Passthoughts on the Go: Effect of Exercise on EEG Authentication (Extended Version)

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Abstract. A series of studies have shown the feasibility of authenticating users based on their electroencephalography (EEG) signals. While these studies report accuracy rates up to 100%, they were run in laboratory settings, with the subjects kept in stationary, resting conditions. We perform an experimental study to quantify the effect of physical exercise on EEG authentication accuracy. Subjects first completed a visual counting task while in a resting state. Then, they repeated the same task after performing one minute of vigorous physical exercise. We quantify the similarity of a subject's brainwave signals before and after exercise, s_{ii}, and compare it against s_{ij}, the similarity of the subject's signal after exercise with other subjects' signals before exercise. This allows us to verify if a subject's post-exercise brainwave signal remains similar to their signal before exercise, or if the signal has changed to be no longer distinguishable from those of the other subjects. We use s_{ii} and s_{ij} as the basis for a simple authentication protocol. A user is authenticated if the s_{ii} from their submitted sample is greater than the s_{ij} for a randomly selected user. Our analysis reveals that signal similarity and authentication accuracy both degrade significantly immediately after exercise, but recover to their original levels after about 45-60 seconds. These results suggest that short-term changes in physiological states can impact the performance of brainwave authentication. They also point to future research that quantifies authentication accuracy under other psycho-physiological conditions such as fatigue, hunger, or stress.

1 Introduction

Using our brainwaves as a biometric has been the lore of science fiction for decades. In 2002, Poulos et al. demonstrated the possibility of identifying persons by classifying their electroencephalography (EEG) signals [1]. In 2005, Thorpe et al. proposed the concept of an authentication system based on "passthoughts", where instead of typing in a password, users can provide an EEG sample as their authenticator [2]. Since then, there has been a series of experimental studies confirming the feasibility of user authentication using EEG. Marcel and Del Millan [3] and Palaniappan [4] achieved authentication accuracy as high as 100% using clinical-grade EEG technology. Ashby et al. also achieved 100% accuracy using consumer-grade multi-channel EEG [5]. Most recently, Chuang et al. achieved a 99% authentication accuracy using consumer-grade single-channel EEG [6]. Unlike previous studies, in which the subjects performed identical mental tasks, they allowed participants to perform several mental tasks involving secret thoughts known only to the participants. This meant that, like passwords, these "passthoughts" can be easily changed by the users, in contrast to traditional biometrics such as fingerprints and iris patterns which are not easily changeable. At the same time, brainwave authentication also affords some security advantages over passwords, such as robustness against shoulder-surfing, keylogging, and smudge attacks.

In parallel, significant progress has been made in developing Mobile EEG devices that are wireless and portable [7–9], allowing researchers to run experimental studies outside of traditional lab settings for ecological validity reasons [10–12]. Several companies have developed low-cost EEG headsets (e.g., [13, 14]) to target the consumer market, which are currently focused on neurogaming and neurofeedback applications. Researchers are also investigating novel EEG sensing platforms, such as EarEEG that captures signals from within the ear canal, which may offer significant aesthetic and usability benefits over traditional head-worn devices [15, 16].

If brainwave authentication is to become a real-world application of mobile EEG technology, we must investigate its robustness in realistic settings. In all of the previous EEG authentication studies, participants were always in a sitting and resting state, which may not accurately simulate conditions in the real world. If the user has just engaged in some form of activity that altered their physiological state, e.g., physical activity like jogging, or running late to a meeting, we do not know whether there may be significant impact on the accuracy of EEG authentication.

Behavioral neuroscientists have investigated the effect of exercise on brainwave activity, finding increases in post-exercise α-wave activity that is likely correlated with a state of relaxation [17, 18]. On the other hand, physical activities that lead to stress or increase in attention are linked to cortical arousal with an increase in β-wave activity and a decrease in α-wave activity [19, 20]. It remains an open question how these short-term cortical changes may impact the performance of EEG authentication.

