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INVESTIGATING WRITTEN TEXT READABILITY FOR PASSIVE BCI BASED NEUROADAPTIVE SPEED READING APPLICATIONS

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ABSTRACT: Rapid serial visual presentation (RSVP) can prove useful as a reading technique when text is presented on small screens. Optimal text presentation speed for text reading depends on the reader himself, context and features of the text. Readability is a measure which estimates the ease with which a reader can understand a written meaningful text.

The presented study investigated whether a passive Brain-Computer Interface (pBCI) can be used to distinguish between texts of distinct levels of readability presented at different presentation speeds. A predictive model was trained on EEG data derived from a cognitive load paradigm. The model was then applied to data collected while participants read easy and difficult texts at a self-adjusted speed and at an increased speed level.

Results suggest that predictions made by the predictive model could be used as an estimate for categorization and adaptation of longer text passages, though its robustness and potential for the use in neuroadaptive reading applications should be further investigated.

INTRODUCTION

Reading is the written form of a language and serves communication and information sharing in societies. Textual information nowadays is distributed as digital media presentations on electronic displays (e.g., monitors, mobile phones, eReaders, etc.) and is accessible in a broad and fast way through advanced communication technology. With decrease in size of mobile devices, smaller screen sizes are a consequence and constitute challenges for the way text material can be presented. Scrolling and paging in text presentation can be bothersome and inconvenient for the reader [1]. Hence new forms of text presentation for mobile devices recently have emerged and are developed.

Rapid serial visual presentation (RSVP) is a popular approach to build a text presentation method appropriate for reading on (very) small displays. In this presentation form, words of a text are presented sequentially one word at a time at a fixed screen location [2]. It was claimed that in contrast to traditional left to right text body reading, texts can be read faster at constant comprehension levels [3]. It is suggested that a reduction of saccades, small and rapid eye movements to fixate the next word, due to a constant fixation point while reading, leads to an increase of overall reading speed in RSVP reading methods [4]. Over the past years claims like these have been subjected to several studies examining RSVP reading effects on text comprehension and reading speed [5, 6]. It emerged that reading comprehension and efficiency depend on nuanced features of the textual information to be read, such as text difficulty, length, and reading speed. Readability is a measure of the ease with which the meaning of a text can be comprehended. Readability ratings traditionally are obtained using readability formulas such as Flesch-Kincaid Grade Level [7] or the Flesch Reading Ease [8]. Most readability formulas are based on a combination of easily countable features such as word length and sentence length.

Recently commercial speed reading applications were made available for RSVP reading on electronic devices. Reading speed in these applications is regulated manually and stays static if the user does not alter it throughout the reading process. Here a less intrusive form of presentation speed regulation would prove useful, especially if features of the read text material, e.g., text readability, differ over time. Then the cognitive load of the reader might change according to different levels of text difficulty.

Passive Brain-Computer Interfaces [pBCIs, 9] are a technology which uses neurophysiological signals to distinguish between different cognitive states [10]. Data recorded by Electroencephalography (EEG) while different cognitive states are evoked in a person, can be used to train a BCI to distinguish between these different

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states and evaluate new data when it is recorded. This evaluation of a BCI then can be used to generate a signal to change the state of a system. In the process the user does not need to actively generate a signal towards the machine, but her cognitive state is monitored and interpreted continuously. A reader would not be required to pay attention and conscious effort to generate a signal to change e.g. the reading speed appropriate to her current state. Such an automatic adaptation to a user's current cognitive state through the application of a pBCI would be a realization of neuroadaptive technology [11]. This technology enhances the interaction between user and machine as it provides knowledge about the situational user state to the machine. A neuroadaptive reading application could make the reading process more pleasant and efficient. Additionally, the generated information about the user state could be used to generate an assessment of the user's individual text difficulty levels and readability skills. Such a measure detecting the relation between the user's current level of cognitive load and a text of a given level of difficulty could be useful in learning contexts to generate personalized learning content. Here, the pBCI could be utilized to find appropriate learning material which can be optimized to fit the learner's current needs and abilities.
The aim of the presented work was to examine whether a pBCI can be trained to distinguish between different levels of text difficulty while reading with a speed reading application. Moreover, the effects of reading speed on this measure were investigated. As connections to other words become more complex with the position of a word within a sentence, it was also investigated whether this relationship is reflected in the output from the pBCI. Moreover, long sentences should be more difficult to understand than short ones as they are more complex in structure and relations between words. Therefore, is was also investigated whether the average output of the pBCI shows a difference between short and long sentences. The outcomes were interpreted according to their applicability in neuroadaptive technologies.

