Smart reading aid for detecting problems with reading fluency and comprehension

Rusak, Zoltan; van de Water, Niels; Horvath, Imre; de Smit, Bram; van der Vegte, Wilfred

DOI
10.1115/DETC2016-59130

Publication date
2016

Document Version
Final published version

Published in
Proceedings of the ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference

Proceedings of the ASME 2016 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference
IDETC/CIE 2016
August 21-24, 2016, Charlotte, North Carolina, USA

IDETC2016-59130

SMART READING AID FOR DETECTING PROBLEMS WITH READING FLUENCY AND COMPREHENSION

Zoltán Rusák
Department of Design Engineering
Delft University of Technology
The Netherlands

Niels van de Water
Department of Design Engineering
Delft University of Technology
The Netherlands

Bram de Smit
Department of Design Engineering
Delft University of Technology
The Netherlands

Imre Horváth
Department of Design Engineering
Delft University of Technology
The Netherlands

Wilfred van der Vegte
Department of Design Engineering
Delft University of Technology
The Netherlands

ABSTRACT

Brain signal and eye tracking technology have been intensively applied in cognitive science in order to study reading, listening and learning processes. Though promising results have been found in laboratory experiments, there are no smart reading aids that are capable to estimate difficulty during normal reading. This paper presents a new concept that aims to tackle this challenge. Based on a literature study and an experiment, we have identified several indicators for characterizing word processing difficulty by interpreting electroencelography (EEG) and electrooculography (EOG) signals. We have defined a computational model based on fuzzy set theory, which estimates the probability of word processing and comprehension difficulty during normal reading. The paper also presents a concept and functional prototype of a smart reading aid, which is used to demonstrate the feasibility of our solution. The results of our research proves that it is possible to implement a smart reading aid that is capable to detect reading difficulty in real time. We show that the most reliable indicators are related to eye movement (i.e. fixation and regression), while brain signals are less dependable sources for indicating word processing difficulty during continuous reading.

INTRODUCTION

It is estimated is that about 10 million children have difficulties learning to read. Dyslexia is the most commonly known form of reading and learning difficulty. It often results from complications with the auditory processing part of language and hinders accurate, fluent word reading, which in turn can result in problems with reading comprehension. Identifying problems with reading fluency and comprehension at an early age is therefore essential to prevent any delay in children’s development. To address this problem, we have developed a smart wearable system that is able to monitor reading fluency and estimate reading comprehension based on eye movements and brain signals generated during reading in an everyday setup. This paper presents (1) the results of an experiment, which aimed to show how patterns of EEG and EOG signals can be combined to interpret indicators of reading difficulties, (2) an algorithmic solution for parallel processing signals of electrooculography and electroencelography in order to identify indicators of reading difficulties, and (3) a proof-of-concept prototype system that implements a smart reading aid for helping readers with problems with reading fluency and comprehension.

In our experiment, we have investigated if electrooculography can produce as accurate signals as IR based eye tracking technologies for identifying indicators of reading fluency and reading comprehension. Our experiment also aimed to explore if commercial low cost EEG and EOG devices can produce accurate input for identifying reading difficulties.
In the third section of the paper, we present a fuzzy logic based signal processing algorithm to estimate reading difficulty using a combined membership function of various indicators, i.e. saccades, fixation time of eye tracking data and spectrum analysis and event/fixation related potential of brain signals.

Finally, we propose a concept model for a device, which integrates EEG, EOG, and webcam into a wearable reading aid. A functional prototype of this system was tested and compared to the results in our experiment. The results demonstrate that a feasibility of low cost reading aid for detecting reading difficulties, however, a large scale study should be conducted to validate our results in rigorous manner. Besides this specific application, the proposed system can be extended with augmented reality and can be used as a reading aid to help reading comprehension of users by providing additional explanations in forms of texts, images and videos or translations.

INDICATORS OF READING DIFFICULTY IN LAB SETUP

Brain signal and eye tracking technology has been intensively applied in research in order to study the reading, listening and learning processes of humans. Understanding the perception and cognition processes during reading is a well-studied domain of cognitive sciences and biological psychology. This concise review of the state of the art literature on eye movement and brain signal based evaluation of language comprehension aims to explore seminal contributions to real time monitoring of reading fluency and comprehension.

Several studies have been investigating the eye movements during word processing since the ground breaking work of Frazier et al. [7]. The main conclusions since then is that eye movements are mainly driven by lexical properties of words [3]; [21], and encoding of visual information during reading happens as sequential left-to-right eye movements [13], which consist of fixations that last about 200–250ms and saccades of 20–30ms. The brain, however, only takes in information during fixation as the eyes are not capable to obtain new information during saccades [11]. During reading, 10–15% of the saccades are backward eye movements, so called regressions, which enables rereading of the text to compensate for poor comprehension during first read. It has been also shown that more difficult text implies increased fixation durations, decreased saccade size, and increased regressions. On the other hand, it was also proven that longer fixations at the center of words are related to a higher probability for a regression than fixation at the edges of words [5]. Moreover, longer fixation on a particular word can be also caused by low frequency of appearance of this word in previous parts of the text [9]; [14].

Computational models for examining language processing have introduced large databases with the goal to incorporate lexical properties of words (e.g. frequency, prior knowledge). For instance, Reichle et al. [17][18] implemented a computational model that interprets oculomotor control processes, attention, visual processing, and word identification with respect to eye movements during reading. E-Z Reader considers completion of lexical processing to be the trigger of forward eye movement as opposed to other models that assume autonomous timer.

In contrast to the E-Z Reader model, the SWIFT model [5] assumes that word processing happens with visual attention to several words in parallel. It theorizes that a random timer triggers eye movements at random intervals, which is indirectly influenced by word frequency. Fixation durations are restrained by this random timer and they delay the saccadic movement and increase fixation durations.

