Estimation of user interactivity responsiveness and alertness based on eye blink -application in an e-learning environment

Conference or Workshop Item

ESTIMATION OF USER INTERACTIVITY RESPONSIVENESS AND ALERTNESS BASED ON EYE BLINK -APPLICATION IN AN E-LEARNING ENVIRONMENT

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Most promising methods to deliver effective education at distance are rapidly emerging and evolving as e-learning systems. To support diverse teaching and learning paradigms, e-learning content has to be more than static online text and lackluster material. It is imperative to create a dynamic interaction between e-learning content and users. Technological advances offer new paradigms in distance education and strengthened the distance learning approach on e-learning systems' usability and overall user experience. Distance learning is a cognitive and repetitive task, requiring learners' attention as well as their interest. It is imperative to create a dynamic interaction between e-learning content and users. Therefore, content as well as delivery have to be supported in a highly personalised manner by e-learning systems.

In this paper, the authors present a system which compiles feedback related to the behavioural state of the user (e.g. level of interaction and attention) in the context of reading an electronic document; this is achieved using eye-blink measures to identify alertness and responsiveness to the e-learning material. The real-time vision-based system used a novel evaluation approach to identify the level of alertness by performance correlated against user physiological properties (e.g. eye-blink parameters).

Finally, the authors present an innovative interaction and alertness measure experiment to exemplify learner's responsiveness to the online material presented. Therefore, when delivering content, in addition to the pragmatic functionality of an e-learning system the visual interactivity experience is emphasized as a significant feature for effective content development and delivery. This trend includes but is not limited to e-learning it can be used for microlearning, personalized learning and Massive Open Online Courses (MOOC) content development.

Keywords: E-learning, Education, Distance Learning, Eye Blink, Vision-based system, MOOC, Microlearning, Personalized learning.

INTRODUCTION

To promote online learning, there is a need to create more effective interaction between E-learning content and learners [1]. New learning technologies and techniques always emerging and evolving in the E-learning industry. New trends by putting information online to use can enhance the learning experience. However, in order to support different teaching and learning models, E-learning should incorporate more than simply reading online materials. Therefore, content, as well as communication, have to be interactive and adaptive learning to make sure each learner is engaged in learning path built around learning content for the entire learning process. Towards this goal, many developed e-learning systems have a failure to deliver functionalities like user interactivity techniques, gamification techniques and tracking of learners' input and significance feedback [2]. Several approaches have been proposed in order to collect user experience and preference information about learners, providing adaptation capabilities to such systems.

In this paper, authors build a real-time vision-based system which estimated from behaviour-related features (alertness, level of interest and interaction) of users reading documents in a computer screen. More specifically, we use a system that uses interactivity responsiveness measurement to virtual learning material and correlation of physiological parameters to detect the level of alertness (eye blink duration and blink frequency were important parameters in detecting alertness) [3]. The eye bink parameters provide an indication of particular user interactivity responsiveness into the e-learning materials. Furthermore, as a complementary task, the reaction time measurement system used separately in a combined manner to detect a level of alertness because no single unobtrusive operational measure appears adequate in reliably detecting of alertness [4]. This information is then used to determine the behavioural state of the user towards the E-learning material, i.e. the level of interest and attention. To this aim, resulting system architecture proposes an engaging learning content which stimulates and enhances learner responsiveness to the E-learning material.

1 METHODOLOGY

The proposed system captures eye blink from the front of the eye and measures the eye blink durations and frequency to correlate with reaction time performance data to measures the alertness of the user and interactivity with the E-learning material. Eye-blink activities have been assessed by different investigators over the last 75 years for the systematic analysis of human alertness for different purposes [5]. The eye-blink detection system was utilised to determine direct interaction of the user with the online materials and measure how much time was spent on each part. Reaction time to interactive activity data is correlated with eye-blink parameters to develop an algorithm to measure alertness.