MATERALS AND METHODS

Participants: Eight participants, five female, took part in the experiment. The mean age was 29 years (*SD* = 3.2 years). All participants had normal or corrected-to-normal vision and their native language was German. Prior to the experiment participants gave their written informed consent to participate in the study and were paid thirty euros as expense allowance.

Speed Reading Application: The speed reading application applied in this study was Spritz. The Spritz Application programming interface (API) was provided by Spritz™ (spritzinc.com/) for the use in this study. Together with Psychophysics Toolbox extensions [12] the experimental paradigm was computed in MATLAB.

Stimuli: Texts used in the investigation were extracted from the GEO/GEOlino Corpus [13]. The corpus is a collection of 1066 German texts taken from the German magazine GEO, which covers topics related to nature, culture and science, and the magazine GEOlino, which deals with similar topics, but is targeted at children aged between 8 and 14 years. The texts from GEO therefore are generally more complex than those from the GEOlino magazine. Six texts were chosen from each magazine, all covering similar topics about animals and their habits. Overall the average number of words per text was 493 (*SD* = 34.6 words). GEO texts had an average word count of 472 words (*SD* = 23.1 words) and GEOlino texts of 514 words (*SD* = 31.7 words). GEO texts had an average Flesch reading ease index of 45.1 (*SD* = 2.4), which is equivalent to difficult texts on college level. The Flesch-Kincaid grade level of GEO texts was 10.9 (*SD* = .29). For GEOlino texts, the average Flesch reading ease index was 62 (*SD* = 1.38) which corresponds to a readability suitable for 13 to 15 years old students. These texts had an average Flesch-Kincaid grade level of 7.9 (*SD* = .24).

EEG system and software: During the experiment brain activity was recorded from 64 active Ag/AgCl electrodes (ActiCap, Brain Products, Munich, Germany) applied to an elastic cap according to the extended international 10/20 positioning system. The ground electrode was placed at position AFz and the reference at FCz. All electrodes were connected to a BrainAmp amplifier (Brain Products GmbH, Munich, Germany), which was connected to a laptop through a universal serial bus (USB) 2.0. Electrode impedances were kept below 5 kΩ. Data was recorded using the BrainVision Recorder, BrainVision RDA (Brain Products GmbH, Munich, Germany) and LabRecorder [14]. The sampling rate was set to 500 Hz. The experimental paradigms were run in SNAP [15] and in MATLAB, using the Psychophysics Toolbox extensions. Data was analyzed with the MATLAB embedded EEGLAB toolbox [16]. For classification and BCI model application the open source toolbox BCILAB [17] was used.

Pre-test: Six participants took part in a pre-test to examine whether an increase of 40 percent in text presentation speed would lead to an increase of perceived workload. The participants' mean age was 27.2 years (*SD* = 3.8 years), five were male, all had normal or corrected-to-normal vision and their native language was German. Participants read the twelve texts in blocks of three at a self-adjusted reading speed with the speed reading application. Half of the texts from each difficulty class (easy vs. difficult) were presented at a self-adjusted speed plus 40 percent. After each block, participants filled out a Raw-Task Load Index (RTLX) [18], a modified version of NASA-TLX [19], a standardized questionnaire assessing perceived workload on a Likert scale along six dimensions. A two-way repeated measures ANOVA revealed a significant main effect of presentation speed, F (1,5) = 6.758, p = .048. Workload of texts presented in normal speed was rated lower (M = 45.7, SD = 16.9) than for texts represented with 40 percent increase in speed (M = 53.58, SD = 17.1). There was no significant main effect of text difficulty, F (1,5) = 1.371, p = .294. The interaction of the factors was also not significant, F (1,5) = 0.255, p = 0.635. From these results, it was concluded that an increase of individual reading speed by 40 percent

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was sufficient to increase the subjective workload for participants while reading the texts later used in the main study.

