Fast Algorithm for Dyslexia Detection

Boris Nerusil[1], Jaroslav Polec[1] and Juraj Skunda[1]

[1] Institute of Multimedia ICT, Slovak University of Technology in Bratislava, Slovakia
juraj.skunda@stuba.sk

Abstract. This article describes a method for detection of cognitive defects based on eye tracking during reading. The aim of this research is to pursue and extend the experiments conducted in Sweden by introducing Conventional signal theory. The dataset used for experiment was acquired by the authors of the research article Screening for Dyslexia Using Eye Tracking during Reading. The provided data consist of 185 subjects divided into two groups. The first group comprises of 88 low risk (LR) subjects and the second group comprises of 97 high risk (HR) subjects. Our measurements achieved a classification accuracy score 86.164% by classifying the subjects into the correct groups.

Keywords: Dyslexia, Eye Tracking, KNN, Conventional Signal Theory.

1 Introduction

Using tracking eye movements during reading we are able to create the path of visual attention. Cognitive defects in a subject can be detected by detailed investigation of visual path. Various types of cognitive disorders as autism, schizophrenia, dementia can be identified by using eye tracking. Important scientific publications that focuses on modeling human visual attention have been published since 1988 [1]. Early diagnosis of cognitive disorders is essential in order to detect them at an early stage and begin the treatment. Currently, there are several active researches dealing with visual attention of subjects regarding various cognitive disorders [2], [3], [4]. Tracking eye movement of the individual is used in the detection of cognitive disorders, which form basic indicators of cognitive processes. For tracking eye movements and regions of interest of the pictures are commonly employed, for example ROR pictures were used for the identifying the subjects with schizophrenia [2]. In the other cases for the detection of cognitive disorders in subjects with autism or dementia, the text was presented to subjects for reading and based on eye movements the differences between individuals with and without detected dyslexia [6], [7]. This article is specifically dedicated to dyslexia. Eye movements in subjects with dyslexia differ from eye movements in subjects without dyslexia. Individuals with dyslexia require more time to decode particular words and it results in longer and more frequent fixation periods leading to shorter saccades. Fixations are defined as a state when eyes remain steady at least for 50 milliseconds, saccades are determined as movements above threshold distance [4]. We decided to omit the division of eye movements and the input for our classification represents the coordinates of vector of the whole scanned text. Our research is aimed on the experiment, to proof if it is possible to sort out and classify the subjects through Conventional signal theory and if this method is sufficient for the evaluation of acquired data from eye tracker. The article is organized as follows. The first part includes a description of our approach, designed block scheme and displayed vectors view of selected subjects from LR (low risk) and HR (high risk) group and also magnitude spectrum serving for classification of subjects by classifier. In the second part we describe the experiment and the dataset. The final part is devoted to results of experiment, the comparison with already published research, conclusion, acknowledgment and references.

2 Proposed approach

It was assumed that the data input of coordinates from the right eye (X) and the left eye (Y) which represent the averaged values of coordinates (1) and (2) eye movements of the left eye in the x and y directions (R_x, L_x, R_y, L_y).

$$X= \frac{R_x+L_x}{2} \tag{1}$$

$$Y= \frac{R_y+L_y}{2} \tag{2}$$

A block scheme of the designed system is displayed in Fig. 1. In general the sequences are differently long because subjects had various reading speed, that is why the data were interpolated by DCT3 base function to have the same length,

$$DCT3_{U_{k,n}} = \sqrt{\frac{2}{N}} c_n \, cos\left(\frac{\pi((2k+1)n)}{2N}\right) \tag{3}$$

$k, n = 0,1, \dots, N-1,$

where k represents order in the spectrum and n order in time. Subsequently, the values of the ratio were calculated between original and aligned length. The coordinates in x and y axis were multiplied with the given values of the corresponding subject. The x axis was cut down to particular value, as it is shown in Fig. 2 and Fig. 3. Because subjects paid attention to other points after reading the text that eye tracking captured and the redundant information formed approximately half of the total information.