1.1 Real-Time Eye-Blink Detection System

The system used tracks eye blinks from the front of the eye using a built-in webcam on the computer monitor. The reliable detection of eye blink is important requirements for measuring eye blink duration and blink frequency in detecting of alertness. Image acquisition and image processing algorithms are used for blink detection. There are three steps to the eye blink detection procedure: background estimation, template matching and tracking. MATLAB Simulink software is used to design a video capturing algorithm. The feature of the eye that affects the task of tracking is the eye sclera region, the white area of the eye. In building a system for this task, it is necessary to simplify and use workable models of the eye. It is important to judge these simplifications and the performance of a system for a given application and regard every measured characteristic separately. The purpose of an eye detection system is, simply stated, to monitor eye blink durations and eye blink frequency as accurately as is necessary to characterise a user's level of alertness.

1.1.1 Background Estimation

To measure eye blink precisely it is important to separate the foremost motion fragment (eye blink) from other small muscle movements around the eye. The filtering of small amounts of movements around the eye will generate stable images and background estimation technique filtered this muscle movement and produced stabilized images for accurate blink duration detection. Captured RGB video is converting to Grey image (intensity image) for foremost analysis, and the first few frames of the video stream are used to estimate the background image. This process removes the small movements around the eye to create stabilised output for stable eye blink detection (see Figure 1).

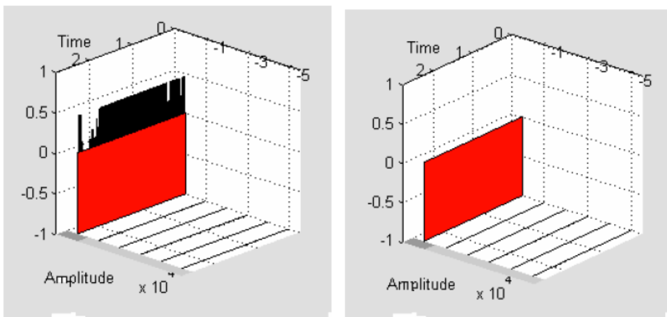


Figure 1. Background estimation and stabilised output for accurate eye blink detection

1.1.2 Template Matching

To locate the eye sclera area, a pattern matching system is used before the blink detection process. Figure 2 illustrates the eye sclera template (binary template for template matching). This process will track the eye sclera region with the use of the template mask, 144x176 pixel sizes and cross-correlation for pattern matching helped to clear the noise around the sclera region. Then the Blob Analysis method is used to calculate statistics for labelled regions in the binary image and returns the area of each element. With 'rough' searching, the eye sclera area can be envisaged as connected blobs [6]. Parameters of the ellipse such as the shape of the eye, aspect of short and long axes, and the size of area are used to decide the area of eye sclera section.

Figure 2. Grey scale morphology of captured eye sclera area

Figure 3 shows the system architecture of three steps eye blink detection system.

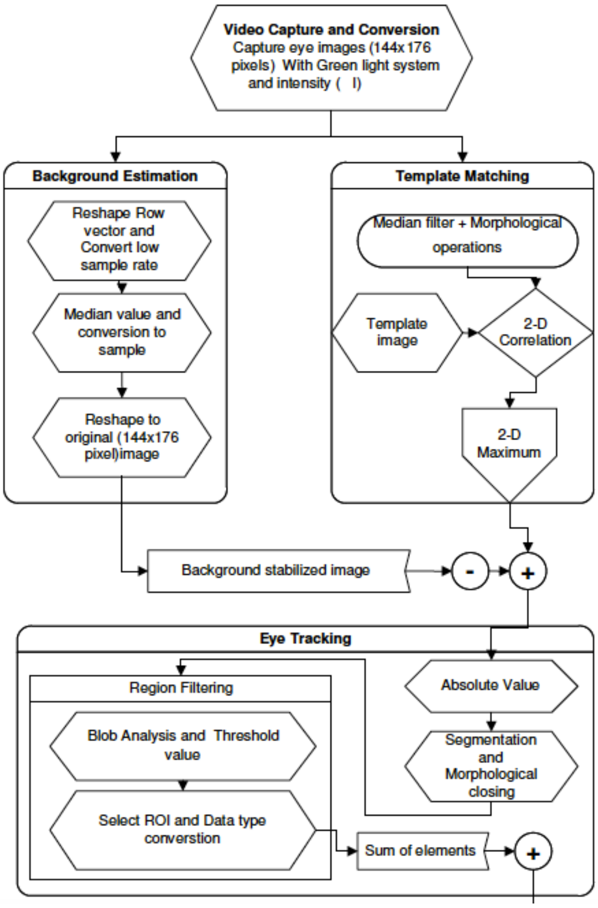


Figure 3. The eye blink tracking system with Background estimation, Template matching and Eye sclera tracking.

