Muse headband: Measuring Tool or a Collaborative Gadget?

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Abstract We have conducted an observational study on persons participating passively in public lectures. During a lecture we were measuring the level of focus of listeners using the Muse EEG-headband as well as conducting an observational study of the usage of the device by experiment participants. The purpose was to understand to what extent commercially available portable EEG-devices can record synchronicity of experience among the audience. While we got some preliminary insights, we found that the usefulness in measuring EEG signal of consumer-grade devices such as Muse is extremely limited in non-laboratory conditions.

1 Introduction and theoretical background

Simultaneously to self-tracking community formation the users were able to experience the evolution of tracking hardware and software. Responding to the need for “ambient intelligence”(Calvo and Peters 2014) in which intelligent devices can be integrated into the everyday surroundings and provide diverse services to everyone, trackers became sophisticated technologies that uncovered users’ activity that would otherwise be inaccessible. We observe the change from simple assisting devices to the rise of more and more sophisticated trackers, including those that measure brain activity (such as Muse[1] - the brain sensing headband for training relaxation and meditation, as well as similar brain-trackers such as Melon, Emotiv and several others). These trackers enter a different level of interaction with users and bring about profound changes in how the role of a tracker is understood._They are more personalized, unobtrusive, and usable anytime and anywhere. Despite the fact that they measure very complex activities (such as affects or emotions) and provide feedback on them, they have a high degree of portability. Thus, people can use them in various spaces, for instance at group meetings or workplaces (such collaborative relaxation sessions is what Muse users are encouraged to do). Moreover, the rise of big data analytics is enabling more insightful analyses of all users digital footprints.
Increasing numbers of mind-related wearable devices becomes commercially available. Some of these devices fulfill purely passive functions, whereas others actively support alterations of

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cognitive states ((Mazurek and Tkaczyk 2016), (Kopeć et al. 2015), (Calvo and Peters 2014). In our series of experiments the intention was to investigate brain activity tracking of commercially available wearable devices' effects on attention building. Among currently available devices, most popular are those that introduce motivation building programs, allowing users to foster increased creativity or work productivity and/or reduce stress. These technologies aspire to foster human well-being and potential and can be classified as "positive computing" devices. `in our case, the wearable technology under investigation was Muse - the brain sensing headband.

2 Literature review and motivation

There is a significant body of research conducted with the usage of classical EEG and related to attention measurement ((Pfurtscheller, Aranibar, and Wege 1980), (Keil, Gruber, and Müller 2001), (Thut et al. 2006), (Gouma, Busch, and van Gulik 2010). Moreover, there are some studies related to the usage of various portable EEG wearable devices ((O'Connell et al., n.d.) 2009; (van der Wal and Irrmischer 2015). Quite recently, there also appeared studies related to using wearable and wireless EEG-based brain -computer interface device for gaming control (Liao et al. 2012) as well as studies related to brain computer interaction and using portable EEG devices to control humanoid robots (Güneysu and Akin 2013) as well as other psychophysiological signal detection for chatbots (Ciechanowski, Przegalinska, and Wegner 2018).

Taking into account previous research related to wearable EEG devices, we have conducted an observational study on persons participating passively in events where knowledge is shared. For the experiment we were measuring the level of focus of listeners during a lecture using the Muse headband. Researchers provided strong evidence (Abujelala et al. 2016),(Wiechert et al. 2016), (Alrige and Chatterjee 2015) that Muse might be used outside its prior functionality (meditation training device) and become an effective portable tool for attention measurement while performing various assigned tasks. For instance, in a recent study, Muse has been already used for experiments in which users' focus was measured while they were playing video games (Abujelala et al. 2016)) or while listening to recorded lectures (Kasperiuniene et al. 2016), whereas live lectures were not examined so far.

Via EEG studies, mindfulness meditation has been associated with measurable changes to brain waves including major changes in alpha waves and certain increases in theta and gamma rhythms(Lutz et al. 2008). Other authors (Chiesa and Serretti 2009) report that, in addition to significant increases in alpha and theta activity, the states of mindfulness and meditation are associated with activation of the prefrontal cortex and anterior cingulate cortex, areas related to attention. Thus, Muse can also serve as "attention recorder" capturing alpha waves while performing some (usually passive) tasks. Muse was initially designed as a personal meditation assistant. It is portable, and can be paired with any tablet or smartphone and operate with the Muse application, which also trains the user in meditation exercises and records EEG data. Muse uses two frontal channels on the left and two on the right of forehead, and thus can explore hemispheric asymmetries. Muse is also equipped with two micro-USB ports on the back of the ear pods where two auxiliary electrodes can be attached. These electrodes can be used to measure EMG, ECG, or EEG on other areas of the head or body.

