Real-time Mental State Recognition using a Wearable EEG

Robert Richer[1]*, Nan Zhao[2], Judith Amores[2], Bjoern M. Eskofier[1] and Joseph A. Paradiso[2]

Abstract— **The increasing quality and availability of low-cost EEG systems offer new possibilities for non-medical purposes. Existing openly available algorithms to assess the user's mental state in real-time have been mainly performed with medical-grade equipment. In this paper, an approach to assess the user's Focus or Relax states in real-time using a consumer-grade, wearable EEG headband is evaluated. One naive measure and four entropy-based measures, computed using relative frequency band powers in the EEG signal, were introduced. Classifiers for relax and focus state detection, based on the estimation of probability distributions, were developed and evaluated in a user study. Results showed that the *Tsallis* entropy-based measure performed best for the *Focus* score, whereas the *Renyi* measure performed best for the *Relax* score. Sensitivities of 82.0 % and 80.4 % with specificities of 82.8 % and 80.8 % were achieved for the *Focus* and *Relax* scores, respectively. The results demonstrated the possibilities of using a wearable EEG system for real-time mental state recognition.**

I. Introduction

Traditionally, the electroencephalogram (EEG) is a standard, noninvasive method in neuroscience and cognitive science for monitoring and analyzing the state of the brain, with applications for sleep and memory research, epilepsy monitoring, or attention deficit hyperactivity disorder (ADHD) [1]. Due to the increasing availability of EEG recording systems as low cost wearable devices, a new range of applications for non-therapeutic purposes have been developed. For instance, even though tethered EEG headbands have been used in gaming for over a decade, recent work uses wireless EEG devices for brain computer interfaces (BCIs) or biofeedback applications [2][3]. Moreover, these kind of tools could also be applied to implicitly control advanced context-aware applications, such as lighting systems or virtual reality environments that respond to the user's state of mind and learn over time which settings help the user to relax or focus.

As examples of context-aware applications, several research groups have applied EEG to increase road safety by assessing and quantifying drivers fatigue. For instance, Jap et al. used ratios of EEG spectral components to estimate drowsiness [4]. Additionally, other research groups proposed driver fatigue detection and quantification algorithms using entropy-based measures [5]. Steps beyond the assessment of drowsiness and fatigue are the recognition of different mental states based on EEG data [6], as well as the analysis of cognitive performance [7] or attention [8].

However, many of those experiments used visually evoked potentials that require a distinct visual stimulus in order to segment it from the regular EEG signal. Furthermore, they were conducted under controlled laboratory conditions and with clinical, obtrusive EEG systems. Because the understanding of complex cognitive procedures requires the context to be as realistic as possible [9], the existing solutions are not suitable for daily life use. Therefore, there is a need for a solution that is able to assess the user's mental state in real-time and in a regular, daily life environment.

Commercially available wearable EEG headsets like NeuroSky (NeuroSky Inc., San Jose, CA, USA) or Emotiv (Emotiv Inc., San Francisco, CA, USA) provide energy-based indicators for mental states, such as stress, excitement, and relaxation [10][11]. However, it is unclear how those indicators are computed, as the algorithms are not openly accessible. Furthermore, there is a lack of published studies evaluating these indicators and their proprietary algorithms.

For that reason, this work introduces and evaluates different approaches for mental state recognition by computing scores that quantify in real-time how focused or relaxed a person is using a simple EEG headband. The resulting scores can be used by context-aware systems that aim to increase productivity, calmness and wellbeing.

II. Methods

A. Data Acquisition

1) Sensor Hardware: EEG data were acquired using a Muse Headband (InteraXon Inc., Toronto, Canada)[1]. It is a commercially available and portable EEG system with four active electrodes (denoted as channels 1-4) and a common mode reference electrode, which also acts as driven right leg (see Fig. 1). The EEG consists of a variety of frequencies that are associated with different mental states and are traditionally divided into five frequency bands [12]. Table I shows the division used by the Muse headband with its corresponding frequency ranges and the associated mental states. The headband initially oversamples the EEG signal at a sampling rate of 12 kHz and subsequently downsamples it to 220 Hz. Further on-board processing computes relative frequency band powers as percentages of linear-scale band powers in each frequency band with an output rate of 10 Hz (see Table I).