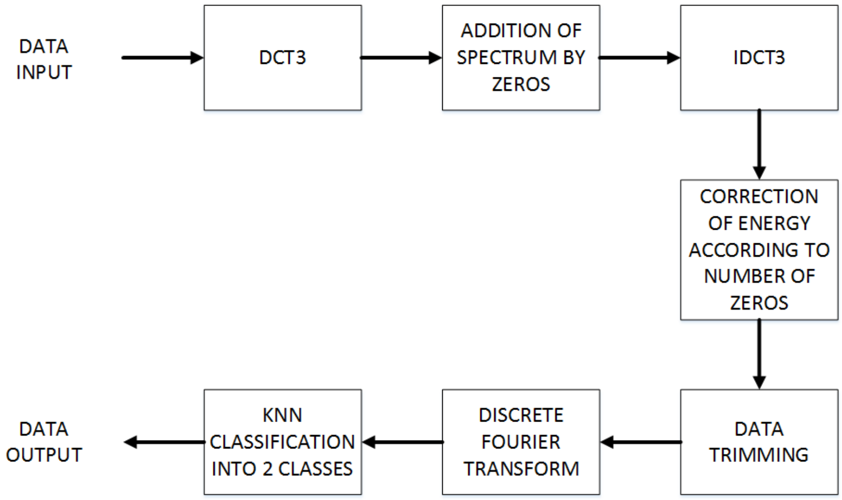

Fig. 1. Block scheme of the designed system.

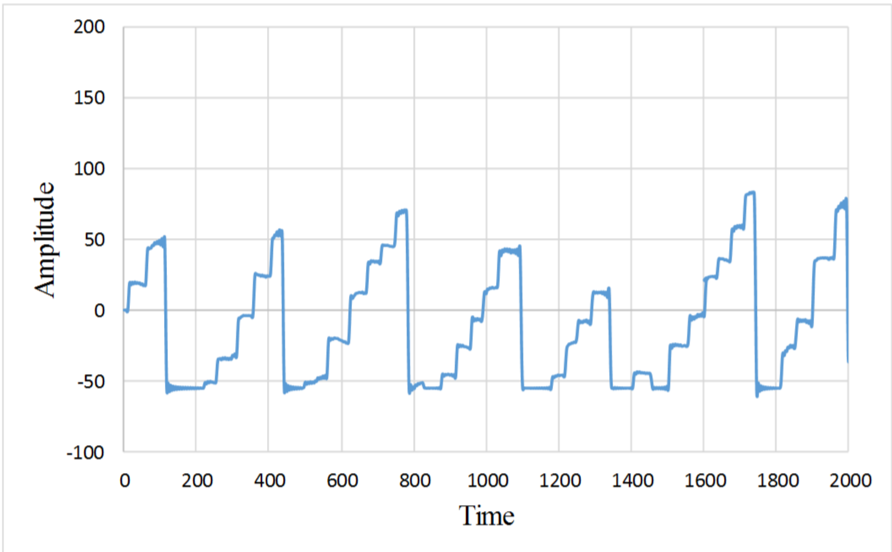

Fig. 2. The eye movement of subject 3 LR in the horizontal direction.

The coordinates of vector are different for subject LR and HR during comparing the amplitudes of the subjects over the time. Fluent course is visible on the x axis of subject 3 LR which is displayed as saw-tooth course and the amplitude is proportional to the line length. Whilst the subject 93 HR does not recognize the course, the eye movement along the x axis is unpredictable during reading particular lines. The eye movement in the horizontal direction was sufficient the most (x axis), that is why vertical eye movement was excluded (y axis). The Discrete Fourier Transform (DFT) was applied to the coordinates of vector of the x axis. The half of the magnitude spectrum of all subjects from LR and HR group was an input into the classifier, Fig 4 and Fig. 5. DC component was omitted from the magnitude spectrum.

