consisting of furrows (sulci) and convoluted ridges (gyri). Gyri located beneath an electrode will contribute most strongly to the EEG signal, but owing to volume conduction, remote sources will also contribute. This contribution, however, is moderated by distance from the electrode (Olejniczak, 2006).

Electrical Activity in the Brain During Exercise

EEG has been used in numerous scientific domains including the sport and exercise sciences. Schneider, Askew, Abel, Mierau, and Strüder (2010) examined brain function before and after an exhaustive running task. The incremental treadmill test caused an immediate increase in alpha 1 (7.5–10 Hz) activity after exercise. Alpha 1 increase was mainly localised in the left frontal regions of the brain by use of source estimation analysis. The researchers postulated that this increase in low-frequency alpha waves was associated primarily with emotional processing. Their postulate was based on the long-held view that left-hemisphere regions of the brain are linked to positive feelings such as happiness and joy, and that the right hemisphere is associated with negative affect (cf. The Valence Model; Demaree, Everhart, Youngstrom, & Harrison, 2005). Moreover, increases in alpha activity may be indicative of decreases in cortical arousal. Hence, psychological and peripheral physiological responses to exercise (e.g., affective valence and muscle electrical activity) may be investigated in tandem with EEG (Gutmann et al., 2015), as a means by which to elucidate the effects of exercise-related interventions on bodily reactions.

The use of brain assessment techniques during exercise is usually limited to isometric modes of contraction (i.e., when the joints are static) because head and body movements cause artefacts that compromise the quality of the raw data (Bigliassi et al., 2016a). To address this limitation, researchers have developed EEG systems based on wireless connections, which improve the range of motion and reduce electrical artefacts (for a pioneering study, see Hughes & Hendrix, 1968; for contemporary applications, see Losonczi, Márton, Brassai, & Farkas, 2014; Szu, Hsu, Moon, Yamakawa, & Tran, 2013). Nonetheless, wireless systems are limited in real-life situations; for example, where there are walls present or when a participant needs to travel beyond ~200 m from the signal receiver. Moreover, brisk contractions (e.g., jumping) may generate more artefacts than repetitive movement patterns such as walking. In such instances, EEG devices can be integrated with electromyography (EMG) systems in order to identify and discard movement-related artefacts after data collection. Moreover, new EEG devices such as Muse (Krigolson, Williams, Norton, Hassall, & Colino, 2017) and Emotiv (Duvinage et al., 2013) are attached to triaxial accelerometers that quantify body movements and apply compensatory methods as a form of online correction that protects the biological signal.

Bigliassi, Karageorghis, Wright, Orgs, and Nowicky (2017) investigated the effects of music on brain activity and motor unit recruitment during cycle exercise performed at moderate-to-light intensity. They found that the EEG frequency (i.e., synchronisation of alpha rhythm; Peper, 1971) over the sensorimotor cortex controlling the working muscles was reduced in the presence of music. The authors postulated that this psychophysiological response could have influenced the electrical activity in the quadriceps given the inference that fewer signals per unit time were reaching the musculature (i.e., a suppression of EEG resynchronisation). The researchers also processed the electromyographic (EMG) activity in the time-domain (i.e., examining the amplitude of the signal) and identified that more motor units (Farina, Fosci, & Merletti, 2002) were recruited in the presence of music. This physiological response could potentially indicate that a compensatory mechanism takes place as a means by which to sustain a given exercise intensity (i.e., a reduction in EEG frequency is compensated by increases in EMG amplitude).

The analysis of EEG extends beyond the identification of brain frequencies. For example, the event-related potential (ERP) technique facilitates examination of brain response to sensory stimuli, motor tasks, or cognitive demands (Light et al., 2010). The synchronous samples (i.e., time-locked signals) display a characteristic shape, meaning that modification of the curve profile is indicative of a different phenomenon having occurred over time. Such phenomena are usually introduced by researchers as a means by which to identify the effects of sensory stimuli or cognitive processes on brain responses (e.g., Scanlon, Sieben, Holyk, & Mathewson, 2017). In addition, neuropathological conditions can elicit changes in ERPs. Such changes can be identified through the comparison of diseased and healthy individuals or between dissimilar experimental conditions (see Groppe, Makeig, & Kutas, 2008 for a review).

A variety of sensory stimuli such as music and video have been used to induce ERPs (e.g., Tervaniemi, Just, Koelsch, Widmann, & Schröger, 2005). The modulation of ERP components such as P1 (positive peak that occurs at ~100 ms after the stimulus onset) and N1 (negative peak that occurs at ~100–200 ms after the stimulus onset) varies in accord with the type of stimulus used. It has been proposed that attention allocation modulates the curve design of P1 and N1 during visual tasks (Luck et al., 2000). Interestingly, similar effects are evident during auditory stimulation (Coch, Sanders, & Neville, 2005). Thus, by examining the curve profile of the brain's electrical activity, researchers are able to identify cerebral responses to different cognitive processes. This technique has been applied extensively in the area of cognitive neuroscience (Landa, Krpoun, Kolarova, & Kasparek, 2014; Sur & Sinha, 2009), and affords a high level of reliability when the guidelines for the application of EEG are followed judiciously (see Keil et al., 2014).

Recording Clean EEG Data

Scientists with experience in EEG techniques are well aware of the need for a systematic approach to noise reduction and elimination. It is possible to remove various types of noise from the EEG signal after recording by use of software algorithms such as digital filtering, averaging, threshold-based artefact rejection, and independent components analysis (ICA; Keil et al., 2014). However, each of these methods is characterised by some loss or distortion of the signal. There is really no substitute for recording a clean EEG signal and eliminating artefacts, as far as is possible, at source. We shall consider some of these sources of noise and how they can be reduced or eliminated.