*Responsible author

[1]R. Richer and B. M. Eskofier are with the Machine Learning and Data Analytics Lab, Department of Computer Science, Friedrich-Alexander-Universitt Erlangen-Nrnberg (FAU), 91058 Erlangen, Germany robert.richer@fau.de, bjoern.eskofier@fau.de

[2]N. Zhao and J. A. Paradiso are with the Responsive Environments Group, Judith Amores is with the Fluid Interfaces Group, MIT Media Lab, Cambridge, MA 02139, USA nanzhao@media.mit.edu, amores@media.mit.edu, joep@media.mit.edu

[1]http://www.choosemuse.com

Name	Freq. range	Mental state
θ (Theta)	4-8 Hz	Drowsiness, hypnagogia [13]
α (Alpha)	7.5-13 Hz	Quiet, resting, eyes closed [1]
β (Beta)	13-30 Hz	Attention focused to specific task [14]
γ (Gamma)	30-44 Hz	High level mental processing, binding of senses [14]

TABLE I: EEG frequency bands provided by Muse headband [15].

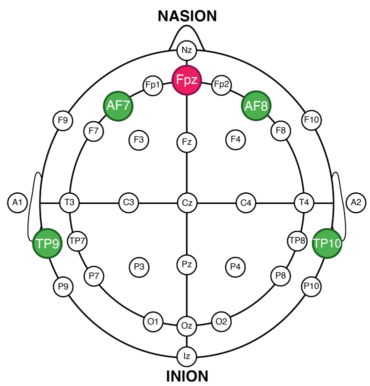

Fig. 1: Muse electrodes on 10-20 electrode positioning system with channel (green) and reference electrodes (red).

The acquired data were streamed to a computer running an instance of the *MuseIO* application included in the SDK. It handled the communication with the Muse headband via User Datagram Protocol (UDP) and passed EEG data to a Python client for further data processing.

2) Study Design: Eleven subjects aged 28.1 $\pm$ 4.6 years (M $\pm$ SD) participated in the data collection which was conducted in an office space. All subjects gave written consent about their participation in the study. During the procedure, the subjects wore the MUSE headband as proposed by the manufacturer.

Task	Duration	Category
Intro	3 min	Neutral
Mental Arithmetic	3 min	Focus
Pause (w/ nature scene)	3 min	Relax
Dictation	3 min	Focus
Pause (w/ nature scene)	3 min	Relax
Where's Waldo	3 min	Focus
Pause (w/ nature scene)	3 min	Relax
Outro	3 min	Neutral

TABLE II: Study protocol for EEG data acquisition.

The study procedure (as listed in Table II) consisted of multiple tasks. Each of them were associated with one of three possible categories, corresponding to different mental states: *Neutral*, *Focus*, *Relax*. The *Neutral* phases were used as reference measurements with no specific instructions given, except not to close their eyes. During the *Focus* phases the subjects were asked to perform different tasks that were all supposed to generate high levels of mental processing and binding different senses [16]. During the *Relax* phases, subjects were asked to relax themselves. Additionally, they chose between different nature scenes to be displayed on a laptop computer, such as beach, forest or mountain, which had been proven to have a positive effect on achieving a relaxed mental state [17].

B. Data Processing

In the first step, live data received from the *MuseIO* application were preprocessed. Subsequently, different approaches of of computing Focus and Relax scores were performed: One *naive* as well as four *entropy*-based approaches.

1) Preprocessing: Only relative band power samples of channels 1 and 4 (see Figure 1) were considered and dropped if the signal quality indicator (one integer value per channel, provided by the headband) was not sufficient. Histograms were created for each frequency band and each channel, respectively. They were updated with each valid sample being added using the *P^2Algorithm* [18], which allows a dynamic calculation of percentiles and histograms without having to store all observations. Samples falling between the 10th and the 90th percentiles of the histogram were normalized between 0 and 1, whereas other values were considered as outliers and therefore rejected. Subsequent computations were performed on the mean value of the last 10 samples (further denoted as *processed samples*).

2) Naive score computation: The naive approach for the computation of Focus and Relax scores was purely based on the relative alpha and gamma band powers of the recorded EEG data. Therefore, the *Naive Relax* and *Naive Focus* scores were derived from the alpha and gamma band by averaging the *processed samples*, respectively. A 20-point-moving-average low-pass filter was applied to the output values to filter out short-time mental state fluctuations.