Experimental procedure: In the main experiment, participants first completed an experimental paradigm, which was applied to induce two different levels of cognitive load [20]. This so-called ‘sparkles’ paradigm was developed by Team PhyPA (TU Berlin) [21]. In several experiments the classifier trained on the data obtained from this paradigm was tested while participants completed not only arithmetic assignments, as during data collection, but tasks from other task domains. It was used, e.g., while the participant verbally described a complex context or solved anagrams, where the classifier could reliably distinguish between phases of high and low workload. Due to its applicability to multiple domains the classifier can be seen as a form of task-independent classifier for cognitive load.

During half of the paradigm the participant saw colorful spots moving around slowly on an otherwise black screen. In this phase, the participant was supposed to relax and simply focus on watching the spots flying around with eyes open. This part of the paradigm was supposed to induce low workload. To induce higher workload, from time to time an arithmetic subtraction assignment appeared at the center of the screen. At its appearance the participant was supposed to silently subtract the number standing on the right side (range between 6 and 20) iteratively from the number on the left (range between 200 and 1200). After some time, the arithmetic assignment disappeared again, whereat the participant stopped subtracting and turned towards watching the spots again. Overall 40 trials of low or high induced workload were performed with a length of 10 seconds per trial.

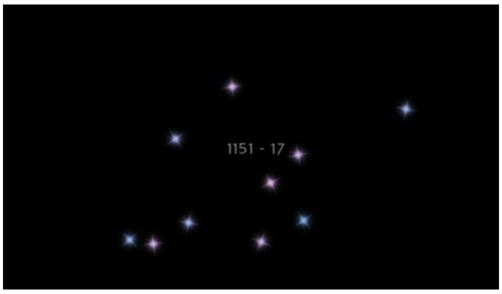

Figure 1: Screenshot of the workload (‘sparkles’) paradigm. The arithmetic assignment is presented in the center of the screen. Colorful dots are moving around the black background at a slow pace.

After completion of the workload paradigm participants familiarized with the speed-reading application. They read passages of a German novel and incrementally adjusted the presentation speed to a level they felt comfortable reading with.

Then participants read all twelve texts in blocks of three. All texts of a block were either easy or difficult texts and presented in the self-adjusted reading speed or with an increase of 40 percent (as determined in the pre-study). After each text, participants answered three questions regarding literal text comprehension. Under each question four possible answers were displayed, of which one was the right choice. If, e.g., the text had read ‘The warm sun hatches the eggs in the sand’, the question could have been: ‘Who hatches the eggs of the turtle?’, then of the possible answers a) the father, b) a cormorant c) the sun and d) the mother, c) would have been the right choice. Participants selected their answer by key press. Each participant answered 3x12 literal comprehension questions, a total of 36 questions.

After each of the four text blocks participants were handed a RTLX questionnaire to assess subjective ratings of perceived workload. Overall each participant completed the RTLX four times.

Analyses: Individually adjusted presentation rates were averaged over participants from the pre- and main study. Ratings collected in the RTLX questionnaire were converted to workload scores according to NASA-TLX procedures. The workload scores of all eight participants were subjected to a two-way repeated measures ANOVA with the within-subject factors presentation speed (normal vs. plus 40 percent) and text difficulty (easy vs. difficult). The numbers of correct answers to literal text comprehension questions of each participant within each of the four text blocks were added. These scores per block then were subjected to a two-way repeated measures ANOVA with within-subject factors presentation speed (normal vs. plus 40 percent) and text difficulty (easy vs. normal).

Due to a recording software problem, only data from seven of the eight participants was used for classification. For feature extraction, a filter bank common spatial patterns (fbCSPs) approach [22] was used. Two frequency band (4-7, expected increase with increasing workload and 7-13, expected decrease with increasing workload) Hz was selected and epochs of 5 seconds length starting at stimulus were extracted. Linear discriminant analysis (LDA) regularized by shrinkage [23] was used as a classifier and a (5x5)-fold cross-validation was employed.

For each participant, the individual predictive model trained on data from the workload paradigm was applied to text reading data. The BCILAB built-in function onl-simulate was used to apply the predictive model to the raw data from all twelve texts, resulting in a predictive value between 0 and 1 for each word of a text. An output with a value of 0 would indicate low load and a value of 1 high load.

