



## Neuroelectric measurement of cognition during aerobic exercise

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### ABSTRACT

The application of neuroimaging techniques to assess changes in brain and cognition during exercise has received little attention due to issues related to artifact associated with gross motor movement inherent in physical activity behaviors. Although many neuroimaging techniques have not yet progressed to a point where movement artifact may be controlled, event-related brain potentials (ERPs), which measure neuroelectric responses to specific events, can account for such issues in controlled environments. This paper discusses the deviations from standard neuroelectric recording procedures and signal processing that are necessary for the collection and analysis of ERPs during gross motor movement. Considerations include the properties of the exercise behavior, task instructions, and the position of materials in the stimulus environment, as well as issues related to electrode impedance, additional reduction techniques, and the plotting of single trials to identify movement artifacts. These techniques provide a means for collecting clean data from the neuroelectric system to provide further understanding of changes in brain and cognition that occur online during exercise behavior, and serves as a novel application of neuroimaging to the kinesiological sciences.

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### 1. Introduction

Over the last decade, heightened interest in understanding the role of health behaviors on the brain has emerged. This interest has been fueled by growing public health concerns, especially with regard to child and adolescent populations, regarding decreased participation in physically active behaviors [1] and the prevalence of being overweight or obese [2,3], resulting in a number of poor health outcomes [4]. Accordingly, growing research efforts have been aimed at identifying and attempting to reverse these recent health trends. During this time, an emerging body of literature has described the relationship between physical activity and cognitive health and function (see [5] for review), which has been bolstered by the application of various neuroimaging techniques (e.g., [6]).

The vast majority of physical activity and cognition research employing neuroimaging techniques have focused on chronic aerobic exercise participation [6–8] in an effort to determine the long-term or lasting effects of a physically active lifestyle on cognitive health and function. A substantially smaller literature exists on the acute effects of exercise on neurocognitive function (e.g., [9,10]; but see [11] for review) to determine some of the more fleeting changes that occur as a function of engaging in a single bout of physical activity. Data from both lines of research indicate that chronic and acute participation in physical activity is generally related to better performance across a variety of cognitive tasks, and that disproportionately larger benefits are derived for tasks

requiring extensive amounts of executive control, which refers to processes mediated by a network that involves the prefrontal cortex [12]. As such, neuroimaging research has demonstrated that physical activity-related alterations in the brain are beneficial to cognitive health and function [13].

Although the benefits derived from chronic and acute physical activity participation are becoming clearer, little is known about changes in brain and cognition during exercise. This question is important from both basic and applied perspectives, since it provides information about the temporal resolution of cognitive change, and may lead to a greater understanding of the exercise dosage required to promote changes in cognitive function. From a practical perspective, this question is important when considering individuals whom may exercise in urban environments (e.g., attention allocation and decision making processes of cyclists in dense traffic), for understanding the cognitive processes of athletes during competition, and for various military environments. Regardless, this research question provides important information regarding cognitive performance while individuals are in motion.

Several studies have used behavioral measures (e.g., reaction time, response accuracy) to pursue this question, with results yielding equivocal findings [14,15]. Thus, the application of neuroimaging techniques may better inform the research community of online alterations in brain and cognition that occur during exercise by demonstrating specific neuronal networks and structures that are influenced by exercise, allowing for inferences to be drawn regarding the specific cognitive functions affected. Given the state of neuroimaging research, techniques with sophisticated spatial resolution (i.e., functional magnetic resonance imaging, positron

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emission tomography, magnetoencephalography) have not yet evolved to a point where gross motor movement may be controlled for during data acquisition, with movement ‘artifact’ resulting in loss of data. However, an earlier technique, known as event-related brain potentials (ERPs), which are time-locked to specific environmental events (e.g., stimulus, response) and located within an electroencephalogram (EEG), have developed in such a manner that data acquisition during gross motor movement is possible, albeit in a confined setting. The ERP approach requires the repetition of events to generate averages and increase the signal to noise ratio. ERPs have sophisticated temporal resolution, allowing for measurement on the order of a millisecond, but notably less spatial resolution relative to other neuroimaging techniques. Because of the rich temporal resolution, this approach allows for inferences regarding which cognitive processes occur between stimulus engagement and response execution. Guided by findings derived from other neuroimaging techniques with sophisticated spatial resolution, inferences may be drawn regarding the underlying neural structures mediating the observed cognitive changes. Further, EEG spatial resolution is improving as current systems employ upwards of 512 individual electrodes to generate high density images of neuroelectric activation.