Electrode-related noise. The most critical element in the EEG recording system is the electrode-scalp interface. Good electrical contact with the scalp is essential to obtain clean EEG recordings. Electrodes should be nonpolarizing, which means that they should not build up electrochemical charges in contact with saline fluids, as reactive metals do. Gold (Au), tin (Sn) and silver coated with silver chloride (Ag/AgCl) are considered to be suitable electrode materials (Keil et al., 2014). Laboratories using Ag/AgCl electrodes and conductive gel will generally aim for electrode-scalp impedances of around 5 KΩ. However, good quality modern EEG amplifiers have high input impedances and noise cancelation, and this means that it is possible to record EEG with an electrode impedance of ~50 KΩ, albeit noise risks are increased.

A factor that has a bearing on electrode impedance is the condition of the participant's scalp. The outer epidermis consisting of dead cells is an electrical insulator, plus the skin secretes oils that are nonconducting. Therefore, participants are asked to wash their hair the night or morning before the recording, and avoid products such as hair gel, spray, or wax. Brushing the hair vigorously can help in terms of removing loose epidermis. Also, most proprietary electrode gels contain mild detergents that can break up oily films, and pumice powder to help remove dead skin. Perhaps, surprisingly, it is possible to record good EEG data from participants with thick and voluminous hair. Calibrated syringes allow experimenters to determine the optimal amount of gel to fill a disc-type electrode. Electrodes should be filled by continuously extruding gel, starting at the scalp surface and gradually withdrawing the needle towards the top of the electrode. It is essential to monitor all electrode impedances prior to initiating a recording, and to remedy all electrodes with out-of-range impedances. Before resorting to applying more gel (which can cause bridging between electrodes) an out-of-range electrode should be gently pressed onto the scalp and rocked. This is usually sufficient to establish good contact. It is also important to highlight that recent EEG devices have been designed to measure electrical activity in the brain using dry electrodes, meaning that gel is not required in capturing the biological signal. Gel-free systems are largely available and active electrode systems can tolerate input impedances up to 100 KΩ. Such devices have been used in a wide variety of contexts and are deemed suitable for research-related purposes (see Lopez-Gordo, Sanchez Morillo, & Pelayo Valle, 2014).

Mechanical instability of the cap. This problem is largely avoided in a geodesic net, where local tensions automatically adjust the fit of the net to the head. However, the 10-20 style caps come in standard sizes with limited flexibility, so a good fit is not guaranteed, and some electrodes may tend to lift away from the scalp. Tubular elastic netting can also be applied to the outside of the cap to improve contact pressure. If mechanical problems are solved, and gel or electrolyte is correctly applied, then recording properties will generally improve over the initial 15–20 min after fitting the cap as the gel or electrolyte acts on the epidermis. It is a good idea, therefore, to ask participants to complete any necessary preliminary questionnaires or other non-EEG data collection while the cap is stabilising.

External electrical noise. The high-gain amplifiers used in EEG will magnify any tiny voltages present at the scalp regardless of their source. Moreover, the human body, when connected to such an amplifier acts as an excellent aerial that will pick up any radio-frequency electromagnetic signals that are broadcast through the air. The human environment is awash with such signals that emanate from electrical devices. Prominent components of such electromagnetic noise are 50/60Hz mains frequency waves and switching transients (spikes) originating from nearby electrical equipment and lighting.

It is impossible to record clean EEG unless such electrical interference is eliminated. There are three main approaches to eliminating these sources of noise. The first of these is screening; an EEG room should ideally be electrically and acoustically screened. Electrical screening is achieved by a conductive metal mesh embedded in the walls, floor, and ceiling, and connected to the ground (earthed). This Faraday cage will prevent any broadcast electrical interference from outside the room reaching the EEG participant, cap, and amplifiers. If your laboratory budget will not stretch to a purpose-built EEG room, then an effective Faraday cage can be built from steel tubes and connectors, covered in 1-cm steel mesh. The second approach is through amplifier design. EEG amplifiers are differential amplifiers that use three electrodes to record activity: an active electrode (A), a reference electrode (R) and a (virtual) ground electrode (G) placed participant's head, thus they will subtract the difference from ground of the active and reference voltage (AG - RG). Since external noise sources will tend to affect AG and RG similarly, this arrangement reduces noise (Luck, 2014). Modern amplifiers can have active noise cancelation and amplifiers that are placed in a headbox as close to the participant as possible. This eliminates cable loss of the unamplified signal. The third approach is to identify and switch off or move possible sources of interference (e.g., fluorescent lights, air conditioning units, or fridges). Some equipment such as computer monitors might, however, need to be placed inside the Faraday cage to present stimuli, and are thus an obvious source of noise. This is particularly a problem with computer screens, which contain large transformers. In such instances, a possible solution is to surround them with a Faraday cage-within-a-cage. Finally, it is important to also ensure that there is no path from the participant to the ground other than via the amplifier. A ground loop system (i.e., a loop created when two parts of the system are connected by a conducting path) can be a safety issue as well as creating mains-frequency interference.

