A First Step Towards Binaural Beat Classification Using Multiple EEG Devices

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Abstract— **This study analyzes the influence of binaural beats, an acoustic phenomenon which rises from two sonic waves of insignificantly different frequencies noticed as a single tone on each ear, on brain activity. Although this topic is not new, few scientific reports have been released. Therefore this study investigates if there is a measurable impact on the EEG activity for different frequency bands using a low budget, a mid-price ranged and a medical EEG device. Probands were exposed to a 12 minute 40 seconds counting task while listening to ambient music. During this task binaural beat samples were played covering different frequency bands, each followed by a pause of 10 seconds where no binaural beat sample was played. The probands were not informed about the presence of binaural beats, the only information given was to count the red shapes moving over the screen. The aim was to classify to which particular frequency the proband was exposed by analyzing their brain activity. The best result was achieved with the medical EEG by the FT classifier with a mean absolute error of 7.14% averaged over 4 datasets. In comparison the best result achieved on the NeuroSky Mindwave headset using the Naive Bayes classifier was a mean absolute error of 26.04%, while introductory experiments with the Emotiv EPOC headset showed a mean absolute error between 2.83% and 27.70%. Further experiments have to be conducted to validate the Emotiv EPOC classification performance. This shows that it is possible to classify the currently played binaural beats frequency rather accurate with appropriate hardware.**

I. Introduction

In recent years the measurement of vital parameters such as skin temperature, blood pressure or more complex features like EEG activity has become a focus of the industry and made available to a wide range of consumers for example in commercial sports devices [1]. There are still a lot of areas where no research for the utility of EEG devices has been conducted. One of them being the influence of binaural beats on brain waves and brain activity [2], which is to be researched in this paper.

Binaural beats can have influence on the emotional states of a person. Nowadays devices for binaural beats are sold worldwide with advertised benefits like increased focus and concentration by listening to the respective binaural beats regularly[1]. Identifying binaural beat samples or frequencies that demonstrably enhance these emotional states can support people to deal with daily activities and improve health care processes [3,4].

Although there has been some research in the past [5,6,7], there was no recent publication which investigated the influence of binaural beats on EEG activity in a detailed manner for all frequency bands. Frequency bands are used to divide and analyze EEG activity, although the determination of the frequency bands is discussed in [8,7] compared the influence of beta and theta frequency bands on the mood. However, authors did not use the full frequency for analysis, but focused on two frequency bands. In [9] the influence of binaural beats to treat anxiety is researched, but the results are based on a self-report of the probands without the usage of machine learning methods. There are still a lot of areas where no research for the utility of EEG devices has been conducted. One of them being the influence of binaural beats on brain waves and brain activity, which is to be researched in this paper.

As no standardized test method for measuring EEG activity exists to the best of our knowledge, we want to propose a method and a set of binaural beat samples to set up a base for further experiments. The second objective of this work is to provide evidence using scientific methods how binaural beats can influence EEG activity using multiple EEG devices. Further we propose the basis for a classification of mental states to determine the specific influence of certain binaural beats. To achieve this, the influence of all frequency bands, each covered by a single binaural beats sample, is analyzed for a corpus, containing data of multiple probands to try to achieve universally valid results. If this study or future studies can demonstrate noticeable influence, there would be a wide range of application.

The paper is structured as follows: Section II gives details about the binaural beats used in this study and how the EEG measurement was done. In section III classifiers are discussed. An analysis of the results is done in section IV. The last section draws conclusions and outlines possible future work.

II. Material & Methods

A. Probands

Five probands were performing the experiments in a quiet room which was illuminated by natural light. Probands were told to perform a counting task while their attention level was allegedly measured, in front of a laptop screen, where moving shapes in different colors could be seen. The actual

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[1]e.g.: http://www.binauralbeats.de/.

background of the experiment was not revealed. Probands were asked to count the number of red shapes displayed. The experiment software is our custom development and is publicly available [2]. During the experiment the proband listened to ambient music through phones without knowing that binaural beats will be played after a specific amount of time.

B. Binaural Beats

The experiment duration was 12 minutes and 40 seconds. At the beginning a 2 minute sample of ambient noise was played without binaural beats. This ambient noise sample was played during the whole time frame of the experiment. After 2 minutes, delta (0,1 - 4 Hz) binaural beats were played additionally. Followed by a 10 second pause, where only the ambient noise was played, then transitioning to theta (4 - 8 Hz) waves. This was repeated for alpha (8 - 13 Hz), beta (13 - 30 Hz) and gamma (> 30 Hz) binaural beats, each separated by a 10 second pause to avoid artifacts. To minimize the impact of artifacts in the data and to get a larger universe each proband had to do the experiment two times, with a break of 5 minutes in between. The binaural beat samples are publicly available[3].