This work represents the first step towards understanding how brainwave authentication may be affected by short-term changes in physiological state. Specifically, we perform an experimental study to quantify the performance of a simple authentication scheme after 60 seconds of physical exercise. While we find that the authentication error does suffer a significant increase immediately after exercise, we also observe that the error rate recovers within 60 seconds in the post-exercise period. These findings have important implications to the design and development of brainwave authentication technologies.

2 Methods

Ten healthy subjects (six female, four male; mean age = 30.7, stdev = 15.8) completed our study protocol, which was approved by the local IRB. Study procedures began with an informed consent process, setup of the EEG device (Neurosky Mindwave Mobile) and data recording software (Neurosky NeuroView), and verification of the EEG signal quality.

The experiment involves four timed steps: 90 seconds of a mental task, 60 seconds of physical exercise, 15 seconds of transition, and 90 seconds of the same mental task. The mental task is a visual color-counting task adapted from [6]. While in a sitting and stationary position, the subject is shown on a computer screen a series of thirty visual images (slides), each displayed for 3 seconds in duration. Each slide consists of thirty equal-sized rectangles of various colors: red, blue, green, yellow, or black, arranged in a 5x6 matrix (Fig. 1). The subject's task is to silently count the number of red rectangles on each slide, restarting from one with each new slide. The number of red rectangles on each slide varies from zero to twelve.

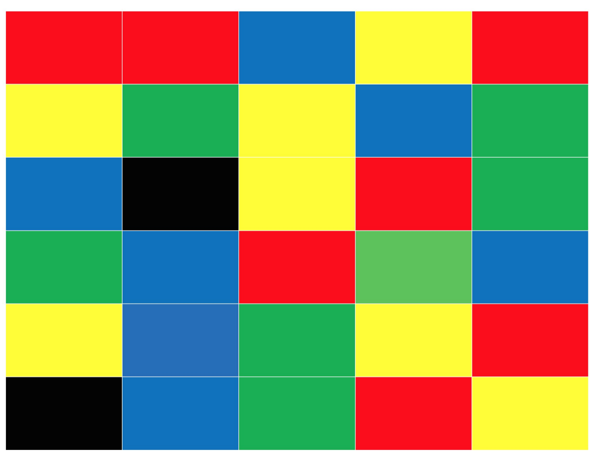

Fig. 1: Sample task slide with 30 rectangles of assorted colors in a 5x6 matrix. The mental task consists of 30 task slides displayed for 3 seconds each. Subjects are instructed to silently count the number of red rectangles on each slide.

After the first mental task, the subject performs 60 seconds of jumping jacks, and during the 15 second transition period, they return to the original sitting position, to repeat the same visual counting task for 90 seconds.

3 Data and Analysis

The experimental protocol produces 90×2 or 180 seconds of EEG data for each subject. The Mindwave Mobile headset outputs a single-channel EEG signal at a sampling rate of 512 Hz. The NeuroView recording software generates one power spectrum sample every 0.5 seconds. The power spectrum has a range of 0 – 256 Hz at a resolution of 0.25 Hz.

First, we compute a power spectrum P_i^{pre} for the 90-second pre-exercise task for subject i by taking the mean (of each frequency component) of their 180 power spectrum samples. We compute the power spectrum P_i^{post} for the 90-second post-exercise task in the same manner.

3.1 Similarity Analysis

We use cosine similarity as the distance measure for comparing the similarity of two power spectra:

$$similarity(u, v) = \cos(\theta) = \frac{u \cdot v}{\|u\|\|v\|} \tag{1}$$

where u and v are vectors representing the power spectra under comparison.

We can quantify the self-similarity for each subject, s_{ii}, as the cosine similarity of their pre-exercise and post-exercise power spectra:

$$s_{ii} = similarity(P_i^{post}, P_i^{pre}) \tag{2}$$

The self-similarity measure for each subject, as well as the mean across ten subjects, are shown in Table I. The mean of 0.658 is consistent with the 0.6664 value reported for the color task in [6].