In our experiment, the main goal was to understand what kind of role the device fulfils, both scientifically and socially, in real life situations. We wanted to see to what extent it accurately records the signal and how is it going to be used by the experiment participants as it is consumer-friendly and open to individual exploration.

3 Methodology

The study included participants participating in a public event (lecture). Through social media channels we selected 8 participants to use Muse headbands while attending a public academic event. However, in the end, we chose 5 persons for analyses, since the EEG signal gathered by Muse was too noisy for the others, to a point that it was entirely non-analysable.

In the experiment, after giving consent to participate in the study, participants answered relevant demographic questions. Then, participants were fitted with the Muse headset. Conductivity for all four channels was checked before proceeding to the experimental phases. After proper connection with the Muse was ensured, the baseline phase (“Relax”) was established. During this time, participants were asked to close their eyes and listen to calming white noise for 120 seconds, while their EEG data was recorded. Subsequently, the active phase (“lecture listening”) was established. During each of these phases, the participants were asked to listen to the lecture for 30 minutes, while their EEG data was recorded on the Muse Monitor application. The main goal of the study was to check the Muse behavior during an outdoor study, and - if successful - assess the level of attentiveness, active engagement, distraction, and concentration during the lectures and compare them between persons.

For the first part of the experiment the researchers have used Muse Monitor to collect raw data. Simultaneously, Muse App designed to collect and visualize data in a simplified and gamified manner was turned on to display the users the results of their session with Muse. Data collected by the Muse App are non-exportable and and the algorithm used for computing them is patent-protected. Muse App shows general results of each Muse session compared with previous results and thus the results may vary according to general experience with the device and the amount of overall time spent with it on.

4 Results

The conducted study has shown that the data collected by Muse headband with a Muse Monitor application, are of poor quality in noisy conditions, such as a public lecture. There were a couple of problems with the data, which we present below.

First of all, the EEG signal looks very noisy just on the face of it. Figure 1 presents the signal for one participant.

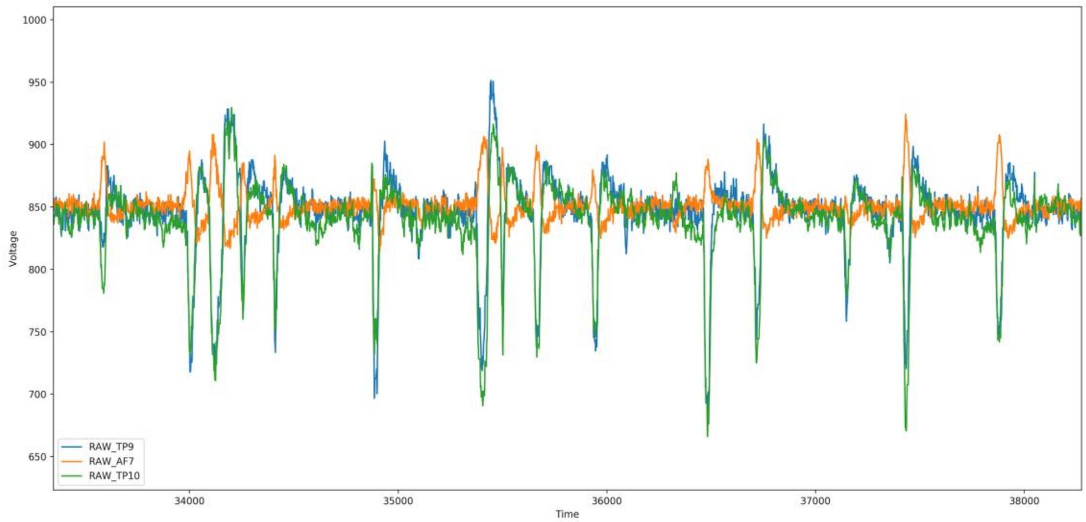

Figure 1. Raw EEG signal for selected subject. It is clearly visible, that the 3 electrodes do not provide a proper signal. Most of it consists of eye blinks and no oscillations of brain origin are present. We removed one electrode from the data for this participant, since it was not properly attached resulting in very noisy data.