1.1.3 Estimate eye sclera area to detect blink duration.

The concept used to calculate the eye blink duration measures major and minor axis lengths of the ellipse change according to eye sclera region changes and blink duration when the eyelids shuts to half - to full close - to half open. This procedure is considered as a complete eye blink. The minor axis coordinates are $(X_{top}, Y_{top} - X_{bottom}, Y_{bottom})$ and will reduce during the eye close to measure lengths change within the range { X_i, Y_i ; i= left, top, right, bottom} from the full eye open to full eye close, and the range of the axis changes is given in the following equation. Figure 4 shows the Blob detection model of eye sclera region detection using ellipse method.

$$I(x,y)=\{I(x,y)|x_{left} \leq x \leq x_{right}, y_{top} \leq y \leq y_{bottom}\}$$

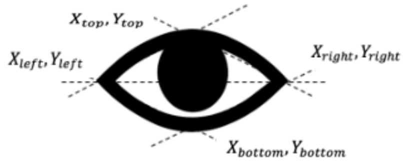


Figure 4. The Blob detection model of eye sclera region detect using ellipse method.

1.1.4 Eye tracking

If the user moves parallel to the PC screen, it keeps the eyes track and the vertical distance between the eyes and the nostrils remain constant. Also, rapid rotations apart from obstructing some of the features or losing tracking makes it difficult for the visible features to be tracked. In such cases, the vector corresponding to pose estimation reduces in length and stays fixed for as long as the user is looking at the screen. Eye tracking algorithm can detect the eyes by template matching technique with the mean displacement of the facial characteristics.

1.2 Participant procedure

Each participant took part in an E-learning session of 45 minutes duration (16 participants participated in different time sessions in a good alert condition, and two of them volunteered in a sleep-deprived condition). The measurement of reaction time was integrated to the E-learning content [7] [8]. Participants were inculcated to pay attention to a colour circle animation in the online materials; they were advised to click on the left mouse button to coincide with the circle changing colour from Red to Green. Once the practice session was completed, the physiological measures and reaction time data were saved for analysis.

1.2.1 Reaction time measuring system

Reaction time is the ability to respond quickly to a stimulus and an important factor of behavioural research activities [9] [10]. Simple reaction time is the time taken between stimulus and action which requires a choice. The reaction time measurement system was designed to measure the response time of the participants to colour graphics animation changes during reading online material. The colour changes randomly (Red to Green). Participants have to press the mouse button when the colour changes from Red to Green. After pressing the reaction button, the green colour circle changes back to red. The time taken between colour change and the reaction (press the button) to change the colour back to red was measured.

2 DATA ANALYSIS

The data analysis for this study composed of two major parts. The first part of the analysis consisted of correlation analyses of physiological and performance data. The purpose of the analysis was to determine which of the variables could possibly link to interactivity measure. The second part of the analysis consisted of linear regression analyses. The purpose of the regression analysis was to find out one or more variables that would best predict impairment resulting from alertness.

Each participant had to complete a questionnaire before the E-learning activity. The subjective information questionnaire was designed to measure the Epworth score (The Epworth Sleepiness Scale (ESS) is a valuable tool to identify people who suffer from excessive sleepiness) [11]. The participant had to rate the likelihood of dozing, from very low (=0), slight (=1), moderate (=2) to high (=3). The total (out of 24) is the ESS score. If the Epworth score is greater than or equal to 11, it indicates that a person is subjectively sleepy.

