Neurofeedback personalized with artificial intelligence to support personal development:a preliminary study

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Personalized neurofeedback has been offered commercially for people with different types of disorders. We explore the backgrounds of quantified EEG (qEEG), the different approaches and underlying paradigs regarding neurofeedback as a tool for personal development. We hypothesize that neurofeedback can be useful for everyone, whether they are diagnosed with a disorder or not. Our personalized approach is inspired by the approach of personalized medicine, that takes the individual differences into account in order to finetune therpeutic interventions. We propose different approaches to offer individuals a way to train their brainwaves, in order to learn how to easily produce or switch between different brainwaves and their correlating states of consciousness. Machine learning techniques can help in making these techniques more widely available, as they remove the need for a professional that is currently necessary to interpret the qEEG and select a neurofeedback protocol.

Introduction

Lately, the perceived dangers of Artificial Intelligence (AI) have risen to the forefront of both the social and scientific discourse. Although we acknowledge it is important to think about these dangers, this paper will explore how AI could contribute to a better world, by means of supporting personal development. We operationalize this question by researching how personalized neurofeedback, combined with Artificial Intelligence, can support this personal development by helping individuals acquire a greater range of freedom in accessing different types of brainwaves and the corresponding states of consciousness at will.

Personal development through personalized neurofeedback

In this paper, we try to investigate the possibility of personal development with the aid of personalized neurofeedback, drawing inspiration from different area's of research. First off, this paper is a preliminary study regarding the literature on brainwaves and neurofeedback. We position ourselves in the landscape of the different paradigms, and suggest some ideas on how we could proceed. Our final goal is to write software that utilizes an existing EEG-device for personal use, the Muse headband (Muse, 2019), that creates an interface capable of measuring typical patterns in brainwave activity, report this back to the user, suggests applicable neurofeedback protocols and eventually gives the user this neurofeedback.

Personalized medicine

The efforts to personalize therapy are adjacent to our research. Even though there are a lot of differences between therapy and personal development, therapy could also be seen as a specific case in the broader domain of personal development. The paradigm we are interested in is the shift away from the 'one-size-fits-all' approach where the differences between clients are minimalised under statistical operations. Now that knowledge and technology in healthcare keeps improving, it starts to become easily achievable to tailor an intervention towards the profile of the client. One of these efforts is the research on *predictors* for the outcome of therapy (Hardy et al., 1995; Rossiter, Agras, Telch, & Schneider, 1993; Rounsaville, Dolinsky, Babor, & Meyer, 1987). However, in the research on predictors the therapy is not adapted to the profile of the patient. Instead, the studies simply establish that some characteristics such as personality traits are correlated with the effectivity of a given therapy. They still offer every patient in the trial the exact same therapy, even though this will be suboptimal for certain patients. For our setup, we explicitly want to personalize the intervention in a way that will maximize the impact of the intervention for the individual. That's why research that looks at *moderators* is much more useful for this approach as a source of inspiration. Moderators are defined as 'predictors of differential response to alternative treatments' (Simon & Perlis, 2010) and are researched by what is known as *personalized medicine*. Even though an important part of personalized medicine is focused at medical problems and thus looks dominantly into physical moderators like metabolomics (Van Der Greef, Hankemeier, & McBurney, 2006; van der Greef et al., 2010; Wietmarschen et al., 2012), the mindset is inspiring to our research. Personalized medicine moves away from a *n=many* approach, towards a *n=1* approach, where the differences between individuals are kept intact instead of being removed through a statistical filter over the data. This way, the treatment is not as uniform as possible, but instead catered to the specific individual.