Second, and it is the most crucial problem - time difference between subsequent samples is unstable. This means that the stream of samples can't be treated as a signal with specified sampling frequency - difference between time stamps reported by Muse for adjacent samples ranges from -10ms to 150 ms (see Figure 2). At most times the consecutive samples properly differ by one millisecond (due to 1000 Hz sampling frequency), while at other times there can be a difference of 100, or occasionally even more than 250 milliseconds. The time differences are non-systematic, therefore making it more difficult to deal with the problem. Such variability is unacceptable for research purposes.

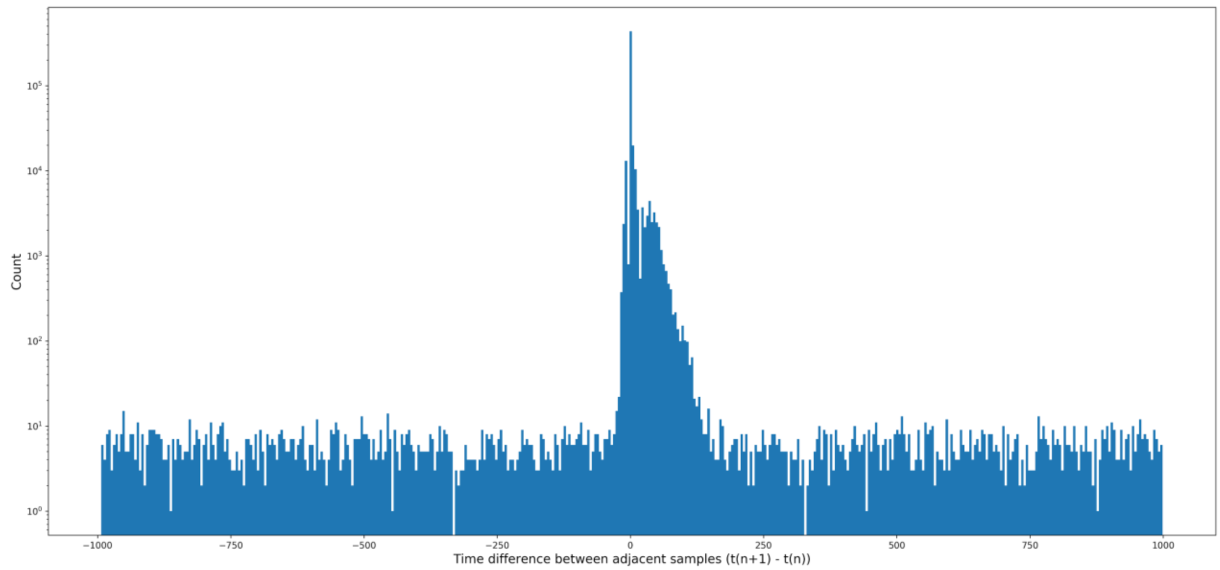

Figure 2. The figure shows the histogram of time differences for subsequent samples. Most differences are within -10ms to 150 ms. This variability shows that the gathered raw signal did not have a proper temporal resolution. Note that the y axis is in logarithmic units.

Third, there is a lot of missing values. The reason for it is unknown; probably Muse is already cleaning the data on the raw-level, or some of the packets sent via Bluetooth to the Muse Monitor application are lost. Figure 3 illustrates the missing values for a representative subject. We observed around 0.01-0.05% missing samples across all participants. While it comprised all in all 1000 samples per subject, it is not that significant - the missing data can be interpolated. Most of the missing samples were marked by muse as eye blinks or similar artifacts - while actual eye blinks were left untouched in the signal. This raises the possibility that artifact detection algorithms used by Muse fail to detect standard artifacts.