Physiological noise. The main sources of physiological noise are: eye blinks and eye movements (electro-oculogram: EOG), skin conductance changes (variously known as galvanic skin response: GSR or skin conductance level/response: SCL/SCR), muscle activity (electromyogram: EMG) and heart activity (electrocardiogram: EKG). Participants should be instructed to blink as little as possible and to keep as still as possible while data are collected; although our experience shows that participants vary greatly in the ability or willingness to suppress blinks. All should be given breaks between blocks of trials in which they can blink, talk, and move. Additionally, vertical and horizontal EOG should be recorded in order to monitor eye movements and blinks, and to assist with the elimination of eye-related artefacts by PCA/ICA methods. GSR can be reduced by good electrode stability and low impedance. EMG interference originates mainly from neck and facial muscles. A relaxed state and comfortable position helps in reducing EMG and given that the dominant frequencies are higher than those of EEG, low-pass filtering is usually sufficient to remove such noises (Kline, Huang, Snyder, & Ferris, 2015). EKG is rarely a problem, but it can also be recorded for purposes of pattern-based artefact reduction.

Dealing with Body and Cable Movements

Dealing with electrical interference caused by external influences such as body and cable movements can present researchers with complications during movement-based protocols (Kline et al., 2015). Some of these electrical noises cannot be removed while processing the data offline, which means that researchers need to reduce the amplitude of electrical artefacts prior to commencement of data collection (Park, Fairweather, & Donaldson, 2015). Notably, recent technological developments have served to reduce the influence of body and cable movements on the EEG signal (Bigliassi, Karageorghis, Nowicky, Wright, & Orgs, 2018). Mobile EEG devices such as eego™sports make use of active shielding technology to protect the core components of the cables. Consequently, extraneous noise caused by body and cable movements is reduced, which allows researchers to collect EEG data during challenging situations such as outdoor walking and cycling. However, it is important to emphasise that active shielding technology only appears to reduce electrical artefacts during repetitive moments performed at light and light-to-moderate intensities (Bigliassi et al., 2017). This is due to the fact that moderate- and severe-intensity exercise manifests contractions of neck muscles (e.g., trapezius) that are extremely difficult to remove when processing the data; this EMG artefact mainly affects temporal and occipital electrodes.

Some wireless systems reduce movement artefacts by mechanically decoupling the EEG recording cap from the main amplification and recording system, and substituting a radio link from a small transmitter attached to the cap (Losonczi et al., 2014; Szu et al., 2013). Besides portability and accessibility (Mihajlovic, Grundlehner, Vullers, & Penders, 2015), the number of available channels, amplified signal quality, and accessibility of software are salient factors in the choice of a portable system.

It is noteworthy that brisk muscular contractions, even if executed at a moderate-intensity, can severely compromise the quality of the electrical signal (Jiang, Bian, & Tian, 2019). This occurs because some of the artefacts generated by body and cable movements exhibit a similar frequency and amplitude to EEG activity, which means that identification methods such as independent component analysis cannot differentiate artefacts from real brain activity. In such instances, researchers are encouraged to design experimental protocols that prioritise closed kinetic chain exercises (e.g., handgrip and ankle-dorsiflexion tasks) performed at relatively light-intensity with a focus on frontal, central, and parietal electrode sites. Modern EEG devices such as Muse and Emotiv can be used for tasks that better represent what people typically do during exercise bouts (e.g., cycling at intensities above the ventilatory threshold). However, the number of electrodes is reduced, which presents a limitation in terms of data processing (e.g., source reconstruction) and interpretation.

Future research and developmental work is necessary to establish new methods that will mitigate the influence of external factors on the fidelity of EEG data. Offline procedures can only partially remove extraneous noises and should be applied carefully in order to preserve the information carried in the raw signal (see Dickter & Kieffaber, 2013). Researchers are also encouraged to collect EMG signals from facial muscles and the trapezius during movement-based EEG experiments. Analogue triggers can also be created subsequently during the offline data processing stage to identify the very onset of muscle contractions (Bigliassi et al., 2017). This approach facilitates the removal of muscle bursts from the EEG signal and enhances the internal validity of an experiment.

Methods Used to Analyse Electrical Activity in the Brain

In order to process the biological signal extracted from the electrical activity of the brain, a series of offline procedures need to be conducted in a sequential manner (Olejniczak, 2006). The workflow should be described in the methods section of an EEG-based research study with sufficient detail to permit study replication (Picton et al., 2000; Tadel et al., 2019; Tivadar & Murray, 2019). The influence of artefacts (e.g., facial muscles and eye blinks) on the electrical signal, filtering processes, epoching, averaging, time-frequency analysis (e.g., wavelet transformations), source reconstruction, and brain connectivity are described herein to provide readers with sufficient background to enable them to interpret the results of EEG experiments in sport and exercise sciences.

Data correction. Firstly, researchers must import the data into computer programs and toolboxes such as Brainstorm (Franois Tadel, Baillet, Mosher, Pantazis, & Leahy, 2011) and EEGLab (Delorme & Makeig, 2004) in order to perform offline analytical procedures. These computer programs represent open source platforms for EEG analysis with active communities to provide support and ongoing development. Secondly, the signal needs to be re-referenced using consistent reference electrodes across trials and participants (e.g., average mastoid reference, using electrode sites [M1 and M2] or common average reference). In EEG, the signal amplitude recorded at each electrode is compared to voltages recorded at reference electrodes. The choice of reference electrode(s) influences the shape of ERPs recorded at different electrode positions, but referencing may be changed in software during offline processing. After recording, the data are visually checked to identify bad electrodes and bad time-segments (e.g., Wright, Gobet, Chassy, & Ramchandani, 2013). This procedure is normally conducted via a check of the signal amplitude of all electrodes (e.g., using a 2-D layout map). Figure 1 provides an example of a bad electrode that has been visually identified at O1 (red signal). This electrode needs to be discarded from further analyses; otherwise its inclusion might compromise final topographical results, estimated sources, and data interpretation. EEG artefacts can also be identified through the application of high-order statistics, frequency decomposition, and ICA; a technique used to separate linearly mixed sources (see Delorme, Sejnowski, & Makeig, 2007).