Studies of brain signals during reading also provided new insights into language processing. Analyses of event-related potential (ERP) of electroencelography (EEG) have focused on after event components of waveform, such as the N400 (a negative-going wave occurring about 400ms after a stimulus). These studies have shown that N400 is influenced by semantic relationships among words [10] and syntactic factors [2]. From this it was concluded that N400 can well reflect the identification of individual words even when it is influenced by word frequency and predictability [4], and can be considered as an indicator of word recognition. However, in normal reading, predictability plays a key role to influence fixations on a word [15]; [14]. In normal reading, fixation lasts less than 250ms on average, which questions the usability of N400 as indicator of word processing.

To overcome this problem simultaneous recording of eye movement and ERPs was proposed. The method of fixation related potential (FRP) has been introduced, which uses fixations for locking events as input for ERP processing of EEG signals. ERP outcomes showed that a lexical effect emerges around 100ms post-stimulus, which is reflected by the P1 component, and then it is followed by the N1 and then P2 components associated with word frequency and regularity, respectively [20]. A marginally stronger effect was found for the amplitude of N1 component at round 120ms post-stimulus. Similarly, a stronger effect was found for non-associated than for non-words for a positive component appearing around at 140ms post-stimulus at the central and frontal recording sites.

The indicators reviewed in this state of the art literature will be further studied by us to investigate their usability and utility under regular reading conditions. We have conducted an experiment, which mimicked reading under normal circumstances.

EXPLORING INDICATORS OF READING DIFFICULTY DURING NORMAL READING

The goal of our explorative study was to identify indicators of word processing difficulty and comprehension in eye tracking and EEG signals and to investigate their applicability in natural reading scenarios. This section of the paper presents the research setup, the conduct of our experiment and the results. The outcome is used as insight to setup a computational model for detecting difficulties with reading fluency and comprehension in natural reading. To achieve these goals the following research questions have been investigated in this study:

- Which indicators reported in the state of the art literature can be reliably measured by low cost commercial EOG and EEG devices?
- Can fixation related potentials be detected by single electrode measurements at FP1 location of EEG?

Figure 1: Research setup

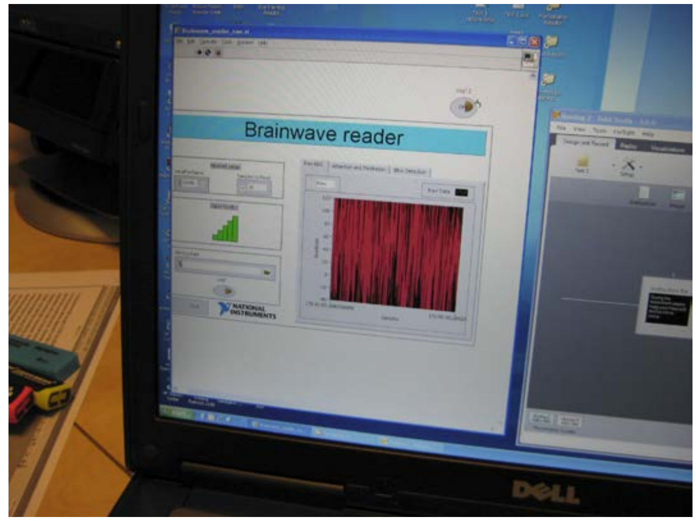

Figure 2: Brainwave reader

Addressing these research questions will help us to validate the feasibility of implementing a low cost smart reading aid that is capable to detect reading difficulties in normal reading conditions. Our goal is to design a minimal viable product that can be a basis for a successful proliferation of reading aids at affordable cost.

Research Design

Participants of our experiment were asked to read two texts in English. The first text was a fairly simple news article, which contained a few unfamiliar words for non-native speakers of English. The second text is a part of a more difficult research article, which contained more difficult sentence structures and several unfamiliar words for most readers. Both articles were displayed on a 20” monitor using eye tracker software, called Tobii Studio 3.0.

The research took place in an office, which was equipped with the necessary research instruments, including one PC, one laptop and a few biometric devices. Biometric data during reading was recorded using a Neurosky MindWave EEG device, Tobii IR eye tracker, and a TMSi Mobi with disposable electrodes was used to measure eye movement based on electrooculography. The laptop of Neurosky Mindwave was running the National Instruments Brainwave Reader software. The desktop computer with which the TMSi Mobi is connected runs PortiLab to record and display the EOG signal. A Tobii X60 Eye Tracker was used to optically track the position of the eyes. This technology is known to be accurate enough to determine the absolute position of the eyes with 0.5 degree precision. The optical eye tracking data was used as a reference for the EOG signal measured by TMSi Mobi. A Logitech webcam on top of the 20” display was used to observe what the participant is doing during the research. If the participant for example scratches his/her head or looks away the webcam captures this on video. The office was chosen as research environment to expose participants to stimulus that represents a natural reading environment. In our setup we made sure that the participants were not disturbed by any external information source and they could focus on the tasks of our experiment.

Participants

We have recruited 25 subjects for our experiment, 16 male and 9 females age of 20-55 years old. They were sampled from people working or studying at the Faculty of Industrial Design Engineering of TUDelft. This will likely mean most subjects in the research have a higher education level. A different study should be made to investigate if there are specific mechanisms working with dyslexic children during reading and how these mechanisms effect indicators of reading fluency and comprehension.

Conduct of the experiment

The participants had to fill in five questionnaires which were used to determine whether the participant comprehended the text while reading it. These questionnaires were used to identify when participants were omitting text or did not comprehend the meaning of the text. During the experiment the every participant had to fill in five questionnaires using a separate laptop. In the post experiment questionnaire the participant is given a printout of the read text and different colored markers to indicate for example words they had trouble with.

Before starting the reading of the text each participant was asked to blink three times. Blinking creates unique artifacts in the signals of IR eye tracking, EEG and EOG measurements, which was used for synchronize the signals.