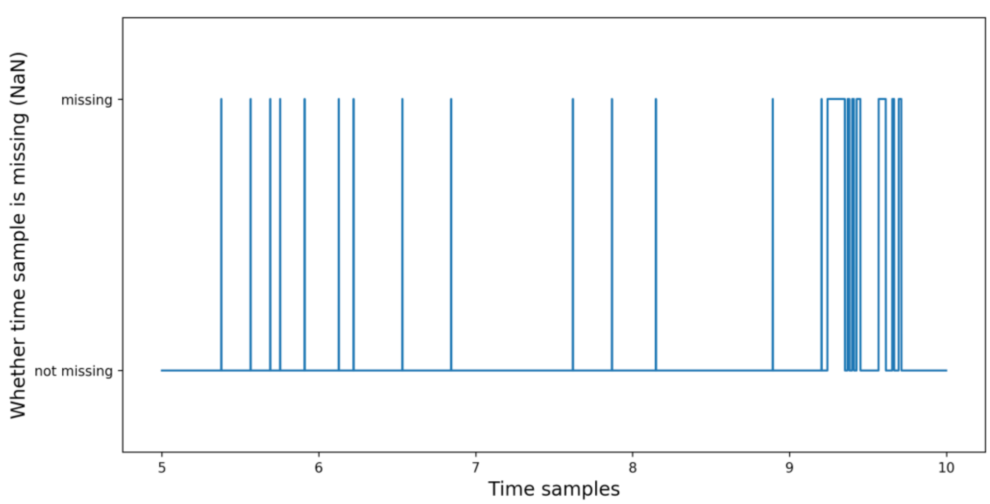

Figure 3. Missing time samples for a selected time range of one participant.

In the end we are presenting a power spectrum derived from the data, since it is often used to assess spontaneous brain activity. The average spectrum seems to contain theta-like peaks, but closer inspection demonstrates that this peak does not reflect brain oscillations but is powered by rare, but strong, events like eye blinks (Figure 4).

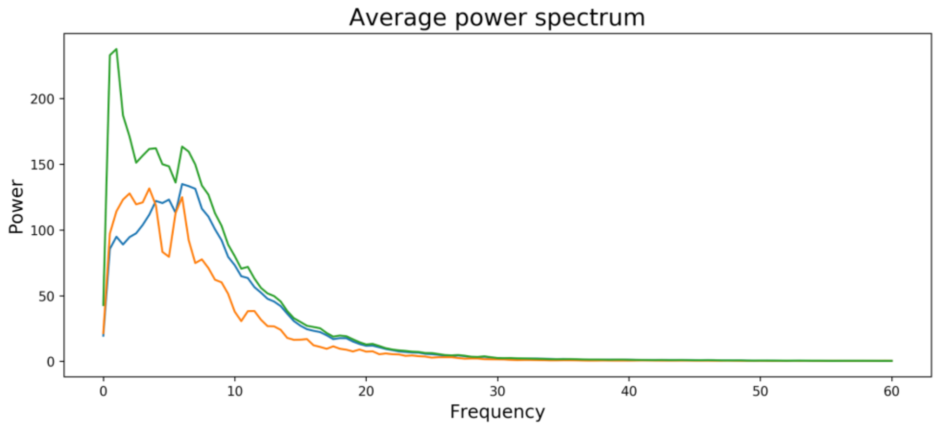

Figure 4. The average power spectrum for representative subject.

This conclusion is further supported by performing median power spectrum where all the peak-like structure evaporates (Figure 5). Taking the median instead of the mean removes influence of eye blinks, and other artifacts, that originally caused the signal to look as if it contained spectral peaks similar to those present in actual brain recordings. Therefore, the spectrum does not provide any evidence of oscillatory signal originating from the brain.

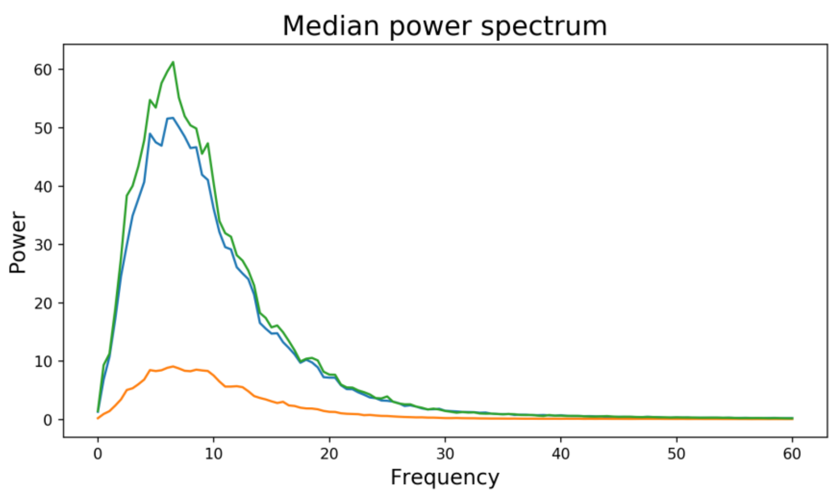

Figure 5. The median power spectrum for a representative subject.