Subject	Self-Similarity
Subject 1	0.702
Subject 2	0.662
Subject 3	0.670
Subject 4	0.646
Subject 5	0.575
Subject 6	0.648
Subject 7	0.713
Subject 8	0.660
Subject 9	0.683
Subject 10	0.625
Mean	0.658

Table 1: Self-Similarity (s_{ii}) by Subject.

We can also quantify the cross-similarity between a pair of subjects, s_{ij}, as the cosine similarity of subject i's post-exercise spectrum and subject j's pre-exercise spectrum:

$$s_{ij} = similarity(P_i^{post}, P_j^{pre}) \tag{3}$$

Figure 2 shows the relationship between s_{ii} and s_{ij}, and the power spectra used to compute them.

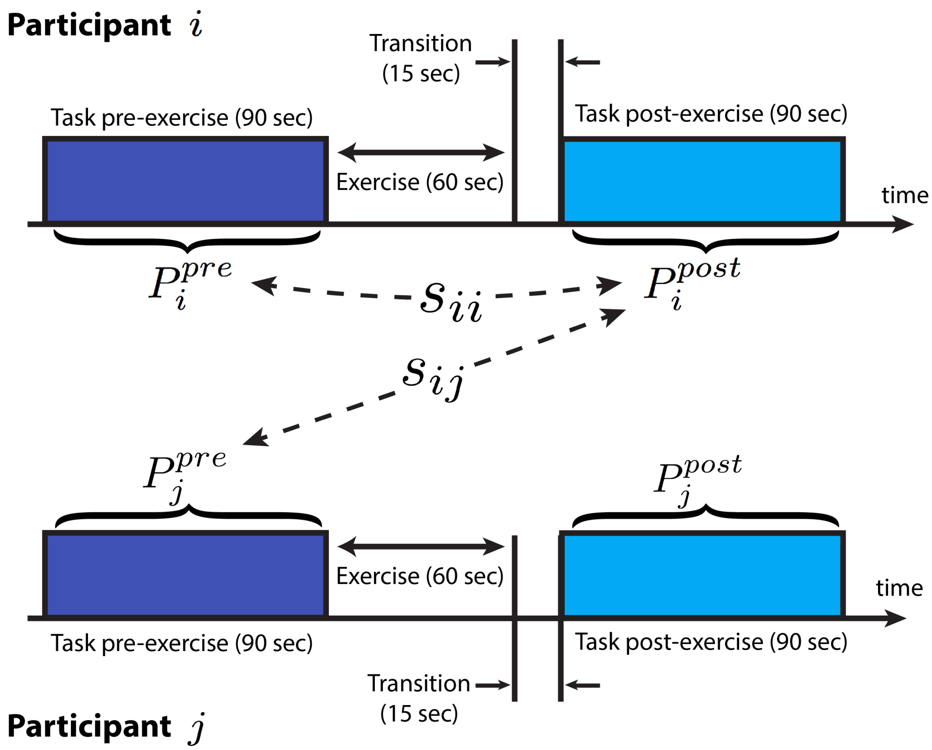

Fig. 2: Computing self-similarity s_{ii} and cross-similarity s_{ij} using power spectra from pre-exercise and post-exercise tasks.

3.2 Authentication Analysis

Authentication performance is typically quantified using two standard metrics: False Acceptance Rate (FAR) and False Rejection Rate (FRR). In this study, we are interested in the scenario where a legitimate user is attempting to authenticate with their EEG signals after exercise. In this case, the ideal authentication protocol should never reject the user, achieving an FRR of zero. Therefore, we focus on the FRR metric in our analysis.

To quantify the performance of post-exercise authentication, we use a simple authentication protocol where we compare, for each subject, their s_{ii} against the s_{ij} value for a randomly selected subject j. The protocol accepts subject i if $s_{ii} \geq s_{ij}$, and rejects the subject otherwise. Given that we are authenticating subject i in this case, an "accept" decision will be considered a *true accept*, whereas a "reject" decision will be considered a *false reject*. With a sample size of 10 subjects, we repeat this authentication protocol 9 times, once for each subject $j \neq i$, to obtain the FRR for each subject (Table II). We find a significant variation in the FRR across the subjects. Nonetheless, the mean FRR of 0.278 is comparable to the Half Total Error Rate of 0.280 reported in [6].