As the participants had to read two texts there is definitely a chance of bias from the first study. For example it might be possible a participant is less distracted during the second text because he/she is familiarized with the environment. It is also possible a participant is actually more distracted during the second text, because he/she is bored for having to read for a second time. To overcome these problems, we have introduced a small break between the two experiments.

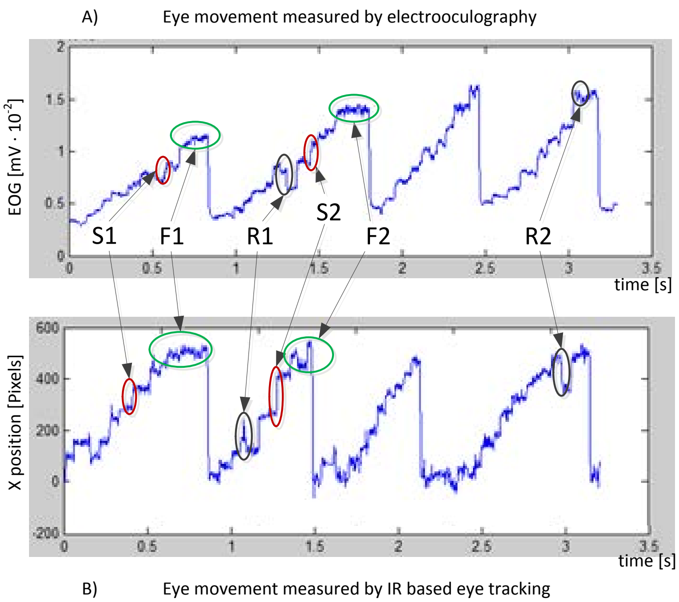

Figure 3: Visual comparison of eye tracking data

Results

Our study aimed to explore if EOG and IR based optical eye tracking can provide the same results for identifying word processing difficulties. To validate the usability of EOG, we have compared the gaze location measured by EOG and IR based optical eye tracking during reading as shown in Figure 3. Though the diagrams do not have exact matches, key features of the plots show similar results. Regression, fixations and saccades have similar characteristics, though there are some small differences. While regression R1 is clearly recognizable by both measurements, R2 appears to be a fixation on the signal of electrooculography rather than a regression. For this reason, we consider regressions to be less reliable indicator of word processing difficulty than fixation or saccades.

We have also analyzed the EEG signals recorded during reading. Analysis of power spectrum of EEG signals 250ms before and 500ms after fixations shows significant differences for word processing with and without difficulty. Fixations have been sorted into two classes, normal word processing (i.e. fixation time < 250ms) and difficult word processing (i.e. fixation time > 250ms). We compared the power spectrum characteristics for these two groups. Figure 4 illustrates the power spectrum for the EEG signals 250ms before and after difficult words and EEG segments with 500ms timeframes of fluent readings. To contrast the characteristics of the power spectrums of EEG signals during reading with and without word processing difficulty, for each frequency range we have identified that specific frequency where the difference is the largest. In the delta frequency range (i.e. 0-4Hz) the power spectrum has a peak around 40dB for reading with fluency, while for reading with difficulty has a maximum around 25dB. In the theta frequency range (i.e. 4-8Hz) the largest difference is at 8Hz with values of 15dB and 24dB. For the alpha