C. EEG Measurement

To conduct the experiments, different EEG devices were used to investigate whether they cause performance differences. The devices that were used are NeuroSky Mindwave headset[4], Emotiv EPOC headset[5], as well as the medical EEG device Brain Products BrainAmp[6]. The two former are affordable, mobile consumer EEG devices and can be set up by naive users. The latter has to be set up by trained personnel. We measured raw data of the EEG activity at a 512 Hz sampling rate for the NeuroSky Mindwave headset, at a 128 Hz sampling rate for the Emotiv EPOC headset and at a 1024 Hz sampling rate for the BrainAmp EEG device. Positioning and the channel naming for the Emotiv EEG (green) & NeuroSky Mindwave (blue) sensors are depicted in figure 1.

We used the open-source software Weka [7] for our classification experiments to create reproducible results for the scientific community.

[2] https://github.com/lcsbdr/binaural_beat_classification
[3] http://jetcityorange.com/binaural-beats/
[4] http://store.neurosky.com/products/mindwave-1
[5] http://www.emotiv.com/epoc.php
[6] http://www.brainproducts.com/
[7] http://www.cs.waikato.ac.nz/ml/weka/

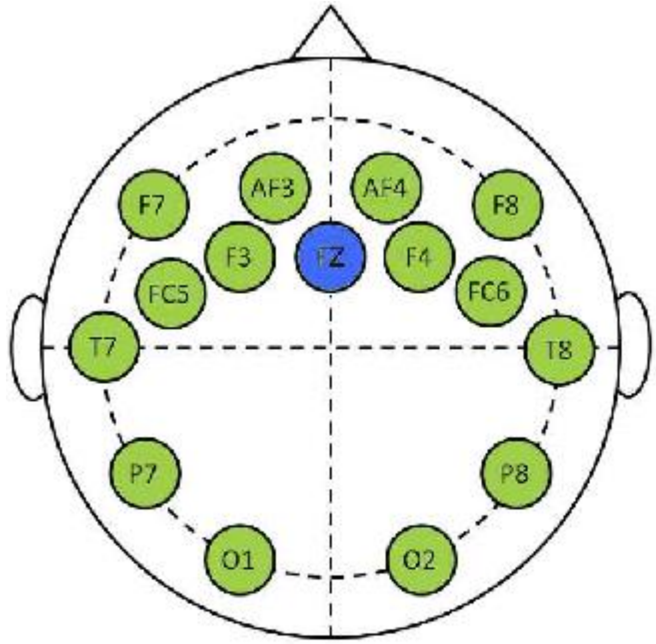

Figure 1. Overview of the sensor position and its respective naming.

D. The Corpus

The corpus for the Mindwave experiment consists of multiple datasets of altogether around 650,000 instances with 6 attributes (5 representing the frequency band data from delta to gamma and one representing the frequency class) in chronological order. The values are taken from raw data of a single electrode that are split up into the respective frequency band information based on fast fourier transformation.

III. Algorithms

The classification of our experimental data was carried out with 39 suitable classifiers from the Weka toolkit. We used classifiers from established categories including statistical-, function-, tree- and rule-based classification. The classifiers were used in default settings and with ten-fold cross-validation.

IV. Results

The results of the experiments averaged over all corpora are shown for the NeuroSky Mindwave and medical EEG in figure 2. The mean absolute error for the stratified results varied between 26% and 28% for the NeuroSky Mindwave. The best results were achieved by the standard classifier *NaiveBayes*, followed by tree- and rule-based classification techniques such as *RandomTree* or *Ridor*. The best result of all test sets was achieved by *NaiveBayes* with a mean absolute error of 26.1%.
The analysis of the BrainAmp medical EEG device resulted in a mean absolute error between 4.74% and 27.68%. The best results were achieved by the *Ridor* classifier considering the

best performing data set, whereas *FT* achieves a mean absolute error of 7.14% averaged over all data sets.

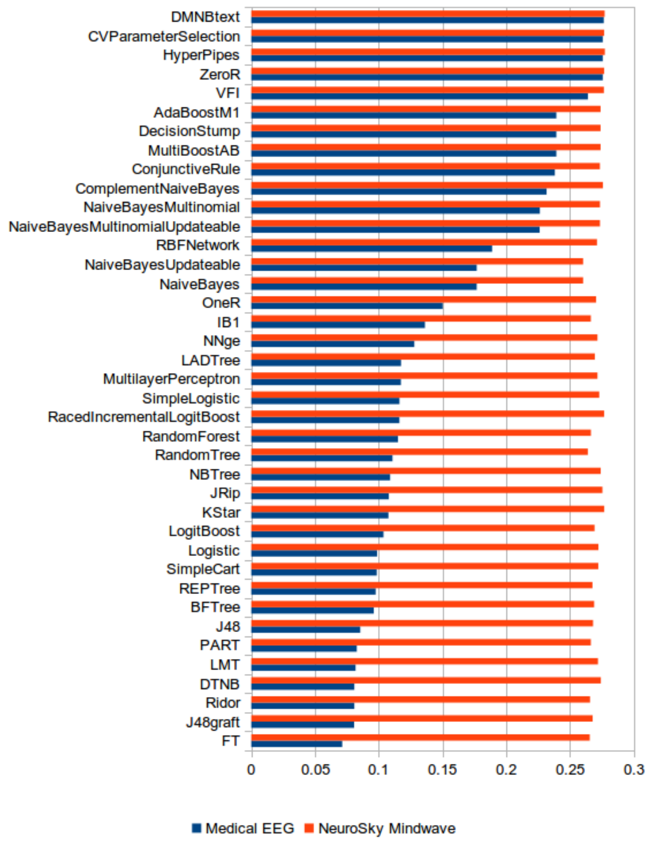

Figure 2. Performance of all classifiers with default settings.