Subject	False Rejection Rate
Subject 1	0.556
Subject 2	0.000
Subject 3	0.000
Subject 4	0.556
Subject 5	0.667
Subject 6	0.111
Subject 7	0.111
Subject 8	0.111
Subject 9	0.333
Subject 10	0.333
Mean	0.278

Table 2: False Rejection Rate by Subject

3.3 Recovery over Time

More importantly, we are interested in how the cosine similarity and FRR measures change over time, as the subjects recover from their physical exercise.

To do this, we employ the power spectra P_i^{pre} and P_i^{post} for each of the thirty individual 3-second slides, rather than for the entire 90-second tasks. We do so by taking the mean (of each frequency component) of the 6 power spectrum samples that correspond to each slide. Now, we can quantify s_{ii} using the same equation (2) for each of the thirty slides, and plot it as a function of time (Figure 3). We see that s_{ii}, averaged across the 10 subjects, is indeed degraded during the first two to four slides, but recovers to the mean level of 0.658 (from Table I) soon thereafter, and stabilizes after about 15 slides, which corresponds to 60 seconds after the end of exercise (15 seconds of transition time plus 45 seconds of slides).

Similarly, we can quantify the False Reject Rate as a function of time by applying the same authentication protocol to s_{ii} and s_{ij} computed on a per-slide basis. We can see in Figure 4 that FRR, averaged across the 10 subjects, rises to as high as 0.6 at the start of the post-exercise mental task, which is 15 seconds after the end of exercise. It experiences a gradual recovery over the

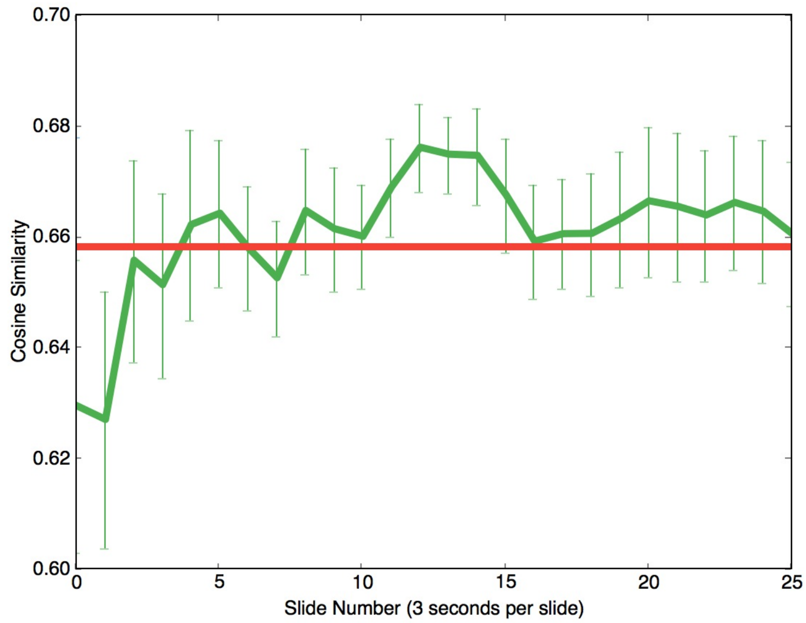

Fig. 3: The recovery of self-similarity (s_{ii}) over time: self-similarity recovers and stabilizes after about 15 slides, which corresponds to 60 seconds after the end of exercise. (Error bars show standard error of mean, with n =10. Red line shows the mean self-similarity of 0.658 for the entire 90-second task, from Table I.)

next ten slides (30 seconds), returning to the baseline level after about 10 slides, corresponding to 45 seconds after the end of exercise.