3) Entropy-based score computation: In general, entropy serves as a measure for randomness or uncertainty of an information source and is very effective in detecting non-stationary events like peaks and bursts [19]. Hence, in this probabilistic concept the EEG signal was considered as the result of a random process. *Processed samples* for each channel were interpreted as random variables $x_i, i \in \{\theta, \alpha, \beta, \gamma\}$ emitted by an information source, satisfying the conditions $p_i \geq 0$ and $\sum_i p_i = 1$.

An EEG signal with relatively equal band power distribution has a high degree of randomness and thus exhibits a high entropy. In comparison, an EEG signal with high relative band power in one specific frequency band indicates a decrease of randomness and results in lower entropy [5]. Leveraging this, *Relax* scores were computed using *processed samples* from alpha and theta frequency bands, whereas gamma and beta band samples were used for the *Focus* score, respectively. In this work, four different entropy measures were used which have been applied to EEG signals by previous work [5]:

- *Shannon entropy* H_{Sh}:

$$H_{Sh} = -\sum_i p_i \cdot log_2(p_i). \tag{1}$$

- *Rényi entropy* H_{Re} of order α ($\alpha \geq 0$ and $\alpha \neq 1$), a generalization of the Shannon entropy:

$$H_{Re} = \frac{1}{1-\alpha} \cdot log_2 \left(\sum_i p_i^{\alpha} \right). \tag{2}$$

- *Tsallis entropy* H_{Ts}, a non-logarithmic parameterized entropy measure:

$$H_{Ts} = \frac{1}{\alpha - 1} \cdot \sum_i (p_i - p_i^{\alpha}). \tag{3}$$

- *Kullback-Leibler divergence* D_{KL}, a measure of the difference between two probability density functions p and q [20]:

$$D_{KL}(p||q) = \sum_i p(i) \cdot log \frac{p(i)}{q(i)}, \tag{4}$$

For H_{Re} and H_{Ts} entropies of order $\alpha = 3$ were used because they have shown to work well on EEG signals with short-range rhythms [5]. For D_{KL}, p and q refer to the *processed samples* of alpha and theta bands for the Relax score and to the *processed samples* of gamma and beta bands for the Focus score, respectively. The computed entropy measures were normalized between 0 and 1 (denoted as H_{norm}) and subtracted from 1 as an increase in being focused or relaxed yields to an decrease of entropy and vice versa. Finally, a 20-point-moving-average low-pass filter was applied to filter out short-time mental state fluctuations.

III. Evaluation

Every data sample was labeled with the associated task during which it was recorded (*Neutral*, *Focus*, *Relax*). Classification was performed by estimating the probability distributions of each score and measure. Therefore, histograms were updated in real-time for each measure and score, respectively, using the P^2*-Algorithm*. Subsequently, a binary classification for both scores was applied using a quantile-based threshold. As this method only relied on live data of the subject itself and hence did not require a previously trained classification model, a separation into training and test sets was not necessary and thus, no cross-validation had to be performed.

Receiver Operating Characteristic (ROC) curves were generated for every measure by computing sensitivity and specificity for quantiles in the interval $[0.05, 0.95]$ with a step size of 0.05. Optimal quantiles for each measure were obtained by selecting the quantile value on the ROC curve with the smallest L_2 norm to the optimal classifier (1.0 True Positive Rate and 0.0 False Positive Rate).

IV. Results

Focus and *Relax* scores recorded for one subject while performing the study protocol are visualized in Figure 2. The ROC curves for the different measures of *Focus* and *Relax* scores are shown with their corresponding AUC values in Figure 3. Results yield that the *Tsallis*-based measure performed best for the *Focus* score, whereas the *Renyi*-based measure performed best for the *Relax* score. The optimal quantiles of each measure with their respective sensitivity and specificity are listed in Table III. It shows that the *Tsallis* measure offers the highest sensitivity, whereas the *Renyi* measure achieved the highest specificity. Results also indicate that 0.65 is the best performing quantile for the *Focus* score, compared to 0.55 for the *Relax* score.

Measure	Focus score			Relax score		
	Q	Sen	Spec	Q	Sen	Spec
Naive	0.55	67.7 %	67.5 %	0.50	75.4 %	74.4 %
Shannon	0.55	69.8 %	71.3 %	0.50	70.7 %	70.9 %
Renyi	0.65	79.8 %	**82.8 %**	0.55	79.3 %	**80.8 %**
Tsallis	0.65	**82.0 %**	78.9 %	0.55	**80.4 %**	79.6 %
KL	0.50	55.3 %	60.0 %	0.50	59.1 %	55.4 %

TABLE III: Performance evaluation for each measure. Q = Quantile, Sen = Sensitivity, Spec = Specificity. The highest values are highlighted.