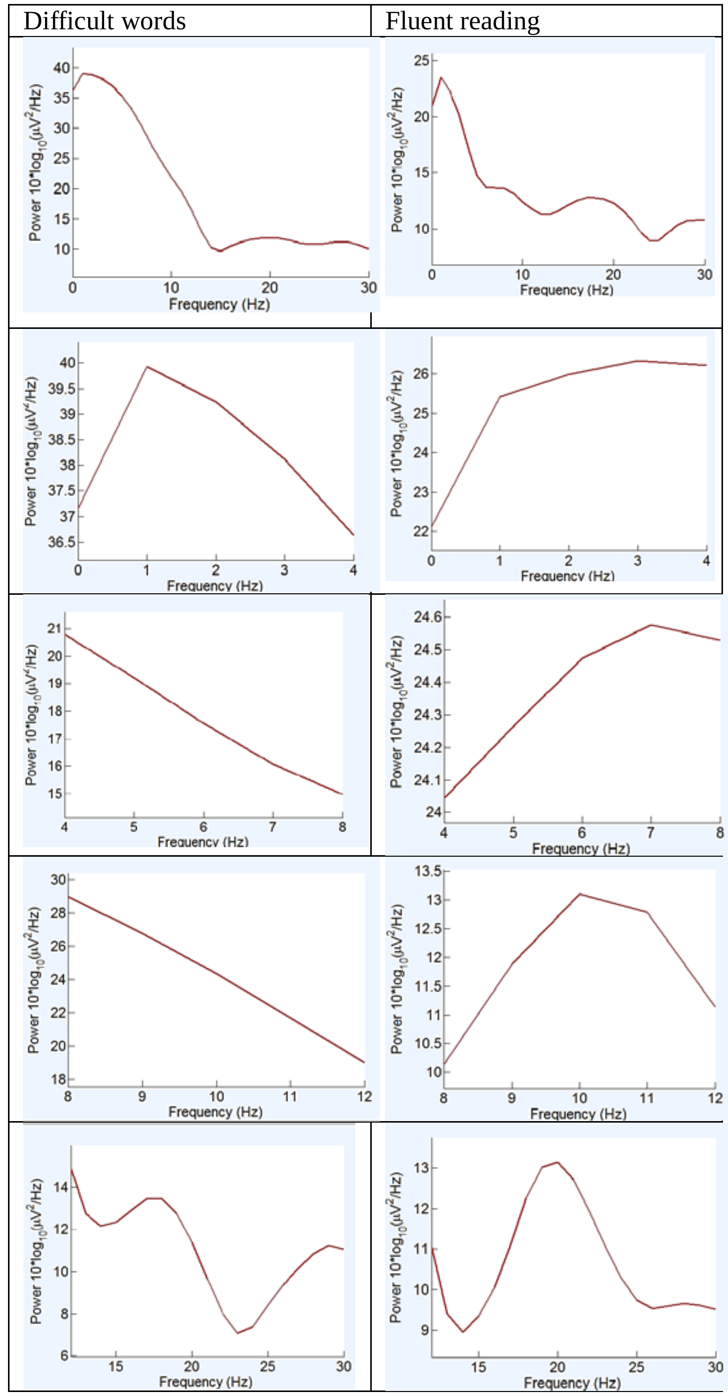

Figure 4: Analysis of power spectrum of EEG signals

frequency range (i.e. 8-12Hz) the characteristic values have been taken at 10Hz with values of 25dB and 13dB. Beta frequency range (i.e. 12-30Hz) we have used 13dB and 9dB at 14Hz. These characteristic values of the power spectrum are used later in our computational model to classify word processing.

Comparison of fixation related potential is illustrated in Figure 5. In our study, we have analyzed the event related potential generated in the range of 0 to 250ms after fixations for normal

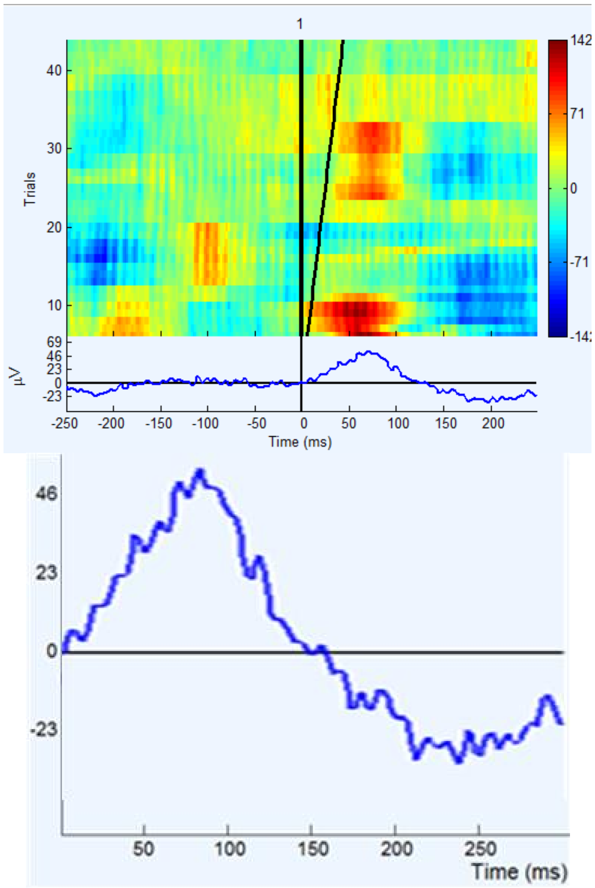

Figure 5a: ERP plot of normal word processing

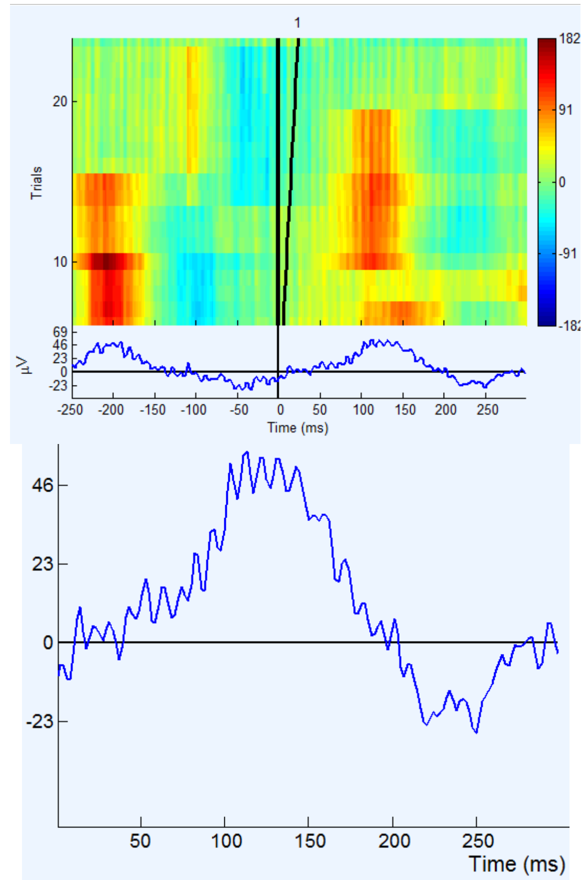

Figure 5b: ERP plot of difficult word processing

word processing and difficult word processing using the EEGLAB software plugin of MatLab. The ERP plots show significant differences for the two classes of fixations in terms of the peak time of P1 and N1 responses. For normal word processing the peak of P1 response occurs around 90ms and N1 response around 200ms. Word processing with difficulty has on the other hand longer response time, so that P1 occurs around 140ms, and N1 response around 230ms. These differences in response times are used to distinguish word processing difficulty based on fixation related potential later in our model.