To date, the utilization of ERPs to understand changes in brain and cognition during exercise has only yielded three studies in the extant literature [16–18]. While all three studies used cycling as the exercise stimulus, only our study [17] employed a high density approach (i.e., >32 electrodes), allowing for the determination of underlying alterations in the neuroelectric system that may relate to changes in cognitive performance. The purpose of this article is to detail aspects of our experimental protocol that required special consideration or deviated from typical ERP acquisition and reduction procedures to provide a more comprehensive understanding of how this technique may be used to assess changes in brain and cognition during gross motor movement.

## 2. Neuroelectric measurement

The investigation of ERPs provides one of the most direct insights into the neurobiological processes underlying perception and cognition. That is, ERPs reflect the synchronous activity of a large population of neurons within the cerebral cortex arranged in an open field configuration [19]. As a result of the neurobiological properties of neuronal communication, ERPs provide a noninvasive, safe and painless means to “image” the neural mechanisms underlying behavioral changes and investigate situations in which an overt response does not occur [20]. This is possible because of the electrical properties of the neuronal tissues that serve as a volume conductor through the provision of a relatively low resistance current pathway between the population of active neurons and the surface of the scalp [20].

In practice, the measurement of ERPs is typically conducted through the use of differential amplification (also known as common mode rejection), which requires the use of a minimum of three electrode sites: a site of interest, a reference site, and a ground site. The process of differential amplification is used to cancel out ambient electrical noise. That is, ambient noise from the environment manifests equally over all electrode sites, therefore by calculating the difference between two electrode sites ( $[Site\ 1 + Noise] - [Site\ 2 + Noise] = [Site\ 1 - Site\ 2] + \{Noise - Noise\}$ ) the noise should cancel out [21]. In practice, a larger array of electrodes is typically utilized by incorporating standardized electrode placements such as the International 10–20 System [22], which places electrodes at sites that are 10% or 20% of a measured length from known landmarks on the skull and ensures that activity at specific electrode sites can be compared across laboratories worldwide. A variety of different reference electrode sites have been used in ERP research

including cephalic references (such as the nose, mastoids, and earlobes), non-cephalic references (such as the collarbone and base of the neck), and average references with each offering distinct advantages and disadvantages [23]. Although there is no one “preferred” reference point, it is important to consider where the reference electrode is located as a function of the neuroelectric activity being investigated, since the polarity of the recorded signal is determined by the reference (a negative polarity indicates that the signal is more negative than the reference electrode).

One issue with ERPs, however, is the use of signal averaging, which can result in the cancelation of other aspects of neuronal activity. That is, signal averaging assumes that the signal of interest occurs in a consistent fashion across trials while the noise occurs at random [21]. As a result, by averaging across trials the signal of interest is strengthened and the noise is diminished. Therefore the resulting “averaged” signal may mask weaker neuronal activity that does not occur in a consistent manner [21]. Given that a complete description of the theoretical underpinnings of ERP activity and the justifications for various ERP methodologies are beyond the scope of this paper, the interested reader is referred to [20,21] for additional information. It is important to note, however, that to record this neuroelectric activity, it is necessary to provide a low resistance current path between the surface of the scalp and an electrode, typically through the use of a conductive gel or paste [21]. A primary problem that results from not achieving similarly low resistances (more commonly referred to as ‘impedances’) across all electrode sites are skin potentials, which occur as a result of changes in the electrical conductance between epidermal layers.

### 2.1. Skin potentials

Skin potentials are particularly troubling for researchers interested in collecting neuroelectric measures during exercise as the two predominate causes of change in skin conductance are sweat and movement [21]. That is, reductions in the impedance between the surface of the scalp and the electrode occur when sweat glands become more active due to the conductive properties of sweat, resulting in changes in voltage that are unrelated to neuronal activity. Similarly, movement of an electrode can result in changes in the electrical impedance between the epidermal layers and that electrode [21]. However, both of these issues can be controlled for and even eliminated using specific techniques.

Specifically, Pontifex and Hillman [17] addressed this issue by ensuring that electrode impedances were below 5 k $\Omega$  prior to the start of neuroelectric measurement, and by instructing participants to exercise for several minutes until a steady state was achieved. By allowing participants the time to acclimate to the exercise stimulus, the changes in skin conductance associated with sweat production had time to stabilize. In addition, previous research has observed that the increased conductance of sweat has little effect when electrode impedances are below 5 k $\Omega$ , resulting in a decreased occurrence of skin potentials [24]. By creating an already low impedance environment during testing and minimizing the dynamic changes in skin conductance, the artifact created by skin potentials can be reduced.