2.1 Variables to be analysed

There are four variables were collected during the experiment as follows:

- Eye blink durations (average eye blink duration) - AVEBLKDU
- Eye blink frequency (average eye blink frequency) - AVEBLKFR

- The average reaction time for colour circle animation changes – AVEREATM, and
- Self-reported measures Epworth sleepiness scale value - ESS

All physiological and reaction time measures data were first computed over one-minute intervals. Data manipulation procedures were then undertaken to prepare data for statistical analysis. All measures collected through time were averaged in 1minute blocks. Then mean and standard deviations were calculated for minutes 1 to 5, 2 to 6, 3 to 7, etc, giving a 5-minute moving average window [12]. After completion of the moving average procedure, all the data was arranged in 5-minute intervals. In addition, the standard deviation (SD) of average blink duration and frequency (SD-AVEBLKDU & SD AVEBLKFR) were used in the linear correlation model with performance measures with the aim of producing a more accurate alertness detection model. Every participant had to respond to random colour changing animation runs with the online material. Total reaction times measured during the 45minute E-learning materials reading go through a moving average filter to sample over a 1minute interval. The standard deviation of average reaction time was calculated for the final linear correlation (SD-AVEREATM).

2.1.1 Accuracy of eye-blinks capture

Generally, all the participants returned a low blink count at the beginning of the reading test and this gradually increased to the end measurement, where the participants showed an average blink count of 22.94. Two participants showed the highest blink counts at the 30th-minute mark. The general blink frequency increases gradually over the session and settles to a normal average human blink rate (23 eye blinks/min) during the last 15 minutes. Table 1 shows the correlation coefficient comparison of SD of AVEBLKDU & AVEBLKFR with AVERBLKDU & AVEBLKFR for all participants (subjects-SUB). The correlation values show a small increment for the SD values. The results of Table 1 show correlation coefficients are slightly higher for SD of averages than for the averages themselves. Therefore, the SD of average values was calculated for physiological measures and predicted variables. Figure 5 shows an example of a randomly selected participant's linear correlation of SD-AVEREATM compared with the linear correlation of AVETRATM with SD values of blink durations. It shows a significant increment in R^2 value between SD and normal average.

Table 1. Linear Correlation Comparison

Participant Number	1	2	3	4	5	6	7	8	9
SD of AVEBLK DU & FR	0.9691	0.992	0.89	0.96	0.809	0.794	0.964	0.918	0.96
AVEBLK DU & FR	0.955	0.981	0.84	0.955	0.792	0.788	0.952	0.901	0.951
Participant Number	10	11	12	13	14	15	16	17	18
SD of AVEBLK DU & FR	0.84	0.806	0.89	0.7	0.968	0.911	0.915	0.801	0.971
AVEBLK DU & FR	0.831	0.801	0.881	0.677	0.961	0.903	0.91	0.793	0.963

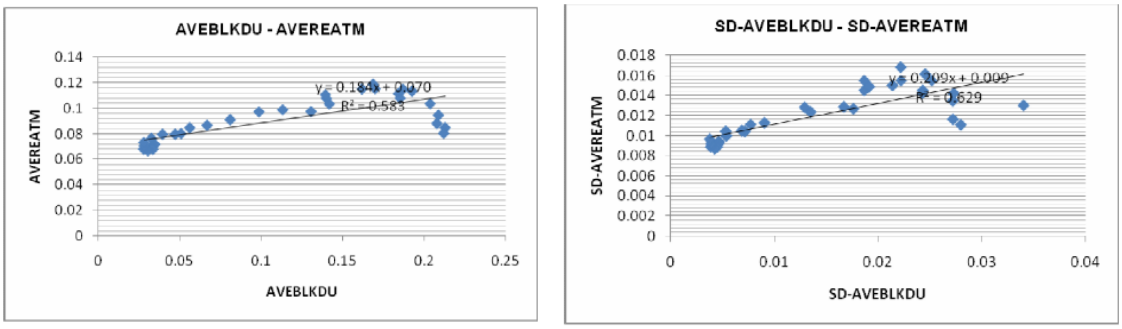


Figure 5. Linear Correlation of SD of average compacted with average on AVEBLKDU and AVEREATM

2.1.2 EPWORTH Sleepiness Scale (ESS)

All participants filled in a questionnaire with the Epworth sleepiness scale. A score of 11 or more is considered sleepy. This scale helps to obtain a general indication of participants' daytime sleepiness. Figure 6 shows the ESS scores for all eighteen participants.