COMPUTATIONAL MODEL FOR EEG AND EOG SIGNAL PROCESSING DURING READING

Concept of signal processing

Figure 6 presents the concept of our signal processing algorithm developed for extracting indicators of word processing difficulties from EEG and EOG signals. Our algorithm relies on signal segmentation based on fixations recognized in EOG signals. The algorithm applies a median filter on the EOG signal and computes the derivative of the signal in order to recognize saccades and fixations. Saccades presenting large negative values are typically representing that the user reached the end of line or rereads part of the text. Saccades are ordered according to their lengths. Knowing that the text has N number of lines to read per page, the longest N saccades are considered to be end of line indicators, while the rest of the negative saccades are taken as regressions. Fixations are identified based on values close to zero of the derivative of EOG signal. Using fixations, saccades and regressions, indicators of word processing difficulties are extracted based on the findings of our experiment and the findings of state of the art literature. Our computation model for identifying indicators of word processing difficulty operates uses fuzzy set principles. We have developed a model that defines fuzzy membership functions for indicators of word processing based on fixation, saccades and regression in eye tracking signal and power spectrum and fixation related potential of EEG signal. Using these fuzzy membership functions, words that are difficult to read are automatically detected and highlighted as illustrated in the right side of Figure 6.

Membership functions defined based on eye tracking

Fixation

Fixation time during normal reading is around 200-250ms. Exceeding this range is an indicator of word processing difficulty. We have defined the fuzzy membership function of word processing, μ_f difficulty as a sigmoid function:

$$\mu_f = \frac{1}{1+e^{-a(t_f-c)}} = sig(t_f; 0.2, 250)$$

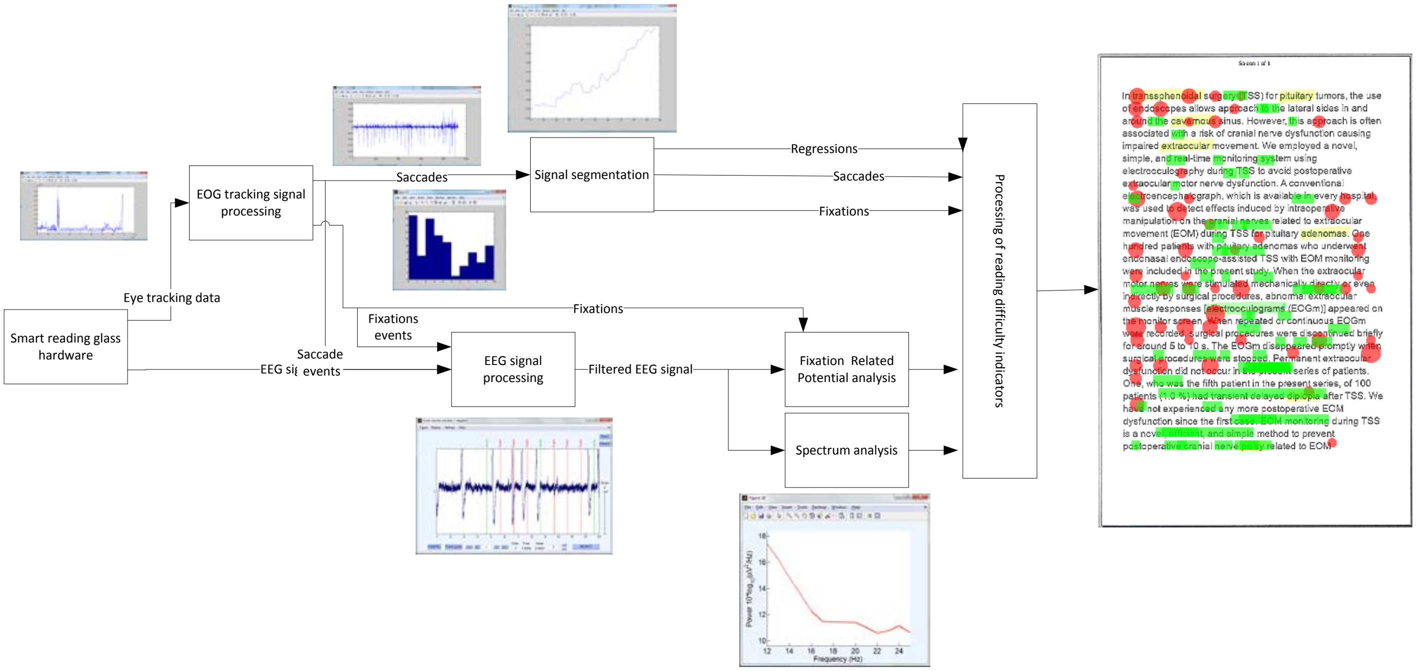

Figure 6: Concept of real time processing of EEG and EOG signals for identifying word processing difficulties

, where t_f is the fixation time, *a*=0.2 controls the slope and creates a sigmoid transition in the range of 225-275ms, and *c*=250ms is taken as a transition point.

Saccade

20-30ms saccades are considered to be part of normal fluent reading when followed by fixations no longer 250ms.

$$\mu_s = sig(t_f; 0.1, 35)$$

Membership function of fluent reading is defined as a series of saccades coupled to normal fixation times. The number of elements in a fuzzy set that contains equal number of fixations and saccades for which

$$\mu_{fl} = \prod_{i=1}^{n} (\mu_{f,i} \cdot \mu_{s,i}),$$

where $\mu_{f,i} \cdot \mu_{s,i} < 0.1$ for $\forall$ element, μ_{fl} member function of fluent reading, n>=4, which guarantees that at least 1000ms second the reading for fluent.