Inclusive personalized neurofeedback

A second domain is research regarding neurofeedback. Within this domain, we encounter different paradigms regarding the analysis of the EEG of a client and what the quantification of the EEG means in terms of treatment. Neurofeedback can be defined as a 'method for retraining brainwave patterns through operant conditioning' (Hammond, 2007). Brain activity can be measured as electropotentials, which can be broken down into multiple waves, each with a specific frequency, phase and amplitude. More on this in section An overview of brainwave frequencies. Retraining brainwave patterns comes down to measuring and quantifying the brainwave patterns of an individual and reinforcing activity with a certain frequency, location or phase. This reinforcement can be done in different ways, for example through visual stimuli or through auditory signals. We encounter different paradigms underlying the different research. One axis along which the paradigms can be classified ranges from *abnormality* to *inclusion*. On one side of the spectrum we find the research of John, Prichep, and Almas (1992) focusing on the treatment of psychiatric patients. They use quantified EEG (qEEG) as an approach to personalize the treatment for the patients. Their paradigm, as reflected in their choice of words, strongly centers about the idea of 'normal' people versus 'abnormal' people. They used the qEEG to describe an 'abnormality vector' in a brain signal space, where they scaled the vector in standard deviations from the mean score. The length of this vector indicates the amount of abnormality of a patient, where the direction of the vector should indicate the nature of their disease (John et al., 1992). The research of Johnstone, Gunkelman, and Lunt (2005) moves somewhat towards the middle of the spectrum and describes the idea of qEEG as an *intermediate phenotype*, defined as "manifestations between genome and behavior". These phenotypes are qualified as (i) highly heritable (ii) reliable indices of brain function (iii) not isomorphic with DSM categories (iv) with implications for therapeutic intervention (Johnstone et al., 2005). Where John et al. (1992) thought it to be important to be able to show the correlation between the DSM diagnostic labels and the qEEG profiles (even though he mentions that 'patients with a homogeneous symptom category may belong to heterogeneous subtypes'), we see that Johnstone et al. (2005) focusses more on the implications of qEEG profiles, regardless of the correlation with DSM-criteria. For example, he states that "it is clear that this pattern [excess frontal Theta frequencies] is not specific to ADD and has been reported in a number of other clinical disorders". Johnstone et al. (2005) tries to translate the qEEG profiles into indicators for therapeutic interventions like suitable medication and neurofeedback protocols. In the research of Arns, Drinkenburg, and Leon Kenemans (2012) we also find the attitude towards the qEEG profiles where 'normal' people are included in the profiles, even though they do not discuss what this implies for 'normal' people: "These EEG phenotypes [as described by Johnstone et al. (2005)] occured in both ADHD subjects as well as healthy control subjects.". A review of Arns, Heinrich, and Strehl (2014) shows that neurofeedback has large effect sizes for inattention and implusivity for individuals with ADHD. When we look at the other end of the spectrum, we find research that is explicitly inlcusive in its paradigm towards using the qEEG. For example, when we look at the research by Fingelkurts, Fingelkurts, and Kallio-Tamminen (2015) about the personalization of meditation, we find an approach where meditation is regarded as a "set of self-regulatory techniques focused on maintaining attention and awareness with the goal to achieve a higher level of well-being and serenity" which is useful for a broad range of individuals, regardless of their degree of 'abnormality'. The qEEG profiles are used to personalize the method for individuals to enhance the effectivity of their meditation and to prevent possible negative effects. Another example is the study of Cha and Lee (2018) that quantifies neural synchronization between collaborating individuals and correlates this with the quality of the teamwork as a way of direct feedback and the prevention of critical errors. While we place our own research at the 'inclusive' end of the spectrum, we can still use methods or techniques that originated in the research that focusses on the 'abnormality'.

Machine learning

A third domain from which we draw inspiration is the general domain of machine learning. A lot of the personalisation in neurofeedback is done on the basis of the evaluation of an expert of the qEEG. A raw EEG is made, and after 'visual inspection' an expert classifies the EEG as belonging to one or more groups of qEEG (Arns, Gunkelman, Breteler, & Spronk, 2008; Arns et al., 2012; Surmeli & Ertem, 2010; Johnstone et al., 2005). A big downside of this approach is the need for an expert to interpret and classify the brainwaves. This is why we focus on the possibilities to use Artificial Intelligence to classify the brainwaves, which already has been shown to be possible. (Tenev et al., 2014; Bird, Manso, Faria, & Ribeiro, 2018)

An overview of brainwave frequencies

The different kinds of brainwaves mentioned in literature are, ordered by frequency, Delta (0.5-3.5 Hz), Theta (3.5-7.0 Hz), Alpha (7.0-13 Hz), Beta (13.0-22.0 Hz) and Gamma (22.0 Hz and up)(Thatcher, Krause, & Hrybyk, 1986). Note that these ranges are a rough estimate, and can differ between researchers, for example Johnstone et al. (2005) gives 8-13 Hz for the Alpha bandwidth and Arns et al. (2012) gives 8.0-12.0 Hz for Alpha and 15.0-20.0 Hz for Beta, putting a bandwidth called SMR in between those at 12.0-15.0 Hz. Now, why are these distinctions made in the first place? Different 'modes of being' have been ascribed to differing frequency ranges from very early on in the research with EEG (Surwillo, 1963). We will describe three main ranges:1. lowrange 2. midrange 3. highrange. Alpha is the first and most exhaustively studied range, hence the name Alpha. Gamma waves, after having been dismissed as 'spare brain noise' for a while, are a more recently studied phenomenon within neuroscience(Iqbal, PP, Khan, & Farooq, 2016). All these types are active to a certain extent on any given time. However, usually one type's amplitude surpasses the others, thus dominating the (un)conscious state of being(Hammond, 2007).

