Real-time Mental State Recognition using a Wearable EEG

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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 [1] 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 [1]).

\begin{table}
\centering
\begin{tabular}{|c|c|c|}
\hline
Frequency Band & Associated Mental States & Corresponding Frequency Range [Hz] \\
\hline
\hline
\end{tabular}
\end{table}

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\url{http://www.choosemuse.com}
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 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 P²Algorithm [18], which allows a dynamic calculation of percentiles and histograms without having to store all observations. Samples falling below 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]:

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

<table>
<thead>
<tr>
<th>Name</th>
<th>Freq. range</th>
<th>Mental state</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$ (Theta)</td>
<td>4-8 Hz</td>
<td>Drowsiness, hypnagogia [13]</td>
</tr>
<tr>
<td>$\alpha$ (Alpha)</td>
<td>7.5-13 Hz</td>
<td>Quiet, resting, eyes closed [1]</td>
</tr>
<tr>
<td>$\beta$ (Beta)</td>
<td>13-30 Hz</td>
<td>Attention focused to specific task [14]</td>
</tr>
<tr>
<td>$\gamma$ (Gamma)</td>
<td>30-44 Hz</td>
<td>High level mental processing, binding of senses [14]</td>
</tr>
</tbody>
</table>

### Table II: Study protocol for EEG data acquisition.

<table>
<thead>
<tr>
<th>Task</th>
<th>Duration</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intro</td>
<td>3 min</td>
<td>Neutral</td>
</tr>
<tr>
<td>Mental Arithmetic</td>
<td>3 min</td>
<td>Focus</td>
</tr>
<tr>
<td>Pause (w/ nature scene)</td>
<td>3 min</td>
<td>Relax</td>
</tr>
<tr>
<td>Dictation</td>
<td>3 min</td>
<td>Focus</td>
</tr>
<tr>
<td>Pause (w/ nature scene)</td>
<td>3 min</td>
<td>Relax</td>
</tr>
<tr>
<td>Where’s Waldo</td>
<td>3 min</td>
<td>Focus</td>
</tr>
<tr>
<td>Pause (w/ nature scene)</td>
<td>3 min</td>
<td>Relax</td>
</tr>
<tr>
<td>Outro</td>
<td>3 min</td>
<td>Neutral</td>
</tr>
</tbody>
</table>

Fig. 1: Muse electrodes on 10-20 electrode positioning system with channel (green) and reference electrodes (red).
- Shannon entropy $H_{Sh}$:
  \[ H_{Sh} = -\sum_i p_i \cdot \log_2(p_i). \]  
- Rényi entropy $H_{Re}$ of order $\alpha$ ($\alpha \geq 0$ and $\alpha \neq 1$), a generalization of the Shannon entropy:
  \[ H_{Re} = \frac{1}{1-\alpha} \cdot \log_2 \left( \sum_i p_i^\alpha \right). \]
- Tsallis entropy $H_{Ts}$, a non-logarithmic parameterized entropy measure:
  \[ H_{Ts} = \frac{1}{\alpha-1} \sum_i (p_i - p_i^\alpha). \]
- Kullback-Leibler divergence $D_{KL}$, a measure of the difference between two probability density functions $p$ and $q$ [20]:
  \[ D_{KL}(p||q) = \sum_i p(i) \cdot \log \frac{p(i)}{q(i)}. \]

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 a 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 Rényi-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 Rényi 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.

### V. Discussion

For the entropy-based measures, input from two adjacent EEG frequency bands ($\alpha$ and $\theta$ for Relax, $\gamma$ and $\beta$ for Focus) were used, whereas the Naive measure only used data from $\alpha$ and $\gamma$ 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 Rényi 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].

### Table III: Performance evaluation for each measure.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Focus score</th>
<th>Relax score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q</td>
<td>Sen</td>
</tr>
<tr>
<td>Naive</td>
<td>0.55</td>
<td>67.7 %</td>
</tr>
<tr>
<td>Shannon</td>
<td>0.55</td>
<td>69.8 %</td>
</tr>
<tr>
<td>Rényi</td>
<td>0.65</td>
<td>79.8 %</td>
</tr>
<tr>
<td>Tsallis</td>
<td>0.65</td>
<td>82.0 %</td>
</tr>
<tr>
<td>KL</td>
<td>0.50</td>
<td>55.3 %</td>
</tr>
</tbody>
</table>

- $Q = $ Quantile, $Sen = $ Sensitivity, $Spec = $ Specificity. The highest values are highlighted.
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 $\alpha$.

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 than they did for Relax tasks, also leading to higher quantile thresholds for the Focus score (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.

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