Regression

Multiple reading of text parts is detected regression in eye tracking data. Skilled readers make regressions back to material already read about 15 percent of the time. The main difference between faster and slower readers is that the latter group consistently shows longer average fixation durations, shorter saccades, and more regressions (Rayner et al. 2010). Following these findings of the literature, we consider the following aspects to define fuzzy membership functions for the indicator of regression. Fuzzy membership function regression is defined as an aggregation of component membership functions: (a) length of regression, which reflects if a longer part of the text is not comprehended by the reader at first reading, (b) the number of times a part is read, and (c) regression time, if it exceeds the average regression time by more than 15%.

$$\mu_{r,i} = \mu_{l,i} + \mu_{s,i} + \overline{\mu_r} =$$
$$= sig(t_{r,i}, 0.2, 30) + sig(n_r, 0.3, 3) + sig(\frac{\sum t_{r,i}}{\sum t_R}, 0.5, 15)$$

Membership functions defined based on EEG signal

Power spectrum

In our analysis we found that the power spectrum of fluent reading and word processing of difficult words is different in the characteristics summarized in Table 1. The membership value of the power spectrum based word processing difficulty indicator is defined as the aggregate

$$\mu_\delta = sig(P_{\delta,1Hz}; 0.75, 33)$$
$$\mu_\theta = 1 - sig(P_{\theta,8Hz}; 0.1, 19)$$
$$\mu_\alpha = sig(P_{\alpha,10Hz}; 0.1, 20)$$
$$\mu_\beta = 1 - sig(P_{\beta,14}; 0.1, 13)$$
$$\mu_{PS} = \min(\mu_\delta \cdot \mu_\theta \cdot \mu_\alpha \cdot \mu_\beta)$$

, where μ_{PS} is the membership function of power spectrum based indicator, defined based on the intersection of the component membership values.

Fixation related potential

Fixation/event related potential is calculated for *k* trials, and *x(t, k)= s(t)+n(t, k)*, where *t* is the time elapsed after the k^{th} event, *s(t)* is the response signal of studied subject and *n(t,k)* is the noise. The average of N trials is:

$$\bar{x}(t) = \frac{1}{N}\sum_{k=1}^{N} x(t,k) = s(t) + \frac{1}{N}\sum_{k=1}^{N} n(t,k)$$

The expected value of x(t) is the signal itself, s(t), assuming that the noise has a normal distribution. Using this principle on a smaller set of samples (N=10-20), we introduce membership function of FPR based indicator of word processing difficulty, $\mu_{FPR,k}$, of k-th word the was fixated during reading. The membership value of the first positive response, P1, of the k-th word for the set of words with fluent reading (i.e. fixation <250ms) is defined as :

$$\mu_{P1,F}(k) = \frac{t(FPR(W_{F,n}),P1) - t(FPR(W_{F,n-k}),P1)}{Var\{t(FPR(W_{F,n}),P1) - t(FPR(W_{F,n-1}),P1)\}_1^N},$$

where $t(FPR(W_{F,n}), P1)$, is the response time of the P1 peak of the fixation related potential of words with fixation smaller than 250ms, $t(FPR(W_{F,n-k}), P1)$, is the response time of the P1 peak of the fixation related potential of words with fixation smaller than 250ms, in which the sample does not include the k-th fixated word,

$Var\{t(FPR(W_{F,n}), P1) - t(FPR(W_{F,n-1}), P1)\}_1^N$

is a variance of a set defined by the response time differences of all words in the sample. Similarly, the membership functions for the N1 response is defined as:

$$\mu_{N1,F}(k) = \frac{t(FPR(W_{F,n}), N1) - t(FPR(W_{F,n-k}), N1)}{Var\{t(FPR(W_{F,n}), N1) - t(FPR(W_{F,n-1}), N1)\}_1^N}$$

The sample set of fixated words with larger than 250ms fixation time (i.e. words indicated as difficult to read based on fixation), the membership functions of P1 and N1 responses of fixation related potentials are defined as follows:

$$\mu_{P1,D}(k) = \frac{t(FPR(W_{D,n}), P1) - t(FPR(W_{D,n-k}), P1)}{Var\{t(FPR(W_{D,n}), P1) - t(FPR(W_{D,n-1}), P1)\}_1^N}$$

$$\mu_{N1,D}(k) = \frac{t(FPR(W_{D,n}), N1) - t(FPR(W_{D,n-k}), N1)}{Var\{t(FPR(W_{D,n}), N1) - t(FPR(W_{D,n-1}), N1)\}_1^N}$$

The membership function based on the fixation related potential is defined as:

$$\mu_{FPR}(k) = (\mu_{N1,D}(k) \cap \mu_{P1,D}(k)) \cap ((1 - \mu_{N1,F}(k)) \cap (1 - \mu_{P1,F}(k))$$

Indicator of word difficulty

Indicators of EOG and EEG signals are used to evaluate the individual words for their difficulty of processing, μ_{RD}, using a truth table as illustrated in Table 1. In this truth table eye fixation is taken as the most reliable indicator of word processing difficulty and taken as a separate measure, while the indicators of saccades and regression as well as the power spectrum and fixation related potential are combined to compound indicators, respectively. This solution provided us with a more simple decision mechanism and it reduced the complexity of the truth table. Qualitative values of the membership functions in the truth table are determined as follows: HIGH, if the membership function value is between 0.66-1, MEDIUM if it is in the range of 0.33-0,66, and LOW between 0-0,33. Using these qualitative values, the processing difficulty of individual words can be sorted into one of the four categories of high, medium, low and no difficulty.

μ_{RD}	μ_F	$\mu_S \cdot \mu_R$	$\mu_{PS} \cdot \mu_{FPR}$
HIGH	HIGH	HIGH	HIGH
	HIGH	HIGH	MEDIUM
	HIGH	HIGH	LOW
	HIGH	MEDIUM	MEDIUM
	HIGH	MEDIUM	HIGH
MEDIUM	HIGH	LOW	HIGH
	HIGH	MEDIUM	LOW
	MEDIUM	HIGH	HIGH
	MEDIUM	HIGH	MEDIUM
	MEDIUM	MEDIUM	HIGH
	MEDIUM	MEDIUM	MEDIUM
	MEDIUM	MEDIUM	LOW
LOW	MEDIUM	LOW	MEDIUM
	MEDIUM	HIGH	LOW
	MEDIUM	HIGH	MEDIUM
	MEDIUM	HIGH	MEDIUM
	HIGH	LOW	MEDIUM
	HIGH	LOW	LOW
	LOW	HIGH	HIGH
	LOW	MEDIUM	HIGH
NO	LOW	LOW	HIGH
	LOW	MEDIUM	MEDIUM
	LOW	HIGH	LOW
	LOW	LOW	MEDIUM
	LOW	MEDIUM	LOW
	MEDIUM	LOW	LOW
	LOW	LOW	LOW