Figure 1

Eye blinks and eye movements. The vertical electro-oculogram (VEOG) recorded from electrodes above and below the eye scans vertical eye movements and blinks. Blink-related activity needs to be removed from EEG signals in order to negate the influence of orbicular muscular contraction on the activity of frontal electrodes (e.g., Girges, Wright, Spencer, & O'Brien, 2014). Independent component analysis is usually applied by modelling blink activity in the VEOG and removing the correlated waveforms of electrical activity from EEG electrodes. This approach possibly represents one of the most necessary methods to be applied during offline EEG procedures (Dickter & Kieffaber, 2013; Keil et al., 2014). This is because signals from both blinks and eye movements are mixed in with the EEG recorded from frontal and frontal-central electrodes. Moreover, ERPs may be confounded by any EOG signals, which have a tendency to occur systematically over time (e.g., where a stimulus trial requires a change in fixation point to complete the task). Consequently, such contractions are epoched and are therefore fully represented in averaged signals. This means that the averaged signals have the potential to indicate false peaks. Similar considerations apply to saccadic eye movements, from both horizontal (HEOG) and vertical (VEOG) eye movements. The solution requires care at the experimental design stage to eliminate any tendency for stimuli to provoke synchronised eye movements or blinks.

Raw EEG data. The continuous biological signal is imported into the database then broken into smaller time samples (i.e., epochs). These samples can be asynchronous (event-unrelated signals) or event-related windows (epoched by triggers; i.e., time-locked). Pre-processing of the raw (or epoched) EEG data includes DC-offset correction in order to prevent the influence of voltage imbalance problems (i.e., baseline variations). Offline filters (e.g., band-pass filters) are usually applied to exclude artefacts such as muscular contractions and electrical interference from external devices (e.g., computers and smartphones). Methods of independent component analysis and signal space projection have also been developed to remove cardiac and respiratory artefacts (e.g., Castellanos & Makarov, 2006).

Averaging. The preprocessed EEG signal usually needs to be averaged in time and/or frequency domains. The time-locked signal can be successfully averaged in time; in this case, amplitude is summed across different samples (Picton et al., 2000). However, event-unrelated samples, referred to as *asynchronous samples*, need to be averaged in the frequency-domain (i.e., FFT is conducted for each segment), otherwise, the time-amplitude average of all the samples will tend towards zero volts because the stimulus onset is random in relation to the EEG signal. In such instances, the brain does not “know” the times at which the samples were taken. This is the mathematical fact that underpins the principle of ERP averaging (Picton et al., 2000). Time-locked signals can be easily averaged using grand average methods; conversely, asynchronous samples are required to be processed in the frequency-domain through the application of methods that decompose the power spectrum into different band waves. It is also important to make clear the main differences between FFT and wavelet transformations. FFT methods provide the size of the component of frequency but no detail regarding the spatial duration. Conversely, wavelet transformations can derive a characteristic time and frequency. For example, time-frequency decomposition methods such as Morlet Complex Wavelets can indicate not only whether the power of theta waves were up-/ downregulated but also precisely when this modulation occurred (Bigliassi et al., 2014).

Topography and source estimation. Asynchronous samples can only be processed in the frequency-domain and present changes in different band frequencies over the cortex surface. Two-dimensional topographical maps are usually generated to illustrate the distribution of various frequencies at different electrodes (Pfurtscheller & Lopes Da Silva, 1999). Time-locked signals are directly linked to triggered stimuli/cognitive processes. When averaged, time-locked signals can be processed in both time- and frequency-domains and allow the reconstruction of estimated sources. Source reconstruction is more accurate for focal sources in the superficial regions of the cortex than it is for extended sources (Wennberg & Cheyne, 2013) or for sources in medial or subcortical regions (Koessler et al., 2014). The source of the brain's electrical signal can subsequently be reconstructed by applying different methods, such as the Minimum Norm Method (wMNE; i.e., an inverse solution method; Grech et al., 2008) or Standardized Low Resolution Brain Electromagnetic Tomography (sLORETA; Pascual-Marqui, 2002). sLORETA is based on current source density (i.e., a current flowing towards the electrode is a source, and a current flowing away from the electrode is a sink; see Kamarajan, Pandey, Chorlian, Porjesz, & Begleiter, 2016). In addition, researchers are required to select the neural orientation of the reconstructed sources.

Source orientation is a biophysical postulate that suggests that each vertex of the cortex surface contains one, two, or three dipoles with orthogonal directions. This anatomical observation is based on the fact that neurons are organised in different macro-columns that are perpendicular to the cortex surface. Unconstrained sources are recommended during EEG-related studies given its poor spatial resolution and the considerable challenge associated with the estimation of precise source locations.

Figure 2

Brain atlas. The final step in identifying the sources of an event-related potential entails the application of atlases to identify the brain regions that exhibit an increase in signal amplitude (e.g., Bigliassi et al., 2018; Jain et al., 2013). Brain atlases are subdivisions of the cortex surface that were created to explore the anatomy of the brain (i.e., brain labelling; see Klein & Hirsch, 2005) and its activation patterns. Computer programs such as Brainstorm provide users with numerous atlases that can be applied to extract amplitude and frequency changes from specific brain regions (see Figure 3).