4 Discussion

The pattern of recovery in EEG signals, as quantified by the self-similarity and FRR measures, is consistent with the patterns of heart rate recovery [21] and respiratory rate recovery after exercise [22]. For example, Adib et al. found that heart rates take between 30 to 60 seconds to recover after participants performed 2 minutes of rope jumping exercise [23]. This suggests that computing applications that rely on the real-time interpretation of bio-signals must account for short-term changes in a user's physiological state due to a variety of different factors, and allow for a recovery period that may vary for different bio-signals and across different individuals.

There are many possible next steps to take with this line of research. First, we only administered one type of mental task in our study, given the constraint of the physical exercise component of our protocol. This is in contrast to previous

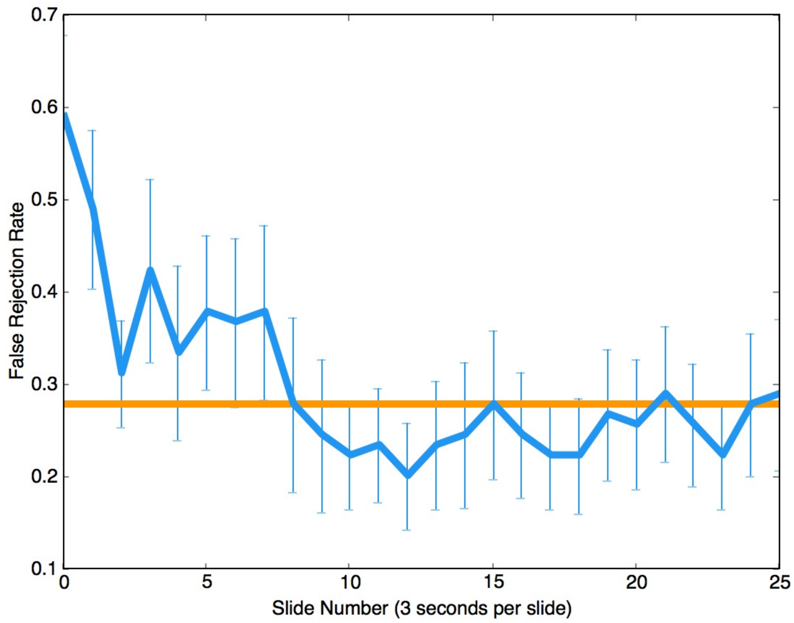

Fig. 4: False rejection rate over time: FRR is elevated immediately after exercise, and recovers to baseline levels after about 10 slides, which corresponds to 45 seconds after the end of exercise. (Error bars show standard error of mean, with n =10. Orange line shows the mean FRR of 0.278 for the entire 90-second task, from Table II.)

EEG authentication studies that leveraged multiple mental tasks per subject to achieve high levels of accuracy. Future work can investigate if other types of mental tasks (e.g., motor imagery, visual imagery), or collections of tasks, produce similar patterns of post-exercise recovery.

The large physical movements during the exercise phase of our experiment necessitated a transition period before EEG data collection could resume. Thus we have a black-out period of 15 seconds immediately following the exercise. It would be worthwhile to investigate solutions that may allow meaningful EEG data to be collected during the transition period, and potentially during the exercise period itself, notwithstanding the electromyography (EMG) signals that will inevitably be present.

This study focused on the effects of physical exertion on EEG authentication. Further research can look at a variety of other pyscho-physiological effects, such as mental fatigue, stress, distraction, changes in affect or mood, or the effects of alcohol, caffeine, sugar, or medication. Together, they can paint a much broader, more detailed picture of the robustness of EEG authentication in the real world.

5 Conclusion

We conducted the first-ever study of the effects of physical exercise on EEG authentication. We find that authentication accuracy is significantly degraded immediately after exercise, but recovers within 45-60 seconds after exercise. These results suggest that short-term changes to a user's physiological state can have a significant impact on the accuracy of EEG authentication systems. As mobile EEG technologies become integrated with head-worn computing devices such as augmented reality or virtual reality systems or in-ear audio assistants, the viability of "passthoughts on the go" will hinge upon its robustness under a variety of real world use cases.

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