Table 1: Truth table combining fuzzy membership functions of indicators of word processing difficulty

PROTOTYPING AND TESTING

The goal of designing and prototyping a smart reading aid was to demonstrate that it is possible to make a wearable product that integrates the EEG and EOG for detecting word processing difficulties. The concept of our design called STUCO is shown in Figure 7. It contains two hard plastic compartments; one for the primary circuit board that processes the various signals and one for the battery and the micro USB port. The USB port is used to both charge the Stuco and update the firmware if needed. The compartments are connected by a flexible band that contains the EEG electrodes and the ground electrode. An elastic band is used to ensure the flexible electrode band is tightly wrapped around the head of every user. The Stuco contains a full HD camera that is used for text and gesture recognition. The camera can be tilted in four different positions. The injection moulded click system makes sure the camera stays in the correct position. Behind the camera runs a thin and bendable connector strip that connects the camera with the processing circuit board of the device. This same strip also connects the electrodes, battery and USB connector with the primary circuit board.

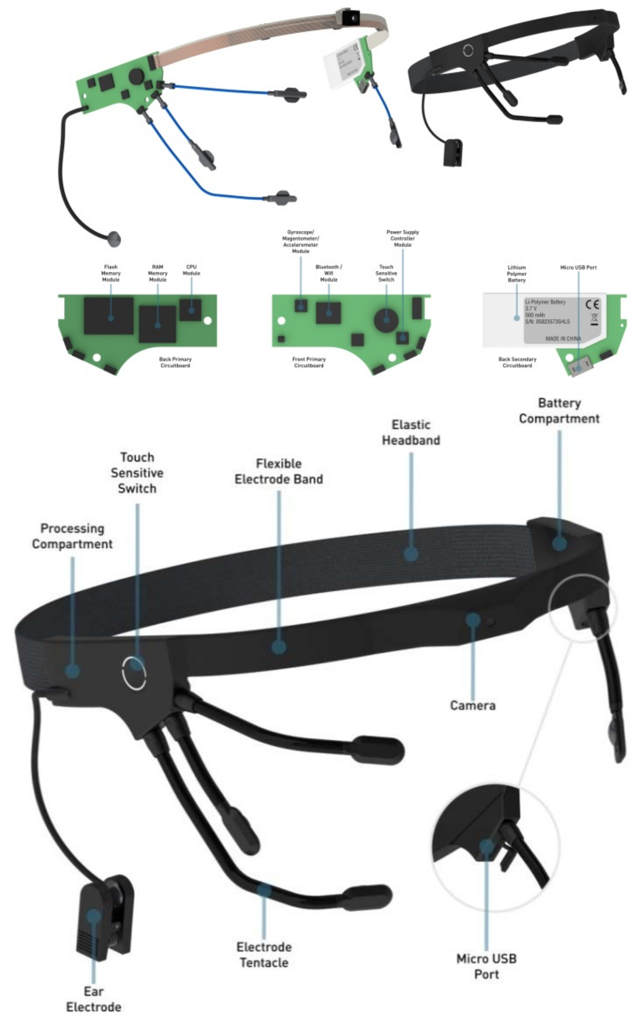

Figure 7: Concept of a smart reading aid

A functional prototype was built with focus on solutions that demonstrate feasibility of acquiring the appropriate input signals without offering correct feedback to the users. Therefore

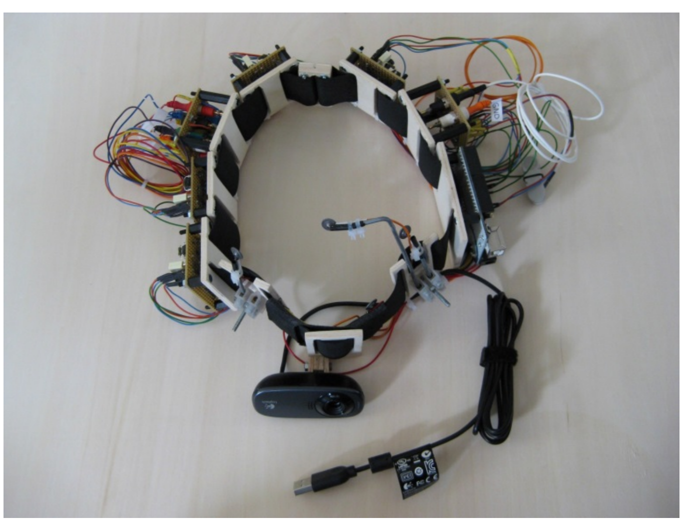

Figure 8: Functional prototype of STUCO

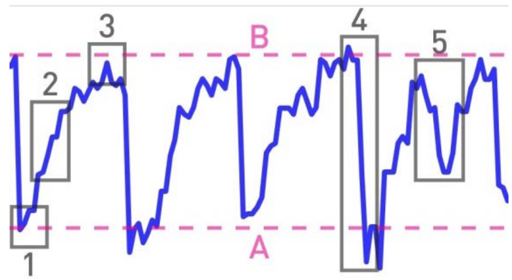

Figure 9: EOG signal measured by the Smart Reading Aid prototype during reading

the prototypes functions and features are reduced significantly compared with the concept and final product. Figure 8 shows the functional prototype of the smart reading aid. The prototype is based on the DIY circuit for measuring EEG signals developed by C. M. Epstein, a specialist in neurophysiology [6]. For EEG measurements the active electrodes consist of the reference electrode and one of the main EEG electrodes. Both electrodes use the same ground electrode. The measured reference signal is subtracted from the measured main EEG signal to remove the noise created by the rest of the brain. After that the circuit amplifies and filters this signal and sends it to a computer using an Arduino. These test were done with a window width of 900 pixels, therefore a sample rate of only 10 fps could be achieved. It would be desirable to have a higher sample rate, although future research should point out the desired minimum sample rate for each signal.