Figure 3

Brain connectivity. Analyses of brain connectivity by statistical methods (e.g., correlation) have been used extensively in the fields of psychophysiology and neuroscience to further understanding of the neural networks that connect different brain regions (Jovanović, Perović, & Borovčanin, 2013). Spectral coherence analysis represents one of the most common methods to analyse brain connectivity and is applied to further understanding of the relationship between two electrical signals in the frequency-domain (Friston, 2011). Signal coherence is usually applied to estimate the means by which different brain regions/electrode sites respond in tandem. The magnitude of signal coherence varies from 0 to 1 and similar to correlational approaches, 1 represents a maximal level of coherence between electrical sources. Other methods such as Bivariate Granger causality analysis have been applied in the field of neuroscience to estimate not only the relationship between two brain regions but also the in-and-out connectivity between two electrical sources (Haufe, Nikulin, & Nolte, 2011). Put another way, this method has been used to indicate the influence of one electrode site on another (see Figure 4). Cortico-muscular coherence (EEG–EMG) is another approach widely used in the field of exercise sciences. By calculating the degree of connectivity between the electrical activity in the brain and muscles, researchers are able to indirectly assess the neural control of working muscles (e.g., Petersen, Willerslev-Olsen, Conway, & Nielsen, 2012).

Partial directed coherence (Baccalá & Sameshima, 2001) and directed transfer function (Kamiński & Blinowska, 1991) are also methods developed to investigate information flow in the brain structures and can be used for very similar purposes in the field of human movement sciences. For example, Mierau et al. (2017) demonstrated how different brain regions communicate during a balance control task through the use of partial directed coherence, which is a time-variant, frequency-selective and directed functional connectivity analysis tool. The authors suggested that balance control is primarily supported by functional networks. In the alpha network, the occipital lobe acts as a source, and the communication with other brain regions propagate towards parietal and central areas. This study demonstrates the way in which brain connectivity analysis can be used to explore how different brain regions are connected during complex physical tasks. Moreover, it puts forward a conceptual framework that is well supported by neurophysiological data.

Figure 4

Interpreting the EEG Data

Interpretation of the EEG data depends primarily on the design of a study and the information available in the extant literature. Correlational analysis can also be implemented at this juncture as a means by which to identify whether changes in the brain's electrical activity are associated with psychological responses (e.g., enjoyment or perceived activation) and/or peripheral physiological reactions (e.g., changes in heart rate variability or muscle electrical activity). It is noteworthy that the temporal resolution of the measures included in a correlational analysis can be slightly different, meaning that strong or weak relationships might not be particularly meaningful. For example, 1-s EEG epochs collected during the execution of movements are unlikely to correlate well with changes in affective valence that were measured immediately after an exercise bout. This is because the 1-s synchronous samples will be potentially linked to the neural control of working muscles, whereas affective responses will be indicative of a much longer time-frame. In such instances, decomposing the electrical signal by use of frequency-domain analysis appears to be a suitable approach in detecting changes in brain activity associated with psychophysical (e.g., perceived exertion; (Bigliassi, Karageorghis, Nowicky, Orgs, & Wright, 2016b) and psychological (e.g., motivation; (Bigliassi et al., 2016a; Bigliassi, Karageorghis, Hoy, & Layne, 2019) responses.

Brain connectivity analysis can also be used as a complementary method to test theoretical propositions. For example, Bigliassi et al. (2017) found that when participants exercised in the presence of music they reported more positive affective responses and felt less fatigued than when they exercised in a no-music control condition. In order to identify which brain mechanisms might be associated with such differences, the authors decided to test the corollary discharge model (see Pageaux, 2016). Accordingly, they calculated the spectral coherence level among electrodes positioned over the central motor command and somatosensory regions. The results indicated that music reduced the communication across somatosensory regions, which could have reduced exercise consciousness and thus led to a more positive affective state and amelioration of fatigue-related sensations.

Safety Issues

When used properly, EEG is a very safe and non-invasive technique. All EEG equipment should meet current safety standards for use with human participants, be properly maintained and installed, and tested for electrical safety. Operators should ensure that participants are protected from ground loops. Particular risk of ground loops may occur if the participant is physically connected to more than one recording and/or stimulating system. Other potential risks to be controlled for include skin irritation or cross-infection from gels and caps. The laboratory environment and cap storage area should be kept clean and tidy at all times. All electrode caps and electrodes should be washed meticulously after use. Water and antibacterial detergent should be used, as recommended by the manufacturer, to gently remove gel residues from electrodes. Blunt needles should always be sterilised. Gel should be hypoallergenic and transferred to a separate container for exclusive use with each participant. Operators should wash hands thoroughly for each testing session and use antibacterial hand gel.

Conclusions and Future Perspectives

In this short review article, we proposed a series of simple and efficient strategies pertaining to the collection of EEG data and reduction of the influence of electrical artefacts typically caused by body and cable movements. We also delineated some of the methods used to process the biological signal and extract meaningful information. This paper has been written to encourage researchers in exercise psychology to look at the brain with different eyes, and perhaps see a possibility to explore complex psychophysiological phenomena during the execution of gross movements. Accordingly, researchers should attempt to measure psychological and psychobiological (e.g., cortisol levels) parameters in tandem with EEG, in order to arrive at a fuller understanding of exercise-related phenomena.