Since the NeuroSky Mindwave EEG headset produces one-dimensional measures, the corpus is relatively sparse. NaiveBayes, which is the most tolerant tested classifier to both data sparseness and noise, was expected to perform better than others in this setup [10]. However, the differences are only marginal over all tested classifiers. The classification of data produced by the medical EEG has more dimensions and a higher frequency, and therefore was expected to provide better results. Indeed the best classification algorithm outperforms the Mindwave NaiveBayes classification by 19%, making it almost four times as efficient. Introductory experiments with the Emotiv EPOC headset were giving results in the range of the NeuroSky Mindwave headset, with few classifiers like IB1 [11] performing extraordinarily well, and even better than the best results of the medical EEG. Therefore, extensive research is needed for the Emotiv EPOC headset to determine whether it can provide the same results regularly.

V. Conclusion

We conducted extensive experiments using the medical EEG equipment, as well as the Mindwave EEG headset device. The results reveal that medical EEG equipment is likely to be suited to classify frequency bands according to influence of binaural beats. The Mindwave EEG headset device does not produce results precise enough to be considered for online classification applications. Further introductive experiments with the Emotiv EEG headset device hint that this device, combining mobility with relatively low classification error rates, might be suitable for such application scenarios.
This study shows that the single electrode of the NeuroSky Mindwave headset isn't sufficient to demonstrate whether EEG activity is influenced by binaural beats and to classify brain activity according to binaural beat influence. Using the more complex EEG devices the influence of different EEG frequencies, which have been detected by numerous researchers in the past (1970-1980), summarized in [12], could be verified.

Acknowledgment

The authors thank the lab at the University of Reading to use the BrainAmp medical EEG with the special permission of Yoshikatsu Hayashi, as well as all probands.

References

[1] M. Ermes, J. Parkka, J. Mantyjarvi and I. & Korhonen, "Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions.," Information Technology in Biomedicine, IEEE Transactions on,, vol. 1, no. 12, pp. 20-26, 2008.

[2] B. Brady and L. Stevens, "Binaural-beat induced theta EEG activity and hypnotic susceptibility," *American Journal of Clinical Hypnosis*, vol. 43, no. 1, pp. 53-69, 2000.

[3] R. O. Sornson, "Using binaural beats to enhance attention," *Hemi-Sync Journal*, vol. 17, no. 4, pp. 1-4, 1999.

[4] J. F. Lubar, M. O. Swartwood, J. N. Swartwood and P. H. O'Donnell, "Evaluation of the effectiveness of EEG neurofeedback training for ADHD in a clinical setting as measured by changes in TOVA scores, behavioral ratings, and WISC-R performance," *Biofeedback and Self-regulation*, vol. 20, no. 1, pp. 83-99, 1995.

[5] H. Wahbeh, C. Calabrese and H. Zwickey, "Binaural beat technology in humans: a pilot study to assess psychologic and physiologic effects," *The Journal of Alternative and Complementary Medicine*, vol. 13, no. 1, pp. 25-32, 2007.

[6] H. Pratt, A. Starr, H. J. Michalewski, A. Dimitrijevic, N. Bleich and N. Mittelman, "Cortical evoked potentials to an auditory illusion: Binaural beats," *Clinical neurophysiology*, vol. 120, no. 8, pp. 1514-1524, 2009.

[7] J. D. Lane, S. J. Kasian, J. E. Owens and G. R. Marsh, "Binaural auditory beats affect vigilance performance and mood," *Physiology & behavior*, vol. 63, no. 2, pp. 249-252, 1998.

[8] W. M. Herrmann, K. Fichte and G. Freund, "Reflections on the topics: EEG frequency bands and regulation of vigilance.," *Pharmacopsychiatry, 12(02), 237-245.*, pp. 237-245, 1979.

[9] R.-P. Le Scouarnec, R.-M. Poirier, J. E. Owens, J. Gauthier, A. Taylor and P. Foresman, "Use of binaural beat tapes for treatment of anxiety: a pilot study of tape preference and outcomes," *Alternative therapies in health and medicine*, vol. 7,

no. 1, pp. 58-63, 2001.

[10] S. B. Kotsiantis, I. Zaharakis and P. Pintelas, "Supervised machine learning: A review of classification techniques," 2007.

[11] D. W. Aha, D. Kibler, and M. K. Alber, "Instance-based learning algorithms," vol. 6, no. 1, pp. 37-66, 1991.

[12] F. H. Atwater, "Inducing altered states of consciousness with binaural beat technology," in *Proceedings of the English International Symposium on New Science*, 1997.