The choice in how electrodes are applied to the scalp can also influence changes in skin conductance associated with electrode movement. There are two predominate methods of electrode application with distinct tradeoffs. One method involves the use of an adhesive to glue individual electrodes in place, which dramatically reduces electrode movement. However, as a result of the time necessary for individual electrode application, a smaller electrode array is typically used. Alternatively, a more contemporary approach utilizes electrodes embedded in an elastic cap that is placed over a participant’s head to accurately place a larger array of electrodes in a shorter period of time. Although this approach

may be prone to artifact resulting from the movement of electrodes, by using a correctly sized elastic electrode cap, and elastic tubular gauze to ensure secure placement [25], movement-related skin potentials may be reduced and a larger array can be used to provide additional information regarding the spatial distribution of cortical activity.

A second issue that emerges in the ERPs signal during exercise, particularly when a larger electrode array is used, involves the formation of electrical bridges between recording electrodes. Electrical bridges typically occur when electrode gel leaks from one electrode to another, resulting in an electrically conductive path linking multiple electrodes to the same strip of epidermal tissue [21]. As a result of this “spatial smearing”, each electrode will show identical activity, rendering analysis of the different activation pattern at each electrode site impossible. As mentioned previously, sweat is electrically conductive; therefore, when an individual exercises at a rate intense enough to cause profuse perspiration, it is possible for sweat to form its own electrical bridge between electrodes sites, and for the sweat to decrease the viscosity of the electrode gel. This issue necessitates a great deal of care in selecting an electrode gel with a high viscosity, careful cap preparation so as to minimize the potential of overfilling electrode wells, and selecting the size of the electrode array in consideration of the intended exercise prescription. In addition, it is important to utilize a controlled environment in which the humidity of the ambient air and room temperature can be controlled during exercise so as to avoid excess perspiration.

## 2.2. Movement artifact

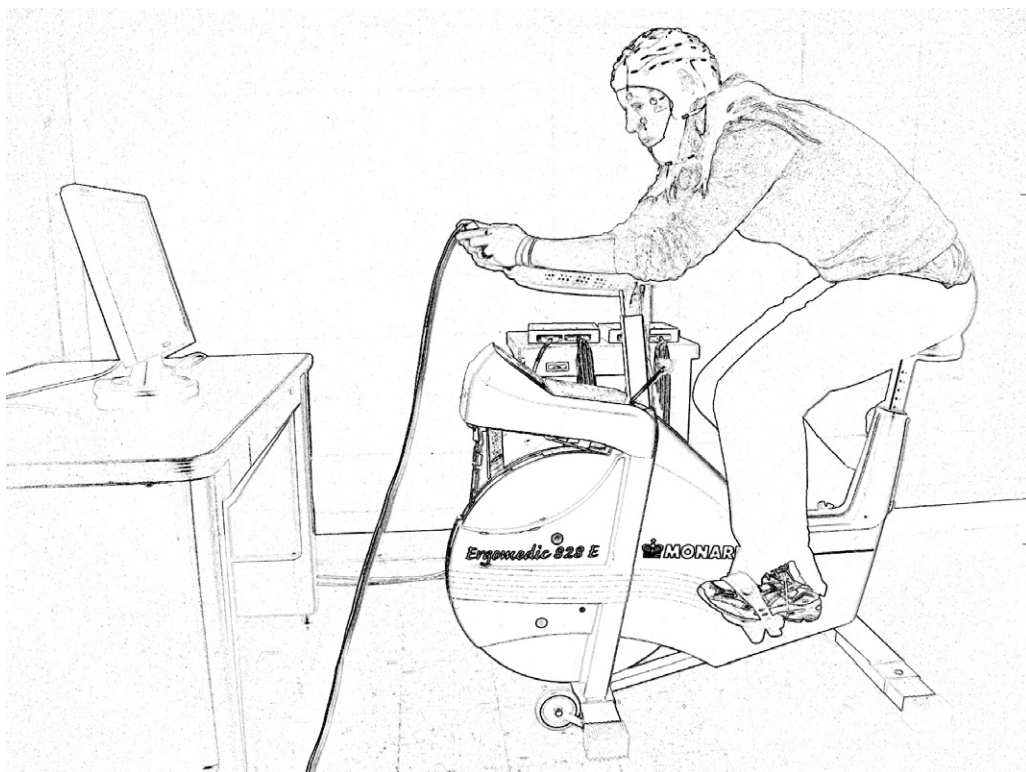
Beyond issues associated with electrical conductance; muscle activity, and the associated movement, result in difficulties collecting neuroelectric activity during exercise. Researchers interested in assessing neuroelectric activity during exercise must instruct their participants to do what most neuroelectric researchers advise against, that is, move. Thus, it is necessary to understand

issues associated with movement to attempt to prevent extraneous artifact (or noise) in the data. Muscle-related artifact during EEG recordings typically occurs as a result of changes in muscle tension in the scalp and facial regions [26], and are characterized by their transient high-amplitude spikes and high frequency noise that is outside of the interest of ERP research (i.e., 0.1–20 Hz) [27]. Because of these characteristics, these types of artifacts can often be avoided by instructing participants to relax their face and jaw. However, in instances when muscle-related artifact still occurs, it is possible to remove this type of artifact during data reduction using low-pass filters (in which frequencies below a set cutoff are selectively attenuated out of the neuroelectric signal) and artifact rejection of contaminated trials (removal of trials in which artifact occurs). However, filters should be used with care in that they may result in distortions of the neuroelectric signal as well as removal of neuroelectric activity that is of interest. The interested reader is referred to [28,29] for additional information regarding filtering neuroelectric signals.