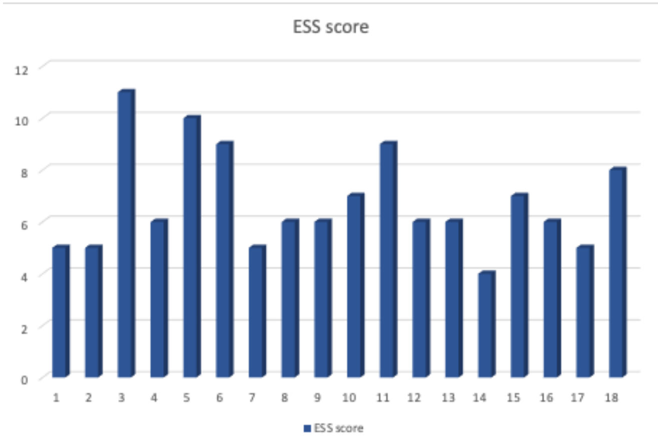


Figure 6. Epworth sleepiness score (ESS) for each participant

3 RESULTS

Regression and correlation analyses were performed on the collected physiological and speed related data with performance data to determine the best indicators of interaction. Correlations were performed between the collected physiological measures and the collected performance measures. The Epworth scale helped to categorize the participants, with their sleep deprivation problem and normal condition. In the analysis, participants with EPWOSCL≥10 were considered as sleepy, because only two participants had high ESS across all 18 participants. In this study, the participants who had EPWOSCL≥11 and the participant who had ESS=10 showed similar performance results. Therefore, EPWOSCL≥10 is considered as a high EPWOSCL for further analysis. Figure 7 shows the Epworth score with reaction time measure data for all 18 participants.

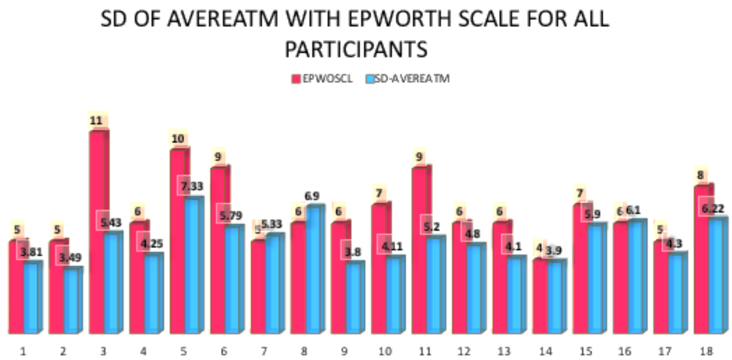


Figure 7. SD of AVEREATM with Epworth score for all participants.

Figure 8 shows the Boxplot of the Epworth score and SD-AVEREATM for eighteen participants. It indicates that the two participants who have EPWOSCL≥10 have longer (slower) reaction times compared to participants who have EPWOSCL≥9. The AVEREATM is categorized by the Epworth score ESS≤9 and ESS≥10. The t-test gives the value $t=0.83$ (d.f=2), which is not significant ($p>0.20$), indicating that the differences in means between the two categories are not significantly different from the zero. The reasons for not detecting a significant difference between the two categories were high variability of reaction time in participants and the small sample. Epworth scale measure may be an indicator of alertness, but it required a large test sample to clarify the significant differences of alertness performance.