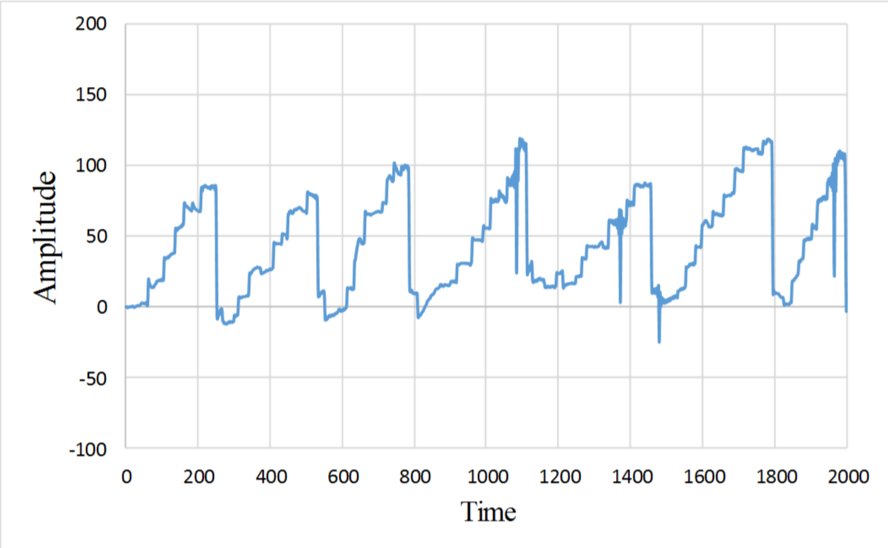

Fig. 3. The eye movement of subject 93 HR in the horizontal direction.

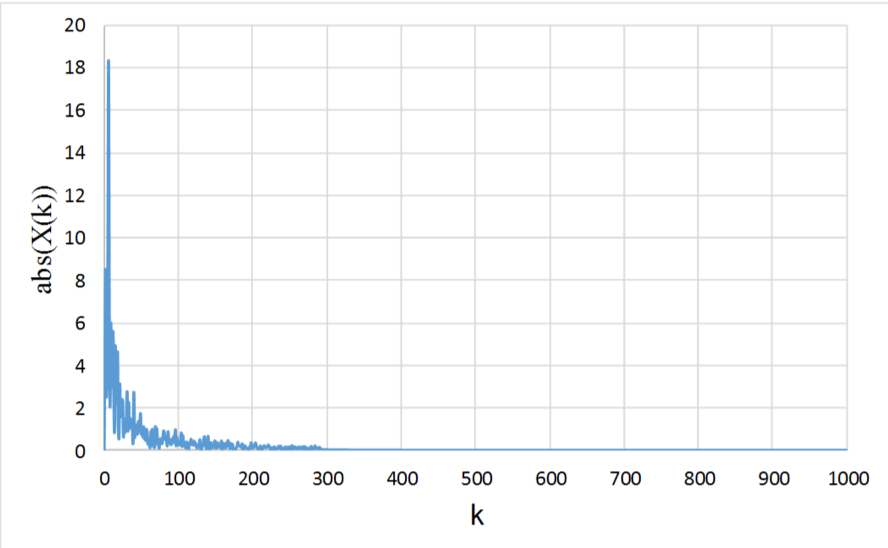

Fig. 4. Magnitude spectrum of subject 3 LR – input into the classifier.

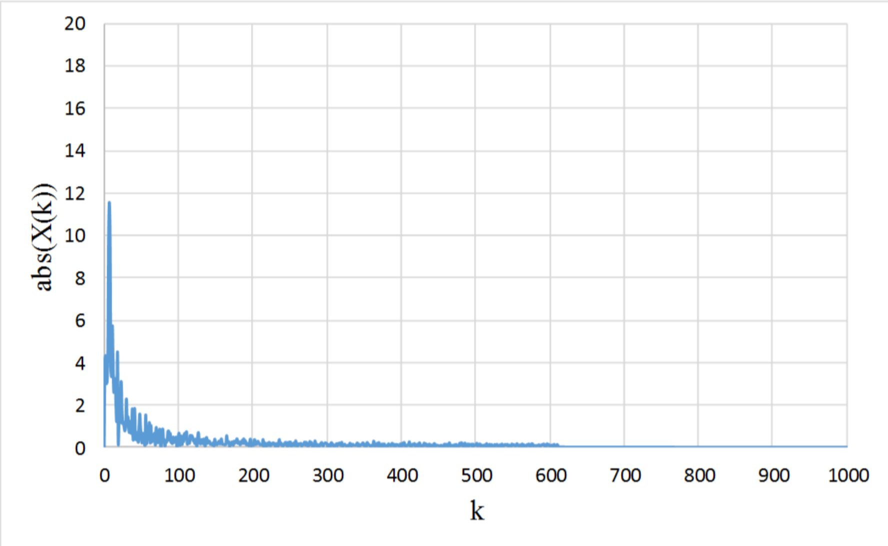

Fig. 5. Magnitude spectrum of subject 93 HR – input into the classifier.

3 Experiments

The text used during experiment consists of 10 sentences divided into 8 lines with an average length of 4.6 words. The text was printed on one side of high contrast white paper. The sentences were selected appropriately for the age group of subjects tested [4].