More problematic from the standpoint of collecting neuroelectric activity during exercise is that movement in general is associated with electrical artifact. Without constraints this artifactual activity can often be erratic and difficult to control; however, this activity can become rhythmical when the movement is repetitive [26,27]. By employing a repetitive exercise stimulus and presenting task-related cognitive stimuli such that they never repeatedly coincide (i.e., phase locking a stimulus to a particular aspect of the exercise), any rhythmical noise should occur at random throughout the stimulus window. As a result, movement-related noise in the data can be treated as background noise that is averaged out of the ERP signal.

## 2.3. Properties of the exercise stimulus

To concisely measure the influence of an exercise stimulus on cognition, it is necessary to address the influence of individual differences in fitness level and its relationship to exercise intensity.

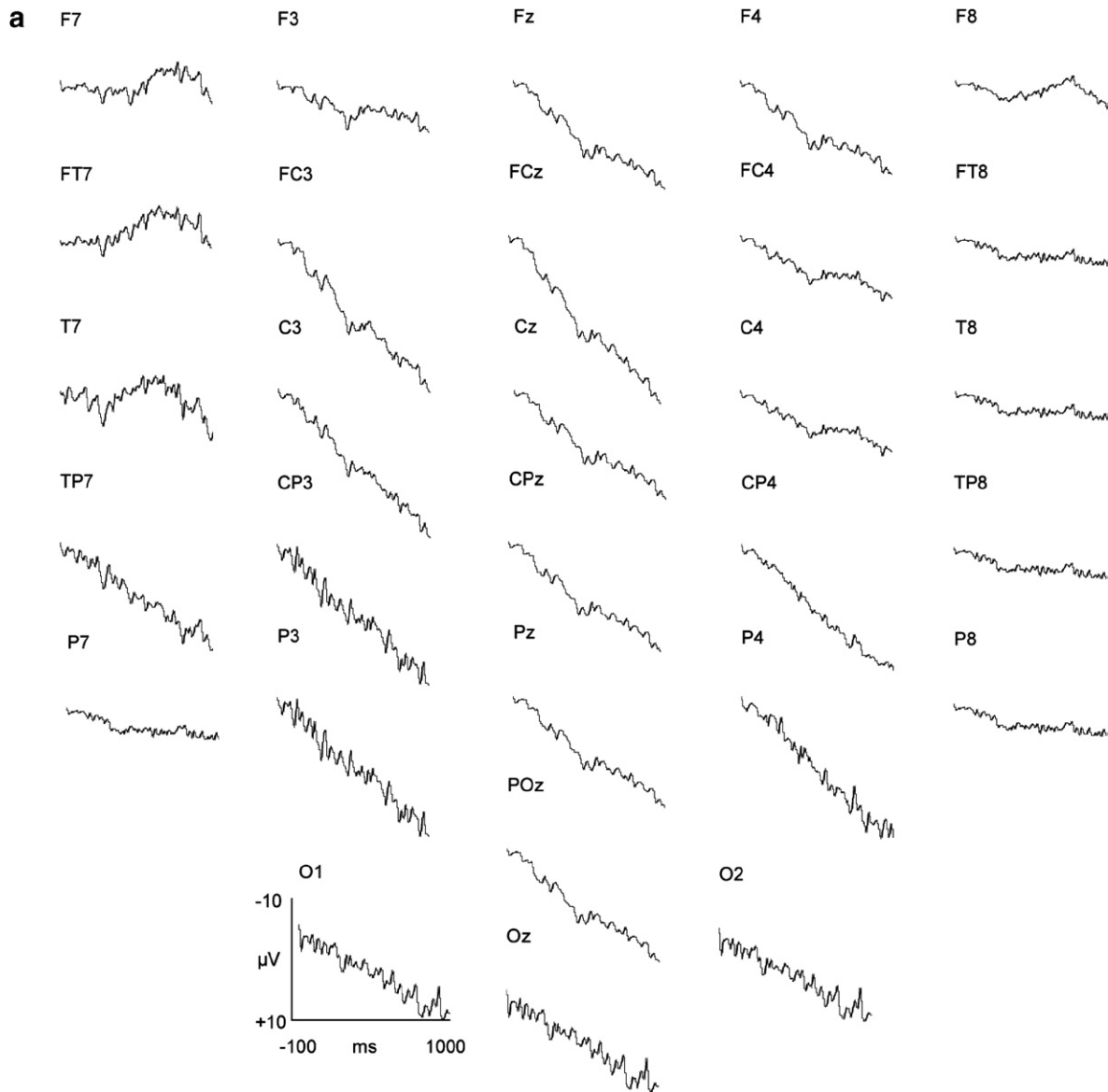


**Fig. 1.** An illustration of the position in which participants cycled to control for extraneous bodily movement.

According to the American College of Sports Medicine [30], “physiologic and perceptual responses to acute exercise vary among individuals and within an individual performing different types of exercise” (p. 136). Therefore, it is necessary to account for these differences when trying to administer a specified dose of exercise. Both Grego et al. [16] and Pontifex and Hillman [17] utilized  $VO_2$ max tests, which are recognized as the criterion measure of cardiorespiratory fitness, to set relative exercise intensities of approximately 66% of maximum oxygen consumption and 60% of maximum heart rate, respectively. Therefore, while the absolute values of the workload may differ across individuals, all participants exercised at the specified relative intensity. Additionally, both