Lowrange waves: Delta and Theta

Delta and Theta correspond to the least frequent and highest in amplitude brainwaves (Shaker, 2006). Delta and Theta waves are most dominant during sleep (Cajochen, Foy, Dijk, et al., 1999). Cajochen et al. (1999) performed research with six sleeping volunteers during which all-night spectral analysis was carried out using an EEG. They found that relative increase of low frequency waves in EEG occur when wakefulness is extended (16-40 hours of not sleeping).

Research of Maquet et al. (2005) used positron emission tomography (PET) recordings during sleep which showed that Delta waves were more dominant during Non Rapid Eye Movement (NREM), the deep (dreamless) sleep. When someone comes in the NREM sleep the amplitude gets higher and the frequency lower. Cantero et al. (2003) showed that Theta waves were associated with Rapid Eye Movement (REM) sleep. In this phase people could also be dreaming. The Theta waves were observed when there was a transition from sleep and during quiet wakefulness. Low Delta has been observed along shallow sleep and poor ability to rejuvenate mind and body (Aftanas & Golocheikine, 2001).

But Delta and Theta waves are also seen in other circumstances then sleep. They are more dominant during childhood, and become less dominant when getting older (Feinberg & Campbell, 2010). High Delta and Theta activity can be indicative of learning problems, as well as some subtypes of ADHD (Arns et al., 2008, 2012).

Theta may be part of learning, memory and stress reduction (Buzsák, 1998; Ward, 2003). It is usually observed along with lower heart rate and slower breathing, as well as daydreaming (Myers & Young, 2012). Jensen, Adachi, and Hakimian (2015) found that hypnosis is associated with Theta frequency activity. Theta waves are also associated with meditation (Lagopoulos et al., 2009; Fingelkurts et al., 2015). Aftanas and Golocheikine (2001) showed that subjective scores of emotional experience with meditation significantly correlate with Theta waves. There are also indications that Theta is correlated with creative processes, as Kruk, Aravich, Deaver, and Debeus (2014) found that clay sculpting elevated Theta power.

Midrange waves: Alpha

Alpha waves, seen as responsible for the common relaxation mode in adults, are most active when reflecting and resting after effort has been made. This relaxed awareness can thus be thought of as a recovery mode.(da Silva, 1991) Cortisol, also known as the stress hormone, has been shown to be negatively correlated with Alpha waves (?, ?). In research conducted by Ward (2003), Alpha along with Gamma brainwaves are suggested to guide attentional processing, suppression and entrainment. They also found that Alpha, unlike Delta and Theta, generally increases with age. In general, Alpha waves "dominate the EEG of humans in the absence of external stimuli when internal life (mind-wandering and spontaneous thoughts) is most pronounced (Fingelkurts, Fingelkurts, & Kallio-Tamminen, 2016). In accordance with these findings, there are correlations found between Alpha power and creative ideation. According to research by Fink et al. (Fink, Graif, & Neubauer, 2009; Fink, Grabner, et al., 2009; Fink & Benedek, 2014), Alpha waves are "positively related to an individuals' creativity level and has been observed to increase as a result of creativity interventions". Sandkühler and Bhattacharya (2008) reports correlations between increases and decreases of Alpha brainwaves during the process of insightful problem solving. However, excess Alpha might lead to inability to focus, or even ADHD (?, ?; Johnstone et al., 2005; Arns et al., 2008, 2012)

Highrange waves: Beta and Gamma

Beta and Gamma brainwaves correlate with alert and focused behaviour, as well as of engagement with the outside world, e.g. conversations, public speaking and complex problem solving (Puzi, Jailani, Norhazman, & Zaini, 2013). Ideally, this would be the dominant brain state in studying and problem solving. For example, Prat, Yamasaki, Kluender, and Stocco (2016) found power in Beta and Low-Gamma frequencies positively correlated with the rate of second language acquisition. The alertness is also reflected in response times. Alertness during high Beta was tested in comparison to alertness during high Alpha. Response times were found to be 12 ms faster in favor of Beta (Dustman, Boswell, & Porter, 1962). A very interesting observation made by Ward, supported by Miller's research independently is that Gamma oscillations seem to directly correspond to the number of items in short-term memory (Ward, 2003; Miller, 1956)