Predicted values from each predictive model were subjected to permutation tests with 50000 permutations per test. All predictions from one group of texts according to text difficulty (easy vs. difficult) and presentation speed (normal vs. fast) were tested within and between the two factors. Tests were one-tailed as the assumptions were that easy texts should result in lower predictive values than difficult texts. Also within one text difficulty category, predictions of texts presented at normal speed were expected be lower than predictions of texts presented at an increased speed. Easy texts

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presented at normal speed were assumed to have lower predictive values than difficult text which were presented fast. Finally, for predictions in easy texts which were presented fast against predictions from difficult texts presented at normal speed, no assumption regarding difficulty was made.
It was further assumed that longer sentences would have an overall higher difficulty as word relations within a longer sentence regularly become more complex in structure than in short sentences. To test if this assumption was manifested in the predictions made by the applied predictive models, predictions within each sentence were averaged. The averaged predictive values alongside with the word count of the respective sentences were subjected to linear regression analysis. Regression analysis was performed once for all sentences of easy texts presented in normal speed and again for sentences from difficult texts presented at normal speed. Moreover, it was performed for all participants together and again for each individual participant.
Another assumption was that predictive values could reflect an increase of complexity of relations towards a word caused by an increase of the word's position within a sentence. To test this assumption words and their predicted values were sorted by their position within sentences. All predictive values for the occurred sentence positions were subjected to a linear regression analysis. Again, the analysis was only performed for easy and difficult texts presented at normal presentation speed, for each participant and also for data from all subjects together.

RESULTS

Individually adjusted presentation rates from the overall 13 participants of the pre-test and the main experiment ranged between 175 and 600 words per minute (wpm). The average adjusted reading speed was 308 wpm (*SD* = 130 wpm).
The two-way repeated measures ANOVA performed on ratings from the RTLX questionnaire from the eight participants revealed significance for the main factor text difficulty, $F\,(1,7) = 8.75$, $p = .021$. Difficult texts (M = 68.4, SD = 26.2) received higher ratings than easy texts (M = 59.1, SD = 18.4). Results for the main factor presentation speed were significant as well, $F\,(1,7)$ = 11.10, $p = .012$. Texts presented at the normal (M = 56.4, SD = 17.3) self-adjusted reading speed received lower RTLX ratings than texts presented with a speed increase of 40 percent (M = 71.1, SD = 25.7). The interaction effect was not significant, $F\,(1,7) = 1.22$, $p = .306$.
The ANOVA performed on correct answers given to literal text comprehension questions revealed neither significant main effects, nor an interaction effect of significance, all $ps > .258$. On average participants answered 6.2 (SD = .48) questions out of nine per text block correctly. An average of 6.9 (SD = 1.96) correct answers was given for easy texts and 6.0 (SD = 1.31) for difficult texts presented at normal speed. For texts blocks with an increased presentation speed, questions on easy texts were answered 5.8 (SD = 1.28) times correctly and difficult texts 6.25 (SD = 1.67) times.
The average cross validation error rate was 23.7 percent (SD = 6.7 percent). See Table 1 for individual classification errors.

Table 1: Classification results of the workload paradigm. Obtained error rates (*ER*) in percent and standard deviations (*SD*) are reported.

participant	*ER* (*SD*)
1	14.1 (3.2)
2	28.5 (14.7)
3	14.8 (4.9)
4	14.5 (2.5)
5	44.3 (7.8)
6	18.9 (4.1)
8	8.3 (1.5)
average	**20.5 (5.5)**

Almost all performed permutation tests were highly significant (all $ps < .0001$). Only for the test of predictions in easy texts which were presented fast against predictions from difficult texts presented at normal speed, results were not significant ($p = .961$). It must be noted though that absolute values of observed differences between classes (M = -.077, SD = .032) were smaller in all tests than variances within classes (M = .086, SD = .008). Effect sizes therefore were small to medium (M = .266, SD = .116).
For linear regressions, no significant equations were found for average word predictions in sentences with different length. Analysis results were neither significant for data from all participants taken together (all $ps > .632$) nor on subject level (all $ps > .072$).
No significant regression equation was found when data of all seven participants was collapsed for analysis performed on predictions for word positions within a sentence, all $ps > .053$. On single subject level, four regression analyses were significant. Half of the slopes for significant equations were negative while the other was positive, ranging between -.003 and .006.