Grego et al. [16] and Pontifex and Hillman [17] utilized the same mode of exercise during the  $VO_2$ max tests and during their cognitive testing protocols, recognizing that the physiological responses to an exercise stressor are specific to that stressor. In other words, the manifestation of a participant’s maximum workload may be different between maximal exercise tests on a cycle ergometer and a motor-driven treadmill with previous research observing 20–30% reductions in

$VO_2$ max when arm ergometry is used relative to treadmill testing [31]. By applying the same mode of exercise during each of the tests, the exercise intensity can more carefully be controlled with regard to individualized physiological responses.

Additional care must also be taken to eliminate all extraneous movements (i.e., movements not part of the exercise stimulus) so as to reduce the occurrence of movement-related artifact in the neuroelectric data. While Yagi et al. [18] used a recumbent cycle ergometer; Pontifex and Hillman [17], following extensive piloting through multiple cycling modalities using various ergometers, observed the least movement of the upper torso when pedaling an upright cycle ergometer with participants resting their forearms across the handlebars in a racing style position (see Fig. 1). In this position, participants were seated on the cycle ergometer such that the monitor was positioned exactly 1 m from the participants’ nasion, with the cycle ergometer centered with the monitor. This position allowed for participants to balance the weight of their upper torso across three points (the seat and each arm) such that there was little movement transfer from the lower body during



**Fig. 2.** A single participant’s averaged ERP illustrating the influence of DC drift across the scalp (a) and the same participant’s averaged ERP after a linear detrend function was applied (b).