Although collecting EEG data had never been possible during complex modes of exercise until just a decade ago, researchers can now use mobile devices to design experiments that are far better representative of real-life situations. There remains a need to prioritise the removal of artefacts given that the quality of the biological signal is of paramount importance. However, “mobile Faraday cages” would allow researchers to reproduce complex social situations and recreate experiences in the real world that were never previously imagined. Mobile EEG devices can be used to shed new light on the mechanisms that underlie attention allocation, fatigue-related symptoms, affective changes, and behavioural outcomes associated with physical activity programmes (e.g., exercise adherence). Looking forward, researchers might attempt to use stimulation methods to alter brain activity (e.g., repetitive transcranial magnetic stimulation [TMS], transcranial direct-current stimulation [tDCS], and transcranial alternating current stimulation [tACS]), manipulate bodily sensations, and ultimately change exercise behaviour.

The main advantages of EEG include its non-invasive nature, close connection to neural activity, superb temporal resolution, as well as relative inexpensiveness and convenience for use with human participants. Furthermore, a very substantial body of research has developed and refined the interpretation of EEG measures, particularly ERP and frequency-related measures, as correlates or indices of cognitive function both in normal and clinical populations. The disadvantages of EEG methods arise from the inverse problem (i.e., source reconstruction analysis), indeterminate source separation, and insufficient signal in relation to noise. A substantial research effort has been devoted to the development of new methods to address such problems. This has facilitated developers’ rapid progress in terms of overcoming the limitations of EEG in areas such as multimodal imaging, time-frequency analysis, and single-trial ERPs. As these new methods enter the mainstream, we can expect the full promise of EEG, as an imaging modality, to be realised by the research community.

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Figure Captions

Figure 1. Diagrammatic representation of a bad electrode in a 2-D layout, 62-channel EEG map.

Figure 2. Time-locked EEG signals and source reconstruction analysis through the use of the wMNE method.

Figure 3. An example of source reconstruction (wMNE) and localisation (Mindboggle).
Note. An increase in signal amplitude can be identified in the left superior parietal gyrus and adjacent areas, such as the left superior parietal, left supramarginal, and left postcentral gyri. The signal amplitude threshold was set at 60% as a means by which to only present the highest values (cf. Jain et al., 2013).

Figure 4. Examples of brain connectivity analyses across 62 electrode sites.
Note. The left figure presents the signal coherence method, while the right figure presents the Bivariate Granger Causality analysis method. The blue areas of the link between two regions represent the electrical output from one electrode site; conversely, the red area represents the electrical input from other electrode sites (i.e., being influenced by other regions).

Figure 1

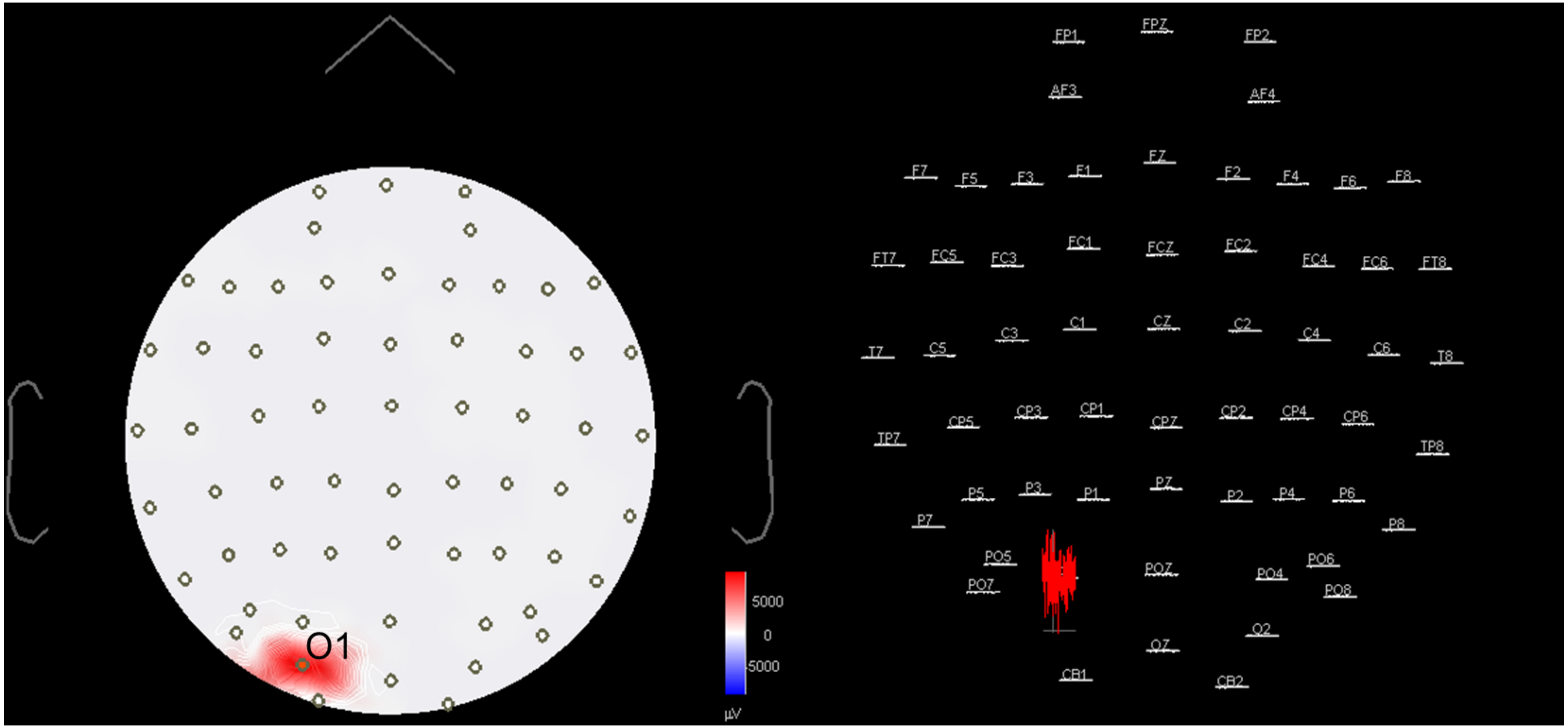
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Figure 2