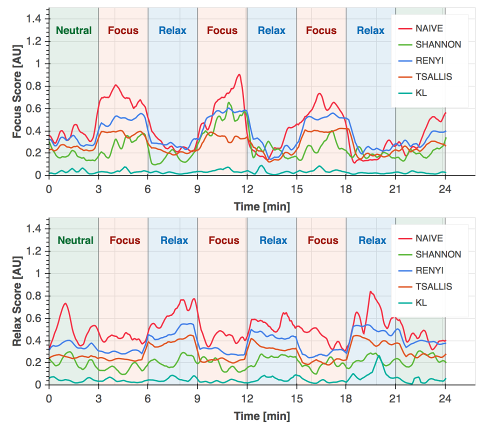

Fig. 2: Course of *Focus* (top) and *Relax* (bottom) score measures for a typical subject during the study.

V. Discussion

For the entropy-based measures, input from two adjacent EEG frequency bands (α and θ for *Relax*, γ and β for *Focus*) were used, whereas the *Naive* measure only used data from α and γ bands, respectively. Because the association of certain tasks or mental states with EEG frequency bands are only considered as guidelines and thus might not completely coincide for every person [12], using information from two adjacent frequency bands might increase the classification performance. Accordingly, entropy-based approaches for EEG analysis had proven to achieve better results than solely using frequency band power or band power ratios [1]. Therefore, results of this work showed that both *Tsallis* and *Renyi* measures outperform the *Naive* approach and work reliably even for low cost consumer EEG devices. Accordingly, previous work had shown that they are more effective in characterizing the complexity of the brain [19]

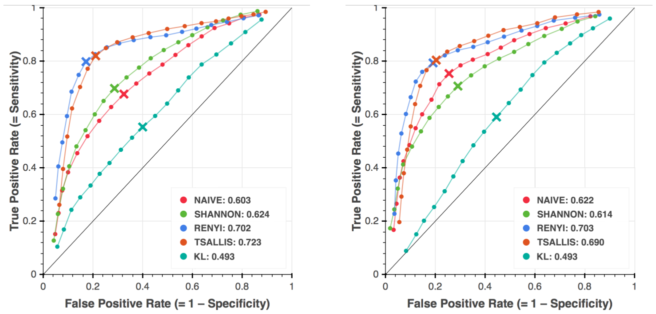

Fig. 3: ROC curves for *Focus* (left) and *Relax* (right) score measures and their corresponding Area Under The Curve (AUC) values. The best performing quantiles are denoted.

than *Shannon* entropy, because H_{Re} and H_{Ts} can be adapted to emphasize either background activity or bursts in EEG frequency bands using the entropic index α.

The *Neutral* phase at the beginning of every recording was required to provide an initial histogram estimation for the measures. This allowed mental state classification to be performed without using any training data acquired beforehand. Results of the study built on the assumption of equal prior probabilities for both *Focus* and *Relax* phases as the durations were the same. When applying this method to other scenarios exhibiting a non-equal class distribution, the histogram would be skewed and the study design should therefore be adapted to for a better histogram estimation.

Because subjects were confronted with concrete, sense-binding *Focus* tasks, they reported that they felt more focused than they felt relaxed during the *Relax* phases, where only a nature video was presented to them. Therefore, the AUC values indicate that the proposed measures perform better for the *Focus* score than for the *Relax* score. Furthermore, Figure 2 yields that measures achieved higher amplitudes and more distinct peaks during *Focus* tasks then they did for *Relax* tasks, also leading to higher quantile thresholds for the *Focus* score (as denoted in Table III).

VI. Conclusion & Outlook

This work presented different measures for real-time focus and relax recognition using a wearable EEG system and proved the possibility of applying this system for brain-computer-interfaces or to control context-aware applications.

A data-driven approach was used by estimating the probability distribution for each person and updating it in real-time. Classification was then performed using quantiles of the estimated histogram as threshold. A *Naive* approach was compared to different entropy-based approaches, showing that the measures using *Renyi* and *Tsallis* entropy performed better than the *Naive* measure. By finding a trade-off between sensitivity and specificity, the best quantile-based thresholds were determined for the *Focus* and *Relax* scores.