5 Discussion and conclusions

Reliability of Muse and similar devices may be questioned. The number of electrodes on these devices is limited compared to the clinical grade devices. Also, their resolution is lower, and the electrodes are usually focused on a specific area of the brain. Eye movement, muscular activity, and other electronic devices in the vicinity introduce artifacts to the signal and disrupt the measurement of actual brain waves. The inability of Muse and similar trackers to cancel out such "noise" generates less reliable signal that does not seem to contain much brain activity. This reliability could and should, however, be improved by including more sensors and using blind source separation algorithms like Independent Component Analysis (ICA) - to separate artifacts and noise from brain activity. However, that increases costs, weight and design of the product making it less attractive for consumers to purchase (Rettner 2016). What is more, the devices currently present on the market are still struggling with devising proper and individualized algorithms that would be able to produce reasonable and truthful output based on psychophysiological data.

It is important to note that frequency spectrum of any signal can be computed and divided into pre-defined frequency ranges like theta and alpha. The sole fact of decomposing the signal into frequency ranges known to be abundant in brain electrical recordings (as muse does) does not constitute measuring actual brain oscillations. In all Muse recordings that we investigated, we found no evidence of brain oscillations. Moreover, it is very possible that eye movements and eye blinks contribute to theta and alpha frequency ranges reported by Muse. Therefore, it is possible that theta and alpha measurements reported by Muse are actually mostly noise-driven.

On the other hand, Muse and several other portable EEG devices are way simpler to set up than typical EEG. They connect well via Bluetooth to a smartphone, a computer, or a microcontroller, where data can be analyzed directly. Dry electrodes used in most of these devices do not require intensive preparation or clean-up, and these electrodes connect to the skin without the need for any liquid. These changes have helped evolve EEG applications in both novel and established fields and allowed consumers to use without any particular expertise or preparations devices previously reserved for medical and scientific purposes only.

Whereas their accuracy for research purposes is problematic, the devices generate interesting social effects. Most users, while returning Muse, reported they have made attempts to stay focused all the time and listen to the lecture very carefully. The researchers also noticed that subjects equipped with Muse formed a collective that one could carefully dub a micro-tribe(Gulati 2007),(Weller 2012). Without any prior suggestions from the researcher supervising the experiment, each time subjects wearing Muse decided to sit together without knowing each other previously. Most of them asked questions after the lecture and then engaged in conversation about the topic of the lecture with others who were using Muse. They were also comparing compiled results of their Muse sessions collected by the Muse App and exchanging information about how to enhance their results in the future. One could assert that subjects equipped with Muse presented certain degree of spontaneous tribalism, possibly based on a strong shared experience of a selected group whose brain activity was accessed and sensitive data were collected. This is how one could explain visible emerging relations of proximity between Muse-wearing experiment participants.

6 Summary

As mentioned before, nowadays, many portable EEG devices are consumer-grade, low-cost devices that are targeted for lifestyle applications. These products also often rebrand EEG data with a simpler, easily-understood term neurofeedback, understood as a type of biofeedback that uses real-time displays of brain activity—most commonly EEG - to teach self-regulation of brain function. It is clear that from self-tracking of simple and easily quantifiable activities we are moving to more collaborative and sophisticated, even though scientifically unsatisfactory forms of tracking.

Trackers such as Muse enter a different level of interaction with users and bring about profound changes in how the role of a tracker is understood. They are more personalized (as data collected by the Muse app adjust to previous Muse sessions) and usable anytime and anywhere. Despite the fact that they provide feedback on very complex activities, they have a high degree of portability. The very nature of our relation with tracking devices is also one of the crucial reasons of why the self-tracking industry is developing so rapidly. From our research, and also from other authors who addressed this problem(Nafus and Tracey 2002; Nafus and Sherman 2014; Lupton 2016) we know that on the individual level self-tracking (if not becoming addictive) frequently becomes either boring or frustrating over time. When, however, it becomes elevated to a level of smaller or bigger group or community is when the collaborative aspect steps in. Most probably, the future of tracking lies in collaborative endeavors, because the individual uses become easily boring. Being part of something larger than themselves can, however, have an empowering and motivating effect. The producers know it, too and this is why their efforts are to bring trackers into wellness programs of organizations and corporations and make them become transparent companions of everyone's routines.

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