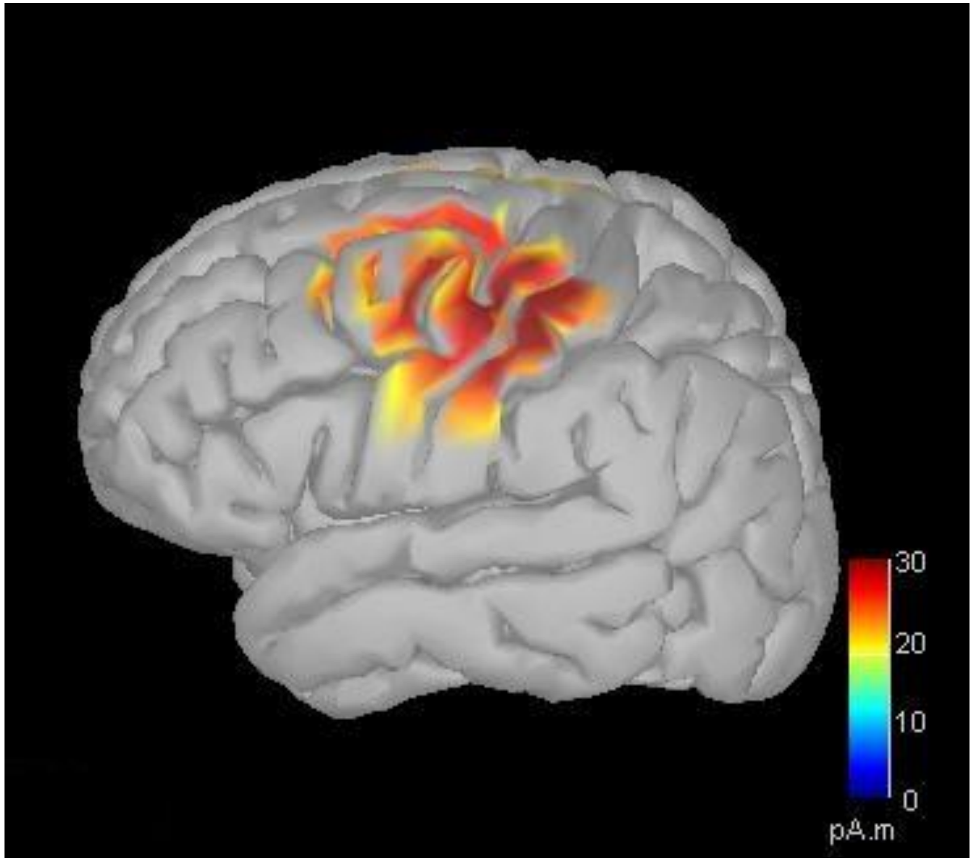


Figure 3

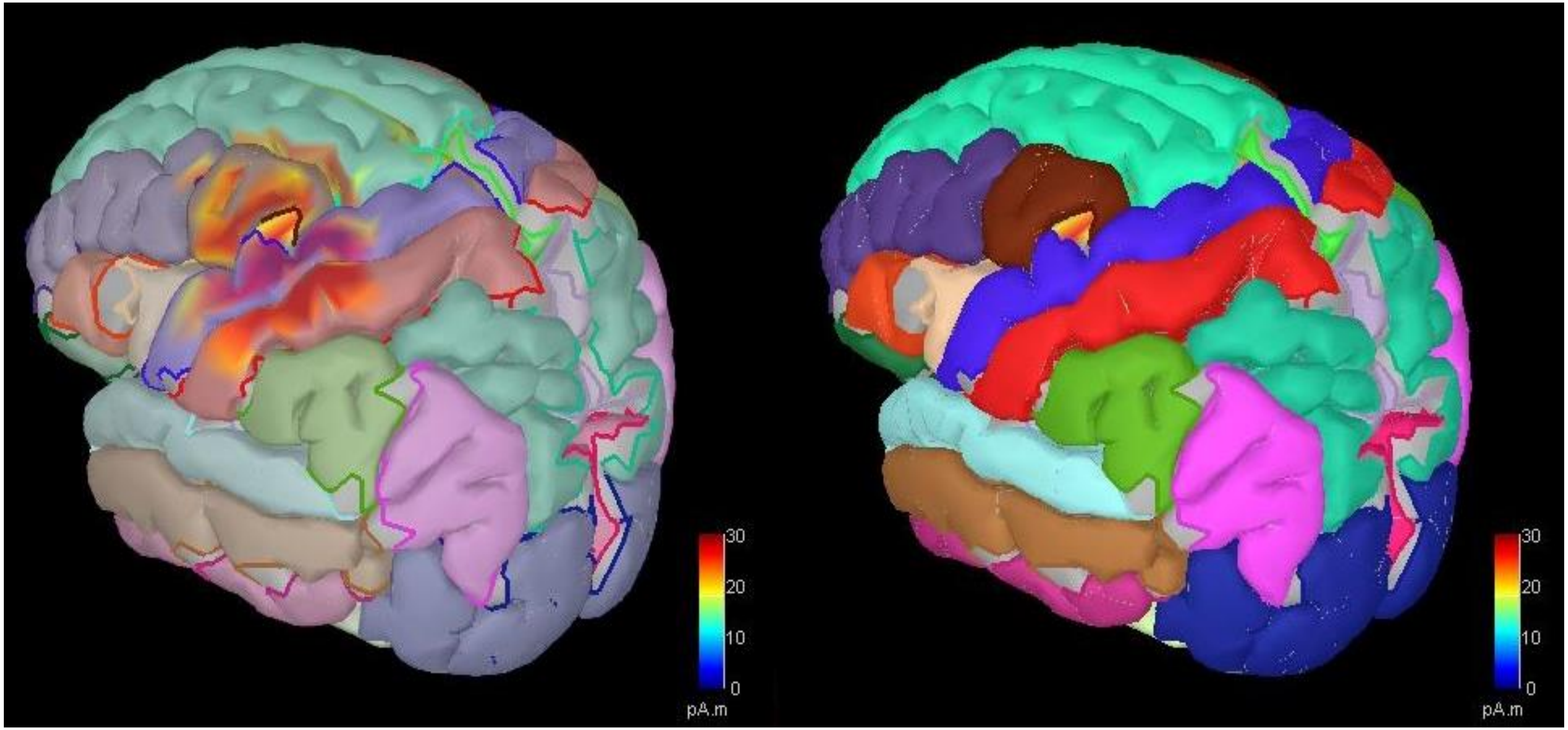