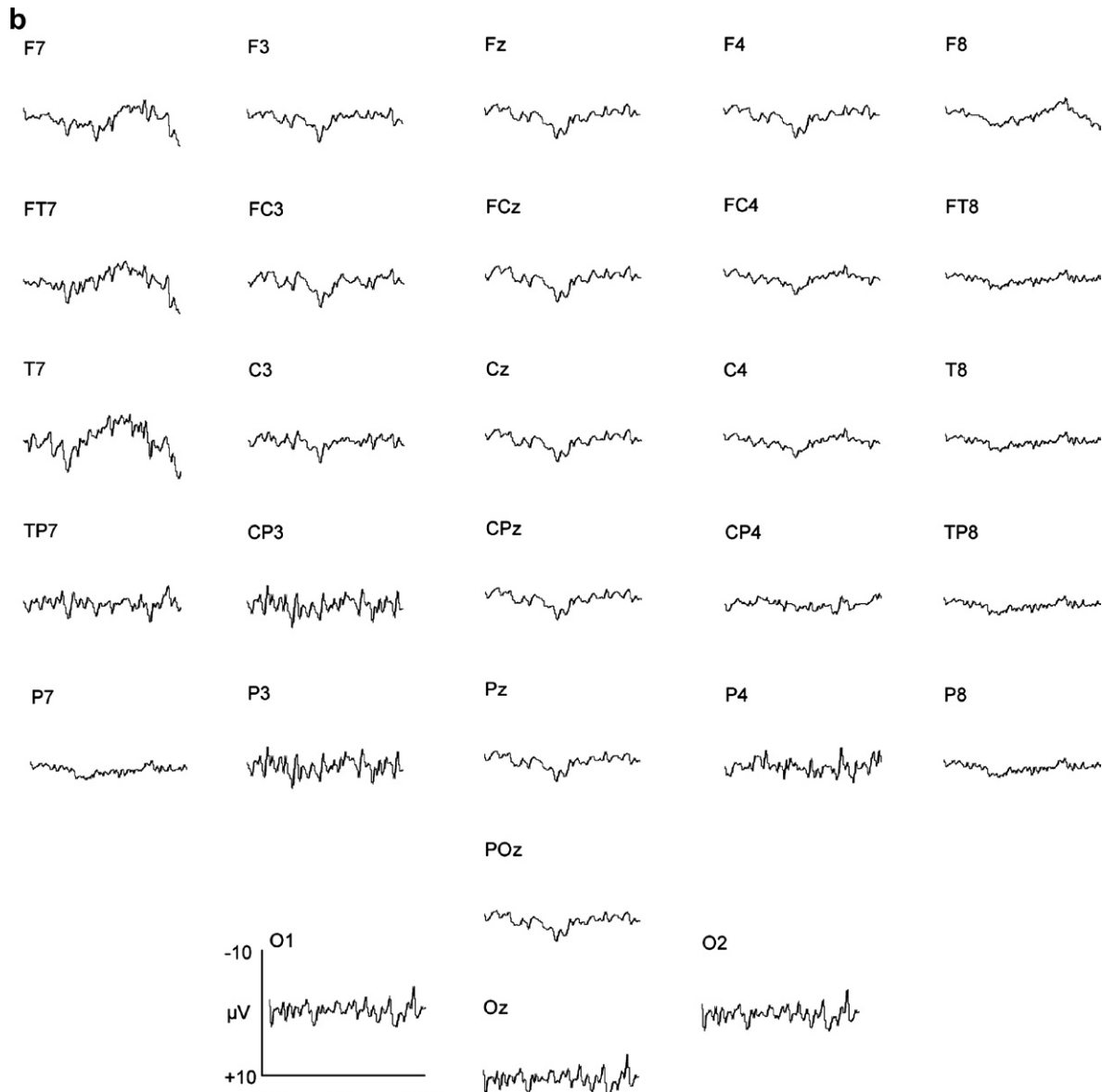


Fig. 2 (continued).

cycling, while at the same time still allowing participants to easily hold a response pad. To further eliminate extraneous movements, participants were instructed during exercise to have their upper torso remain as still as possible, and during the warm-up period an experimenter stayed in the room and coached the participants on only moving their lower body. However, even in non-exercise-related collection of neuroelectric activity, artifacts in the data do occur and must be accounted for during data reduction.

#### 2.4. Data reduction procedures for artifact correction and removal

Various methods have been developed to eliminate or correct for artifacts during and after data collection (for a more in-depth discussion of artifacts and issues related to their removal see Talsma & Woldorff [27]). One particularly common source of artifact is ocular movement. When the eyelid closes during an eye blink, current is able to flow upward from the polarized eyeball towards the frontal regions of the head [32,33] resulting in distortions of the

EEG activity. Similarly, ECG activity detected by the reference electrode(s) can distort the overall neuroelectric signal [27]. That is, because the mastoid electrode sites reside parallel to the horizontal electrode placements (lead 1 of Einthoven's triangle) used to measure ECG activity, it is possible (due to the conductive nature of the body) for these sites to detect the ECG events. Because this ECG activity is larger than the neuroelectric activity measured at the scalp, it is necessary to control for this factor. One way in which to remove these artifacts is to eliminate every ERP trial in which an artifact occurs. This technique is effective in situations where there are few eye blinks over the course of a large number of trials. However, in the case of ECG activity or blink artifact on a larger percentage of trials, alternate methods are preferable to minimize the loss of data [21]. One method that is growing in popularity is the use of spatial filtering, whereby similar artifacts are averaged together and submitted to a spatial singular value decomposition (SVD). The SVD computes a covariance matrix of the major components of the artifact across all electrode sites using principle