3.1 Tested Subjects

Subjects with cognitive disorder were in the HR – reading disorder was identified in 97 subjects (71 male and 21 female subjects). In the LT group were tested 88 subjects (69 male and 19 female subjects). Subjects attended the third grade of elementary school and had 9 to 10 years. None of tested subjects did not suffer mental retardation [4].

3.2 Data Acquisition

To detect eye movements was used goggle-based system Obe-2 TM (formerly Permobil Meditech Inc., Woburn MA,). System operates on recording infrared corner reflection of subject. The eye movements were recorded in horizontal and vertical direction at frequency 100 Hz [4]. The eye movements were averaged for our research and only horizontal eye movements were taken into consideration. Authors of published research [4] tracked the changes in the visual path and eye movements of individuals – fixations, saccades, sweeping movements and transients.

3.3 Process of experiment

The k-nearest neighbors (KNN) algorithm was used for data classification. The tested subject is classified into the appropriate group in this method according to the k-nearest neighbors that influence the subject. The data were divided into two groups of training subjects – 184 subjects and 1 test subject. In the first step, we selected a specific subject from the training data group that served as the test subject. This cycle was repeated 185 times to test each subject for k-nearest neighbors. The correlation coefficient was chosen as metric. After data classification we calculated the positive predictive value PPV – precision (3), TPR – true positive rate, the recall or sensitivity (4), TNR – true negative rate, specificity (5) , F1 score (6) and ACC - accuracy (7) for the HR group with dyslexia.

$$PPV = \frac{TP}{TP + FP} \tag{3}$$

$$TPR = \frac{TP}{TP + FN} \tag{4}$$

$$TNR = \frac{TN}{TN + FP} \tag{5}$$

$$F1 = 2 \times \frac{PPH \times TPR}{PPH + TPR} \tag{6}$$

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

4 Results

Several series of calculations with different value of k neighbors was conducted in the KNN classification. K = 5, 19, 25, 33 a 55. The results show us an overview which of the selected number of k-nearest neighbors provides the best classification result. The highest ACC was achieved at K = 33 and K = 25, where accuracy of correct subject classification was 87.03%. The best score for TPR attained 90.72% at K = 33. For TNR the highest reached value was 84.09% at K = 25 and the lowest value was at K = 5, 79.55%. The highest score F1 reached at K = 33 was 88% and the lowest score reached at K = 5 was 86.14%, all results are in Tab. 1.

Table 1. PPV, TPR, TNR, F1 and ACC score.

	PPV [%]	TPR [%]	TNR [%]	F1 [%]	ACC [%]
K=5	82.86	89.69	79.55	86.14	84.86
K=19	85.29	89.69	82.95	87.43	86.49
K=25	**86.14**	89.69	**84.09**	87.87	**87.03**

K=33	85.44	**90.72**	82.95	**88**	**87.03**
K=55	85	87.63	82.95	86.29	85.41

Recall and precision curves use different probability thresholds and through this they summarize for a predictive model the trade-off between the true positive rate and the positive predictive value, Fig. 6.

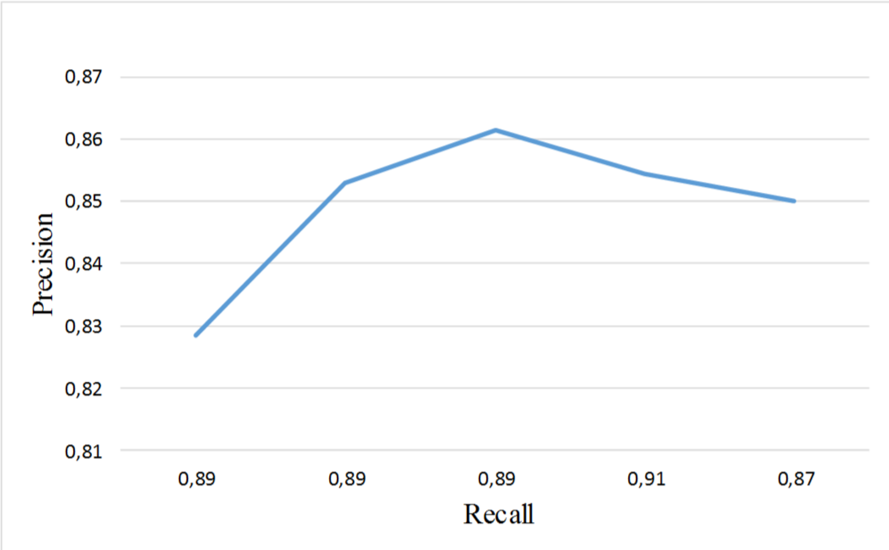

Fig. 6. Recall Precision curve for K= 5, 19, 25, 33, 55.