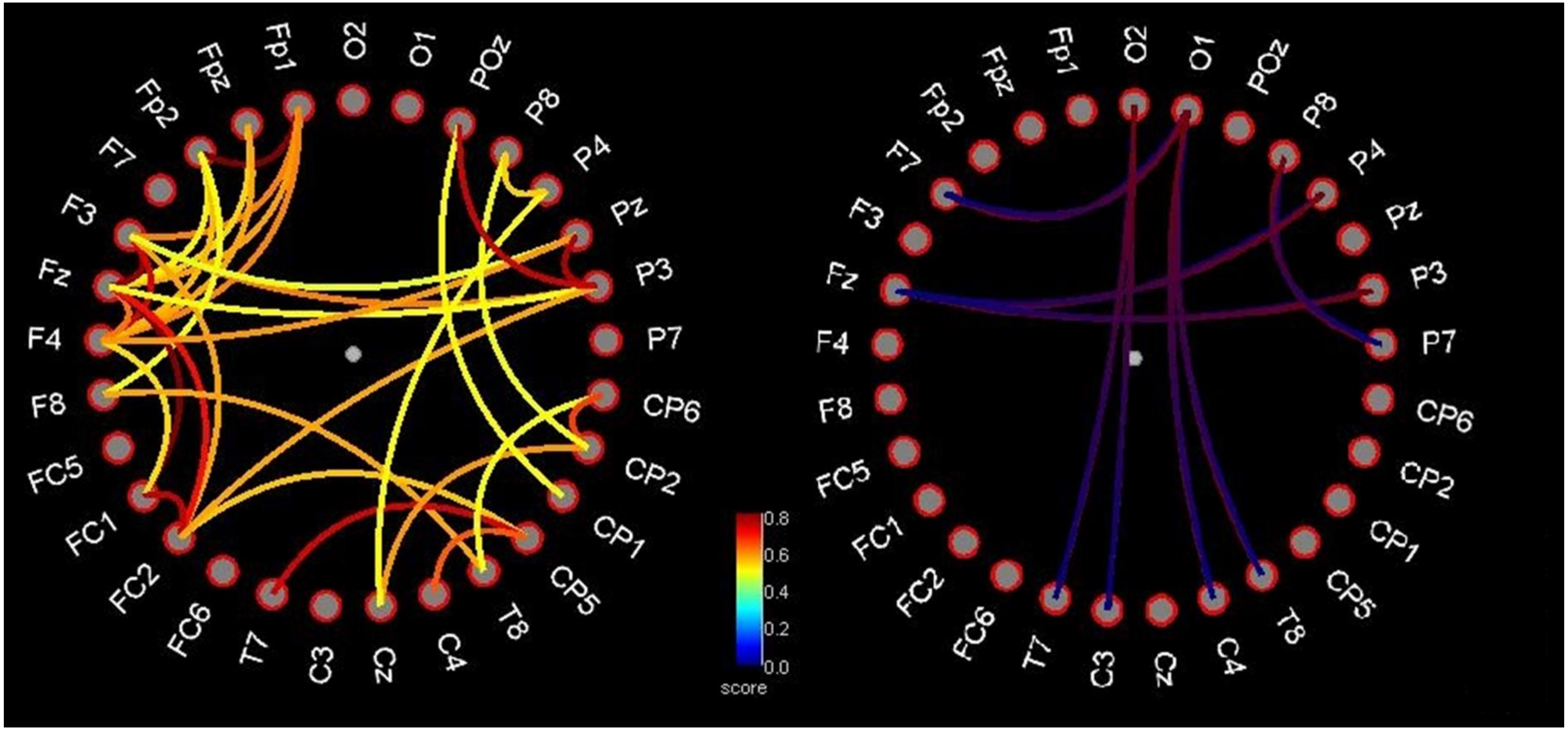


Figure 4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