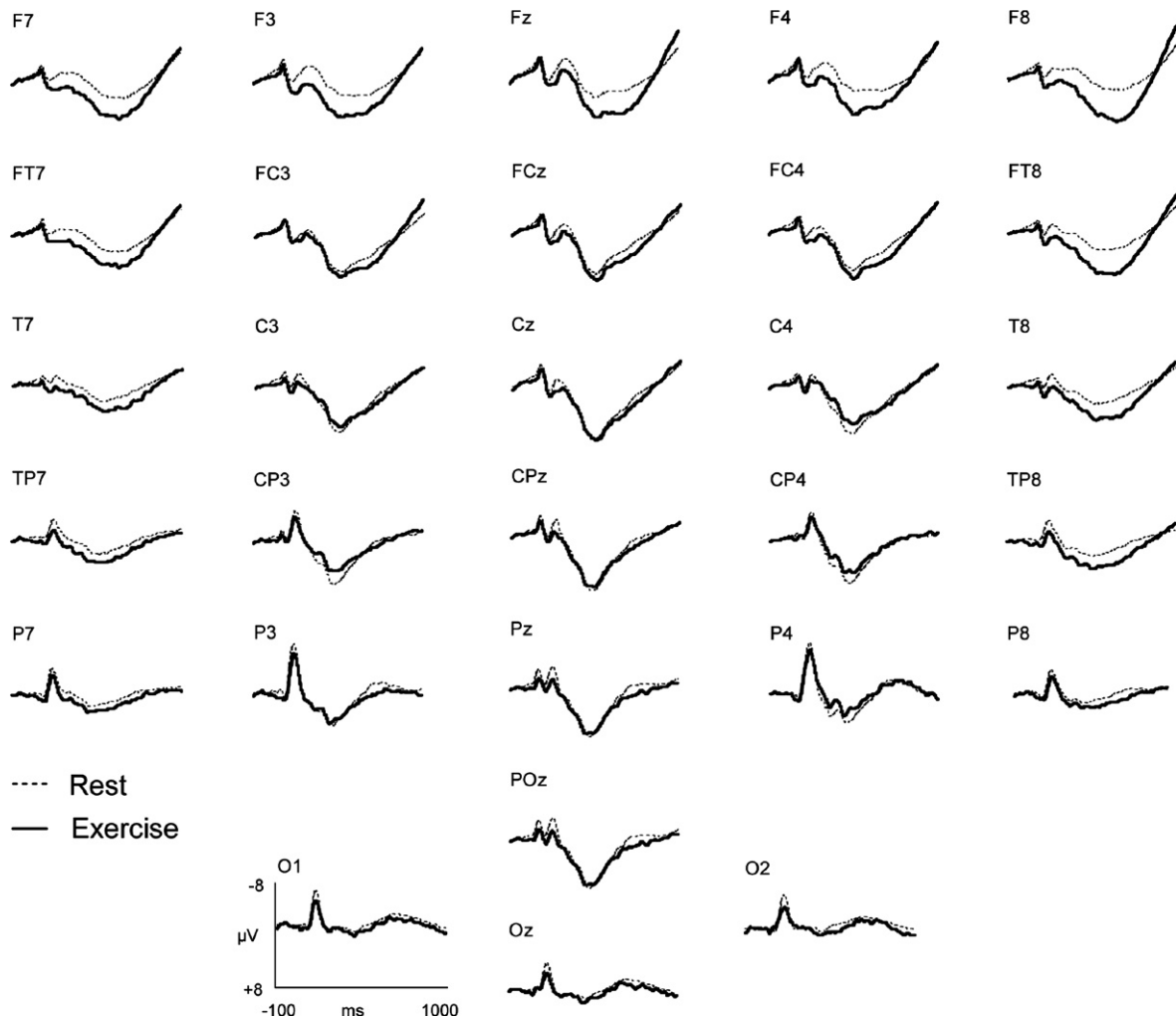
component analysis. A second SVD analysis is performed on an artifact-free segment of data to characterize a covariance matrix of the legitimate EEG activity, and then the spatial filter is applied to remove the artifact components from the data while preserving the legitimate EEG activity [34]. This technique is particularly useful for researchers investigating neuroelectric activity during exercise as it can be applied to ECG and pulse wave artifact in the same manner as eye blink artifacts. That is, because the posterior auricular artery runs near the location of the mastoid electrode sites, increases in cardiac stroke volume (such as during exercise) can lead to artifact resulting from the movement of the mastoid electrodes corresponding to the pulse wave; by applying a spatial filter, this artifact can be safely removed from the data without distortion to the EEG activity.

Another common problem exacerbated by exercise is direct current (DC) drift in the collected EEG signal. DC drift can occur through a variety of mechanisms, including thermal and electrochemical changes in the skin and electrolyte [35], which are even more prevalent during exercise. As a result, changes in the polarization of electrodes result in slow drifts that differ across electrodes and do not attenuate through signal averaging [35] (see Fig. 2a). Because the drifting voltages can interfere with data reduction methods such as peak picking and area under the curve measures by making it difficult to define the various ERP components, it is necessary to remove this drift from the data through linear detrend functions. By plotting a “line of best fit” to the waveform,