Therefore, results show that a mental state recognition can be performed in real-time and without building a classification model using previously recorded training data. However, future work still has deal with the improvement of the classification performance, for instance by combining results of two different score measures.

Acknowledgements

We are grateful to all subjects that participated in the study. This work was supported by a fellowship within the FITweltweit program of the German Academic Exchange Service (DAAD). Bjoern M. Eskofier gratefully acknowledges the support of the German Research Foundation (DFG) within the framework of the Heisenberg professorship programme (grant number ES 434/8-1).

References

[1] N. Thakor and D. Sherman, *EEG signal processing: Theory and applications*. Springer US, 1 2013, pp. 259–303.

[2] J. Amores, X. Benavides, and P. Maes, “PsychicVR: Increasing mindfulness by using Virtual Reality and Brain Computer Interfaces,” in *2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. ACM, 2016, pp. 2–2.

[3] P. Bashivan, I. Rish, and S. Heisig, “Mental State Recognition via Wearable EEG,” *arXiv preprint arXiv*, 2016.

[4] B. T. Jap, S. Lal *et al.*, “Using EEG spectral components to assess algorithms for detecting fatigue,” *Expert Syst Appl*, vol. 36, no. 2, pp. 2352–2359, 2009.

[5] S. Kar, M. Bhagat, and A. Routray, “EEG signal analysis for the assessment and quantification of driver`s fatigue,” *Transp Res Part F Traffic Psychol Behav*, vol. 13, no. 5, pp. 297–306, 2010.

[6] K.-R. Müller, M. Tangermann *et al.*, “Machine learning for real-time single-trial EEG-analysis: from brain–computer interfacing to mental state monitoring,” *J. Neurosci. Methods*, vol. 167, no. 1, pp. 82–90, 2008.

[7] W. Klimesch, “EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis,” *Brain Res Rev*, vol. 29, no. 2, pp. 169–195, 1999.

[8] S. P. Kelly, E. C. Lalor *et al.*, “Visual spatial attention control in an independent brain-computer interface,” *IEEE Trans Biomed Eng*, vol. 52, no. 9, pp. 1588–1596, 2005.

[9] U. Hasson and C. J. Honey, “Future trends in Neuroimaging: Neural processes as expressed within real-life contexts,” *NeuroImage*, vol. 62, no. 2, pp. 1272–1278, 2012.

[10] Emotiv, “Software for Wireless EEG Systems - Emotiv,” https://www.emotiv.com/software, 2017, accessed 2017-09-28.

[11] NeuroSky, “EEG Sensors - EEG Headsets - NeuroSky,” http://neurosky.com/biosensors/eeg-sensor/biosensors, 2017, accessed 2017-10-10.

[12] J. Clark, “The origin of biopotentials,” *Medical Instr, Appl and Design, 3rd ed., John Wiley and Sons Inc., New York*, pp. 121–182, 1998.

[13] D. L. Schacter, “EEG theta waves and psychological phenomena: a review and analysis,” *Biol Psychol*, vol. 5, no. 1, pp. 47–82, 1977.

[14] G. Buzsaki, *Rhythms of the Brain*. Oxford University Press, 2006.

[15] InteraXon, “Muse Research Tools,” http://developer.choosemuse.com, 2017, accessed 2017-09-30.

[16] T. Fernández, T. Harmony *et al.*, “EEG activation patterns during the performance of tasks involving different components of mental calculation,” *Electroencephalogr Clin Neurophysiol*, vol. 94, no. 3, pp. 175–182, 1995.

[17] R. S. Ulrich, “Natural versus urban scenes – some psychophysiological effects,” *Environ Behav*, vol. 13, no. 5, pp. 523–556, 1981.

[18] R. Jain and I. Chlamtac, “The P^2 Algorithm for Dynamic Calculation of Quantiles and Histograms without storing Observations,” *Communications of the ACM*, vol. 28, no. 10, pp. 1076–1085, 1985.

[19] S. Tong, A. Bezerianos *et al.*, “Parameterized entropy analysis of EEG following hypoxic–ischemic brain injury,” *Phys Lett A*, vol. 314, no. 5, pp. 354–361, 2003.

[20] S. Kullback and R. A. Leibler, “On information and sufficiency,” *Ann. Math. Stat.*, vol. 22, no. 1, pp. 79–86, 1951.