Beta and Gamma waves are also correlated with more negative feelings of anxiety and stress, as well as the inability to relax (Heraz & Frasson, 2007). Contrary to Theta and Delta, for Gamma it is the lower than usual levels that have been linked with ADHD and learning issues, as well as depression (Steffert & Steffert, 2010; Arns et al., 2008, 2012; Johnstone et al., 2005; John et al., 1992; Heraz & Frasson, 2007).

Brainwave synchrony and coherence

The last section reviewed the breakdown of EEG patterns into frequency-bands. Another way to quantify EEG patterns is in terms of synchrony or coherence,which can be done in different ways. Thatcher et al. (1986) describes a method to quantify coherence, but since their paper in 1986, several improvements have been suggested. Lachaux, Rodriguez, Martinerie, and Varela (1999) describe a method to quantify frequency-specific synchronization between two neuroelectric signals, called phase-locking statistics (PLS). In order to measure the phase covariance between two signals, the method separates phase and amplitude components. They hypothesized that cognitive tasks that require integration of functional areas distributed over the brain are mediated by neuronal groups that enter into phase-locking. Lachaux et al. (1999) give their PLS-method as an alternative for using frequency coherence, a measure of the linear covariance between two spectra. A downsize of coherence is that it assumes that "each segment of data correspond to the same process with the same spectral properties". As "this assumption of stationarity (in time or across trials) can rarely be validated", Lachaux et al. (1999) prefer the PLS method. Fingelkurts and Fingelkurts (2008) propose another method to measure synchrony, which they call "operational synchrony" (Fingelkurts et al., 2016; Fingelkurts & Fingelkurts, 2008, 2011) which is thought to overcome the disadvantages of multiple other methods to measure synchrony (Fingelkurts & Fingelkurts, 2011). They find that long-term meditation induced changes in the operational synchrony (Fingelkurts et al., 2016). Another approach towards synchrony comes from Cha and Lee (2018), already mentioned in section Inclusive personalized neurofeedback, who correlate the synchrony between individuals with the quality of their teamwork. Travis et al. (2009) reports several studies that indicate higher levels of frontal EEG Alpha coherence, who integrates different measures into a "Brain Integration Scale". We can thus conclude that there is a diversity of methods that are used to measure synchrony or coherence, without a clear consensus between researchers on the exact method. However, regardless of the method used, we think that coherence or synchrony can be an interesting measure of brainwaves for our purposes.

Paradigm on modifying brainwave patterns

While reviewing the different correlations between brainwaves and states of consciousness, it is clear that there are no brainwaves that are 'better' than other brainwaves. Alpha brainwaves might be excellent for mediation and creativity, but they can also be correlated to problems with concentration and focus (Johnstone et al., 2005; Arns et al., 2008). For our application, we are not specifically interested to classify people on an axis of abnormality. In our view, brainwave patterns could be compared to different muscles. Everyone should be able to use all muscles to a certain extent, but different situations require the use of different muscles. This could even differ during the day, as someone might need Beta waves during the day to study, but Alpha waves in the evening to relax and Theta waves to sleep. The research done with neurofeedback for psychiatric clients mainly shows that even individuals with highly deviating brainwave patterns are able to modify these patterns, from which we infer that it should be feasible for people with less deviated patterns to modify their brainwave patterns by training with the aims of neurofeedback (Arns et al., 2014).

We hypothesize that acquiring a greater range of freedom in accessing all types of brainwaves at will would support people in varying area's of their lives. While scoring individuals along an axis of abnormality might be helpful in some cases, we think that people should have the freedom to pursue self-chosen goals in terms of brainwave patterns. It might be the case that someone already has a lot more access to Alpha waves as compared to 'normal' people, but would still be interested to train his these brainwaves because of a certain type of work or personal goals in life.

We envision an application that makes an inventory of an individuals brainwave patterns, makes an analysis of these patterns and suggests multiple neurofeedback protocols, associated with possible goals an individual might want to pursue.

Strategies for the selection of neurofeedback protocol

As we have seen in the previous sections, there are numerous ways to quantify EEG patterns. In addition to this, there are also numerous ways to select an appropriate neurofeedback protocol.