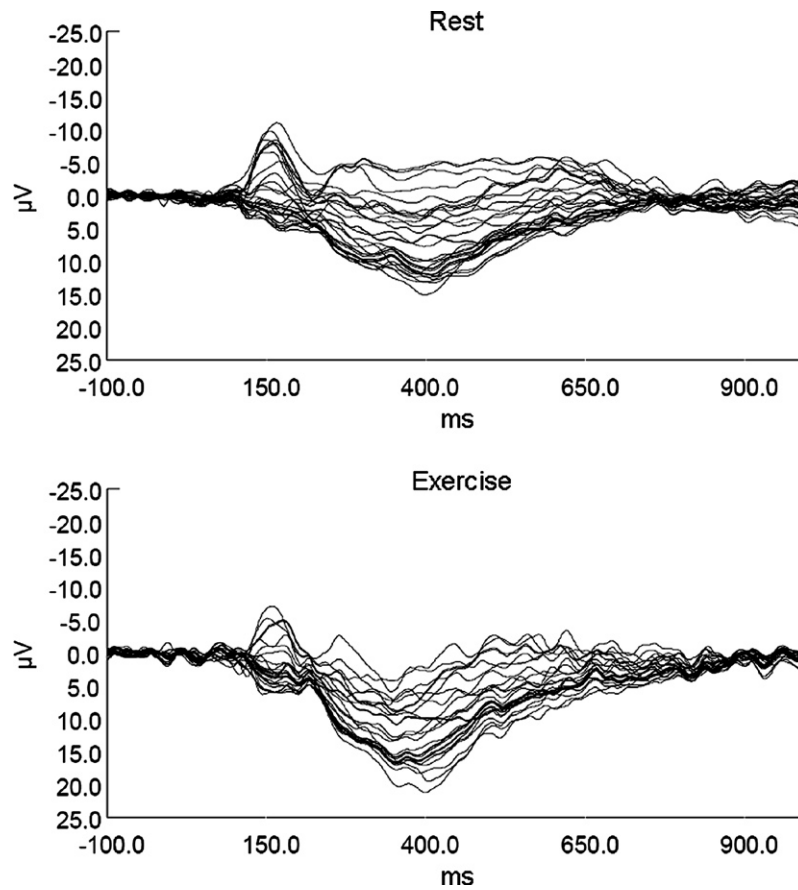
calculating the slope of the line, removing the slope from the waveform, and replotting the waveform; data that would have been previously rendered unusable can be salvaged (see Fig. 2b).

Despite employing these various means of preventing the occurrence of artifact and reducing the effect of those artifacts, some data may still be unusable even during measurement of a baseline condition such as seated rest. One of the benefits of neuroelectric measurement, however, is that it is standard practice to collect a large number of trials so that the elimination of a relatively small number of contaminated trials, referred to as artifact rejection, does not affect the overall average waveform. Previous research into the number of trials necessary for the habituation of the P3 ERP (also known as the P300 or P3b) has found that after 20 trials, the peak amplitude and latency stabilize during a standard oddball task [36] with more trials increasing the signal to noise ratio as a function of the square root of the number of trials [21]. For example, Pontifex and Hillman [17] presented a total of 120 trials during the exercise and rest conditions, with  $103.8 \pm 14.3$  and  $114.6 \pm 6.6$  usable trials included in the respective averages, resulting in clear ERP components (see Fig. 3).

Finally, following averaging, visual inspection of the waveforms through the use of butterfly plots can provide additional information as to any residual artifact within the data. Butterfly plots represent the overall neuroelectric signal by plotting the activity from each electrode site onto the same graph (see Fig. 4). This technique allows for visual inspection of the data for artifact and provides



**Fig. 3.** Grand averaged ERP data from all participants for rest (thin dashed line) and exercise (thick solid line). (Note that this figure is from Pontifex & Hillman [17]—copyright needed.)



**Fig. 4.** A single participant's averaged ERP for both rest and exercise are depicted in a butterfly plot whereby each channel is mapped onto the same graph. Note the clear morphology of the waveform and the relatively small residual noise within the neuroelectric signal in the both the exercise and rest conditions.

information regarding whether the artifactual activity is localized to a single electrode site or is generalized across all electrode sites. Additionally, high frequency noise that is present in the data can be especially evident using butterfly plots as the noise manifests with similar frequency, amplitudes, and phases across all electrode sites. Once the source of the artifact is recognized, the methods described previously can be utilized to ensure the cleanest possible data.

### 3. Conclusion

The ERP technique is advantageous to gaining an understanding of the temporal aspects of information processing, as it allows for investigation into the various cognitive processes that occur between stimulus engagement and response execution. The methodology applied herein represents additional strategies to standard ERP collection and reduction procedures that are crucial for controlling repetitive gross motor movement, and thus allowing for the application of neuroimaging to the study of cognition during exercise. The application of these procedures affords the use of ERPs in an environment, which has received limited attention due to the difficulty in managing movement-related artifacts. The further development of these procedures may continue to improve the collected neuroelectric signal, and might lead to methods for studying cognition during exercise using other neuroimaging techniques.

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