Figure 9 shows a segment of an EOG signal recorded with our prototype for horizontal eye movement during normal reading. The recorded signal shows a similar pattern to the pattern recorded during our experiment. It has a climbing pattern ending with a large saccadic motion, after which the signal returns to its original value. This pattern represents a reading that happens line by line. It shows saccades of quick motions (point 2), fixations (point 3), and regressions (point 5).

CONCLUSIONS

In our paper we have investigated the feasibility of designing a smart reading aid for identifying word processing difficulties in normal reading conditions. We have conducted an experimental study to explore if indicators of word processing difficulties identified in the state of the art are also recognizable under normal reading conditions with commercial low cost devices. We have found that electrooculography and electroencelography can provide reliable source of information on reading difficulties based on characteristic signal properties such as fixation, regression saccades of eye movement signal, and power spectrum and fixation related potential of electroencelography. Using these indicators we proposed a fuzzy set based algorithm to estimate the overall word processing difficulties during normal reading for each fixated word. The paper also presents a hardware solution that is optimized for extracting the most relevant indicators word processing difficulty under normal reading condition. Though the functional prototype of our system is capable to produce similar results to commercial and laboratory equipment, further studies are needed to validate the usability and utility of our device under normal reading conditions.

REFERENCES

[1] Antje Nuthmann, Ralf Engbert, Reinhold Kliegl, Mislocated fixations during reading and the inverted optimal viewing position effect, Vision Research, Volume 45, Issue 17, August 2005, Pages 2201-2217, ISSN 0042-6989,

[2] Bornkessel, I., McElree, B., Schlesewski, M., Friederici, A.D., 2004. Multi-dimensional contributions to garden path strength: dissociating phrase structure from case marking. Journal of Memory and Language 51, 495–522.

[3] Clifton C Jr, Traxler MJ, Mohamed MT, Williams RS, Morris RK, Rayner K. The use of thematic role information in parsing: Syntactic processing autonomy revisited. Journal of Memory and Language. 2003; 49:317–334.

[4] Dambacher, M., Kliegl, R., Hoffman, M., Jacobs, A.M., 2006. Frequency and predictability effects on event-related potentials during reading. Brain Research 1084, 89–103.

[5] Engbert, R., Nuthmann, A., Richter, E.M., Kliegl, R., 2005. SWIFT: a dynamical model of saccade generation during reading. Psychological Review 112, 777–813.

[6] Epstein, C.M., 2008. Homebrew Do-It-Yourself EEG, EKG, and EMG. [online] Available at: https://sites.google.com/site/chipstein/home-page [Accessed 05-05-2013].

[7] Frazier, L., Rayner, K., 1982. Making and correcting errors during sentence comprehension: eye movements in the analysis of structurally ambiguous sentences. Cognitive Psychology 14, 178–210.

[8] Henderson, J.M., Ferreira, F., Effects of foveal processing difficulty on the perceptual span in reading: implications for attention and eye movement control. Journal of Experimental Psychology: Learning, Memory, and Cognition 16 (3), 417

[9] Kliegl, R., Nuthmann, A., & Engbert, R. (2006). Tracking the mind during reading: The influence of past, present, and future words on fixation durations. Journal of Experimental Psychology: General, 135,13-35.

[10] Kutas, M., Van Petten, C., Kluender, R., 2006. Psycholinguistics electrified II (1994– 2005). In: Gernsbacher, M.A., Traxler, M. (Eds.), Handbook of Psycholinguistics. 2nd edition. Elsevier, New York, pp. 655–720.

[11] Matin, E., 1974. Saccadic suppression: a review. Psychological Bulletin 81, 899–917.

[12] Morrone, M. C. et al. A cortical area that responds specifically to optic flow, revealed by function Magnetic Resonance Imaging. *Nature Neuroscience* **3**, 1322-1328 (2000).

[13] Rayner, K., 1998. Eye movements in reading and information processing: 20 years of research. Psychological Bulletin 124, 372–422.

[14] Rayner K., Duffy S.A., Lexical complexity and fixation times in reading: Effects of word frequency, verb complexity, and lexical ambiguity, Memory & Cognition 14 (3), 191-201

[15] Rayner, K., Binder, K.S., Ashby, J., Pollatsek A., Eye movement control in reading: Word predictability has little influence on initial landing positions in words Vision Research 41 (7), 943-954

[16] Rayner, K.; Slattery, Timothy J; Belanger, Nathalie N. (2010). Eye movements, the perceptual span, and reading speed. Psychonomic Bulletin & Review 17(6): 834–39. doi:10.3758/PBR.17.6.834. Retrieved 1 November 2011

[17] Reichle, E.D., Pollatsek, A., Rayner, K., 1998. Toward a model of eye movement control in reading. Psychological Review 105 (1), 125–156.

[18] Reichle, E.D., Rayner, K., Pollatsek, A., 2003. The E-Z Reader model of eye-movement control in reading: comparisons to other models. Behavioral and Brain Sciences 26, 445–476.

[19] Rudell AP1, Hua J. The recognition potential, word difficulty, and individual reading ability: on using event-related potentials to study perception.

[20] Sereno SC1, Rayner K, Posner MI. Establishing a time-line of word recognition: evidence from eye movements and event-related potentials. Neuroreport. 1998 Jul 13;9(10):2195-200.

[21] Staub, A., & Rayner, K. (2007). Eye movements and on-line comprehension processes. In: G. Gaskell (Ed.), The Oxford Handbook of Psycholinguistics (pp. 327-342). Oxford, UK: Oxford University Press.