Quantification of patterns

Z-scores. John et al. (1992) describes the method of representing the qEEG as an abnormality vector in a brain signal space. They do this by scaling the values in Z-scores or standard deviations from the normative mean. We find this approach of comparing brainwave patterns which along this abnormality vector in different studies, mostly studies aimed at psychiatric conditions (Arns et al., 2012, 2008; Johnstone et al., 2005). While we differ with regards to the underlying paradigm, it might still be useful information to compare brainwaves to a normative mean. One's own typical brain patterns might be easier to interpret against the background of the normative scores. This does not mean that an individual should strive to 'normalize' his or her own brainwaves towards the mean, but it could be useful information nevertheless.

Personal ratios. In addition to a comparison with the normative mean, it is possible to obtain the ratio's of an individual's brainwaves, relative to himself, with the Muse headband (Muse, 2019; Bird et al., 2018). For example, someone could learn that his own brainwaves are composed of 50% Beta frequencies regardless of what is considered 'normal'. We could help an individual to interpret this data, by giving information about the correlations between his specific brainwaves and states of consciousness as described in the literature. We want to research if we are able to create individual labels, correlated with specific states of consciousness for an individual. This could be obtained by having an individual wear an portable EEG-dives like the Muse Headband (Muse, 2019) for multiple days, during different states of mind. When the individual labels his own states of consciousness (e.g. focussed, distracted and relaxed) it might be possible to correlate these labels with characteristic patterns for the individual, using basic statistical techniques. This way, an individual could get help to obtain brain states he has shown to be able to reach previously, but just doesn't know how to get back to.

Selection of a neurofeedback protocol

After the current pattern has been characterized, a protocol for neurofeedback can be selected.

Negation combined with heuristics. A commonly found heuristic to select a protocol, is to simply construct the negation of the dominant pattern in combination with some simple heuristics (Johnstone et al., 2005; Arns et al., 2008, 2012). To make this more clear, we can rewrite the qEEG patterns and the protocols with a three-digit code, where the first digit represents the lowrange frequencies, the second digit represents the midrange frequencies and the third digit represents the highrange frequencies. The number '1' would represent an high activity on that frequency range, the number '0' would represent a low activity on that frequency range. With this syntax we can represent a lot of the qEEG phenotypes and protocols described. E.g. the pattern that is characterized by Johnstone et al. (2005) as "increased Delta and Theta, with or without low frequency Alpha" could be represented as 100 or 110. The neurofeedback protocol suggested for this pattern is to "inhibit [...] activity below 10 Hz, add reward Beta frequencies", which could be represented by 001. Another example: "excess temporal lobe Alpha" is characterised as "increased alpha activity generated in temporal lobe" and could be represented as 010. The corresponding protocol is "inhibit 9-12 Hz activity and inhibit frontal slow activity", which could be represented as 001. The heuristic to create a neurofeedback seems to be to negate the pattern with the exception of the low frequencies, that are never reinforced in the protocols described by Johnstone et al. (2005). This heuristic is probably optimised for the specific disorders that Johnstone et al. (2005) worked with. For example, people with sleep disorders might be interested in stimulating Theta waves (Cajochen et al., 1999), as well as people interested in certain aspects of meditation (Lagopoulos et al., 2009; Fingelkurts et al., 2015) or the creative process (Kruk et al., 2014; Myers & Young, 2012).

Informed selection. Another approach could be to make a choice, based on known correlations. For example, as research has found a correlation between the rate of second language acquisition and Beta frequencies it could be helpful for an individual to pursue these specific frequencies, regardless of his own brain patterns. Thus, even though an individual would score a 010 pattern when compared to the normative mean, it could still be useful for this individual to use a 010 protocol to even further train his capacities with regards to the Alpha brainwaves.

Conclusion

We have explored a wide range of literature regarding different types of neurofeedback and correlations between qEEG patterns and activities or states of consciousness. We conclude that there is a wide range of mental processes that seem to flourish under specific brainwave patterns. The research shows that there is a large effect size for people with ADHD, from which we draw the conclusion that it is very well possible to modify one's own brainwave patterns, even if there is a large deviation from the mean. We hypothesize that acquiring more freedom in accessing different types of brainwaves at will, would help people with their personal development and would increase their quality of life. Whether this really is the case, will be the subject of our future research. We end with an overview of different strategies that could be used to quantify the EEG and to select neurofeedback protocols. How to test whether these strategies are useful will also be part of our future research.

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