Compared to the results obtained in the previously published research, the authors took into consideration various eye movements and not the whole coordinates of vector of the scanned text, the overall classification accuracy by using SVM-RFE 95.6% ± 4.5. In our case the overall accuracy reached 86.164% with standard deviation ± 0.88.

Table 2. Comparison of methods.

	KNN	SVM-RFE
Accuracy of detection [%]	86.164 (± 0.88)	95.6 (± 4.5)

In our study, we focused on the correct classification of the individuals in the HR group, where the highest precision classification achieved 90.72%, it means that 88 out of 97 subjects were classified properly in the KNN, when K = 33 and the lowest precision of classification was achieved when K = 55, 85 subjects out of 97 were classified with accuracy 88%. In cases, where misclassification of different subjects is penalized differently, it is not enough to minimize the number of misclassified objects. In medical diagnostics, the misclassification of healthy patient among ill subjects, initiated treatment would have small side effects and it is less dangerous than not providing treatment to seriously ill subject. That means that cost of incorrect classification to the HR group is lower than the cost of incorrect classification to the LR group [5].

5 Conclusion

In comparison to SVMFRE our method propose simpler approach to classification of subjects, due to faster processing of data (only direction of the movement of eyes). The advantage of our system is that the input is only coordinates of vector and there are no other required definitions of events expressing eye movements (number of fixations, length of fixations or length of saccades) and subsequently their selection for vector of features for classification. The answer for our question, whether the Conventional signal theory is suitable for detection reading disorders, is yes, it is. To increase the accuracy it is necessary to analyze the influence and order of shortening the input sequence, its interpolation and the influence of establishing additional relevant feature in the feature vector for classification. Furthermore, it will be interesting to track how another type of classifier will deal with magnitude spectrum of preprocessed signals, for example deep neural network. Whilst this type of reading analysis appears to be appropriate diagnostic methods for other disorders, it might be interesting to monitor if Conventional signal theory would provide good results.

Acknowledgment. I would like to thank the authors for providing the dataset and information regarding the previous research Screening for Dyslexia Using Eye Tracking during Reading. Mattias Nilsson Benfatto, Gustaf Orqvist Seimyr, Jan Ygge, Ten Pansell, Agneta Rydberg, Christer Jacobson.

This research was supported by the VEGA 1/0440/19 research grant.

References

1. L. Itti, C. Koch and E. Niebur, "A model of saliency-based visual attention for rapid scene analysis," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 20, no. 11, Nov 1998, pp. 1254-1259.
2. J. Polec, Jaroslav, R. Vargic, F., Csóka, Filip, E. Smolejová, A. Heretik, M. Bieliková, M. Svrček and R. Móro, "Detection of schizophrenia spectrum disorders using saliency maps," AICT 2017: 11th IEEE International conference on application of information and communication technologies. Moscow, Russia. September 20-22, 2017. Piscataway: IEEE, 2017, pp. 398-402.
3. L. Rello and M. Ballesteros, "Detecting readers with dyslexia using machine learning with eye tracking measures." W4A '15: Proceedings of the 12th Web for All Conference, International Web for All Conference Florence Italy May, 2015, Article No.: 16, Pages 1–8
4. M. N. Benfatto, G. Ö. Seimyr, J. Ygge, T. Pansell, A. Rydberg and C. Jacobson, "Screening for Dyslexia Using Eye Tracking during Reading". PLoS ONE vol. 11(12), 2016.

5. E. Šikudová, Z. Černeková, W. Benešová, Z. Haladová, J. Kučerová, Computer Vision Object Detection and Recognition. Wikina, Praha, 2013.
6. K. C. Fraser, K. L. Fors, D. Kokkinakis, A. Nordlund, "An analysis of eye-movements during reading for detection of mild cognitive impairment" Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pp. 1016–1026.
7. V. Yaneva, L. A. Ha, S. Eraslan, Y. Yesilada, R. Mitkova, "Detecting Autism Based on Eye-Tracking Data from Web Seaching Tasks" W4A '18: Proceedings of the Internet of Accessible Things, The Internet of Accessible Things Lyon France, April 2018 Article No.: 16 , pp. 1–10.