DISCUSSION

Individually adjusted text presentation rates showed a strong variation and an average of 308 wpm. The strong individual variation in adjusted speeds might be caused by differences in preference for the RSVP reading method, as some participants may have felt unconfident with the new reading technique, while others felt more comfortable using it. Such strong variations in preference with speed reading applications were shown before [24]. The average adjusted speed of 308 wpm lies above the average speed for traditional reading, which lies between 250 and 300 wpm [25]. This effect of faster reading with speed reading applications is found in most literature on speed reading applications. Results from the RTLX revealed that perceived load was higher for difficult texts than for easy texts. Cognitive load was also higher for

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texts presented with an increased reading speed than when presented at an individually adjusted speed. Since no differences in literal comprehension emerged between different text difficulties and presentation speeds, it can be concluded that an increased presentation speed did not lead to less comprehension. On average two thirds of questions within one text block were answered correctly. It could have been possible that too high reading speeds would lead to an overextension of participants who become less attentive to understanding the text as a consequence. However, this was not the case and results from literal comprehension questions indicate that participants read all variations of texts attentively at similar levels of literal comprehension.

pBCI classification for cross validation on data from the workload paradigm was on average around 20% and hence acceptable. Permutation tests performed on predictions made by the predictive model showed that difficult texts had significantly higher predictive values than easy texts. Moreover, predictions for texts presented with an increase of 40 percent in reading speed had significantly higher values than texts shown at the individually adjusted speed. However, effect sizes for all tests were very small, as prediction variances within text and speed groups were higher than the observed differences between groups in the permutation tests. The results obtained from permutation tests of predictive suggest that that the cognitive load classifier could be used to distinguish overall difficulty differences between longer passages of texts. This applies for difficulty changes induced by presentation speed and text readability level.

It was assumed that averaged prediction values of words within a sentence would increase with a rise of sentence length due to rising structural complexity of word relations. In regression analysis, no significant equations were found. The results suggest that classifiers trained on the cognitive load paradigm are not suitable to reflect possible effects of higher structural complexity in longer sentences. Predictions from the predictive models therefore cannot be used as an estimate of single sentence difficulty.

Regarding the position of a word within a sentence it was assumed that words appearing later in a sentence would receive higher predictive values. Regression analysis of predictions was only significant on single subject level. Several significant equations were found, but half of the slopes were positive while the others were negative. These ambiguous results indicate that predictions derived from the predictive models trained in this study are not suitable as predictors for single word difficulty based on the complexity of relations the word stands in.

Altogether results showed that the trained BCI models were not applicable for measuring single word or sentence difficulty within texts. Only when all predictions for whole texts are regarded together, the predicted values can be used to distinguish between levels of readability and reading speed. RTLX had shown that perceived workload was higher for difficult texts as well as for reading at increased presentation rates. Results suggest that predictions made for broader text passages contain and reflect this information. For much shorter passages, like single sentences or even single words, immediate changes seem to be absent or are not detectable by the model employed in this study.

CONCLUSION

Broader changes of activity in frequency bands employed in the workload classifier were found to correspond to differences in text readability and presentation speed. Such changes are detectable when single word predictions made for larger text passages are examined together. These results add text readability and presentation speed in RSVP reading to the domains where the task-independent workload classifier can distinguish between levels of cognitive load.

Complex texts also contain many easy words which may prevent classification on sentence or word level, as long as linguistic information about word difficulty is not accessible for integration to the classifier. The results suggest though that the effects on cognitive load are highly responsive and that the employed predictive model is sensitive enough to detect these changes.

For future research the robustness and potential for application of the classifier to full texts should be examined further. The predictive model should be applied to a larger variety of text material of different readability level and text length. The predictive model trained in this study could already be used as an estimate for user modelling in educational practice, e.g., in online tutoring systems, to choose appropriate texts as learning material matching the learner’s individual readability level. In speed reading it could also be used to modify the presentation speed after a sufficient amount of text has been read. The presentation speed could then be de- or increased according to classifier output.

To obtain more fine-tuned information about difficulty levels of single sentences or texts, other measures than investigated in this study need to be found. A neuroadaptive system capable of detecting levels of text readability in real time on a word by word basis could perform text simplification [26]. It would be able to individually adapt to its user to improve reading comprehension, which could be well applied in future learning scenarios. Speed reading applications are seen as especially suitable for reading short texts on mobile devices with small screens [27]. Oblinger and Oblinger [28] describe the so-called net generation, who grew up using mobile devices, are used to instant information access and not reading large amounts of text. Moreover, mobile computer-supported collaborative learning is regarded as a promising approach to support and facilitate learning interactions between students [29]. Neuroadaptive features on the side of technology and devices would be a further enrichment to such approaches to future learning.

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