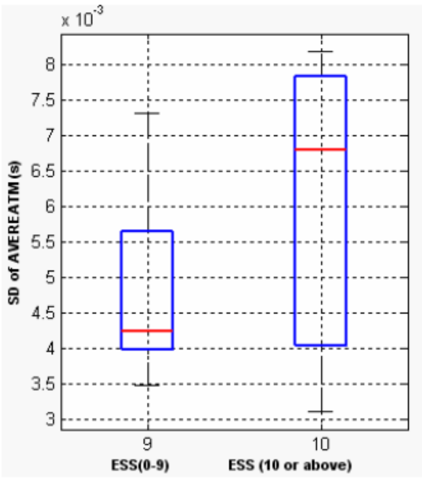


Figure 8. Boxplot of ESS and SD of AVEREATM

3.1 Correlation analysis for SD of AVEBLKDU and AVEBLKFR

An examination of the regression analysis, including the average R scores across all the physiological variables (predictor variables) for the reaction time measures (predicted variable), gives an indication of the strength of their linear interrelationship. The results of the average R score analysis for AVEREATM value shows a better linear relationship with average blink duration and frequency (AVEBLKDU R=0.9411 and AVEBLKFR R=0.940). The increased duration of spontaneous blinks has been suggested as an early indicator of the deprived alertness to the E-learning materials [13]. The test results illustrate that SD of AVEBLKFR and AVEBLKDU increases significantly($p<0.001$) for two sleep deprivation participants. The test results demonstrate that SD values for AVEBLKDU and AVEBLKFR increase significantly during the last 15 minutes on all the participants during reading online materials. SD of AVEREATM categorized into two groups (two sleep deprived participants and 7 to 9 hours sleep participants). The median values of SD-AVEREATM give a clear difference between two groups (sleep deprived, 0.017 and 7 to 9 hours sleep is 0.0048). The t-test results were not significant at 5%, but were significant at 10%, t=1.76 (d.f=3), $p<0.1$. This showed that the difference in the mean value of AVEREATM is significant for the two categories. Considering the results for AVEREATM with sleep durations indicates that sleep duration is potentially an important indicator for alertness impairment.

Correlation analysis was conducted for SD of AVEBLKDU and AVEBLKFR with SD of AVEREATM Table 2 shows the correlation coefficients for the first 15 minutes and last 15 minutes for all the subjects. Correlation results show that SD of AVEREATM is highly correlated with SD of AVEBLKDU and AVEBLKFR in the last 15 minutes for all the subjects.

Table 2. Correlation results for all subjects in the first 15 minutes and last 15 minutes.

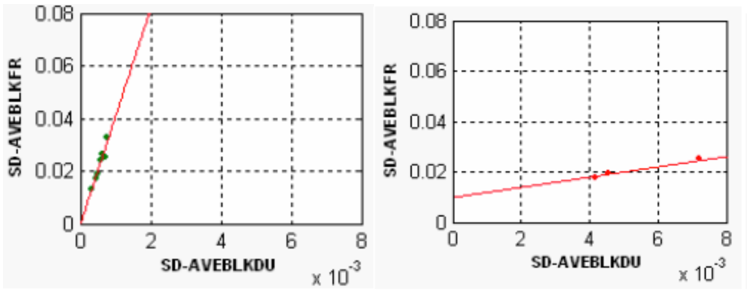
FIRST 15 MINUTES		
ALL PARTICIPANTS	SD-AVEBLKDU	SD-AVEBLKFR
SD-AVEREATM	0.4112	0.2241
LAST 15 MINUTES		
ALL PARTICIPANTS	SD-AVEBLKDU	SD-AVEBLKFR
SD-AVEREATM	0.931	0.8911

Development of the final regression model considered two physiological measures with performance measure (reaction time). Statistical methods have been used for selecting the final regression model variables [14]. The average 'R' values indicated the most significant variables to be used for further analysis. The test results illustrated that SD of AVEBLKFR and AVEBLKDU highly correlated and significant correlation results towards the last 15 minutes of the online reading test ($p<0.001$). SD of AVEBLKFR and AVEBLKDU variables are very highly correlated during the 45 minutes reading (Pearson's $r = 0.98$, $n = 7$, $p<0.001$). The comparable correlation between SD-AVEBLKDU and SD-AVEBLKFR in the first 15 minutes of the reading state was almost as high ($r = 0.97$, $n = 7$, $p<0.001$) but with a different regression slope. The slope of linear regression is higher when participants are more alert to the online materials compared to last 15 minutes of the reading. The statistical model used for linear regression is $y = mx + b$. In this particular equation, the constant 'm' determines the 'slope' or gradient of that line. Figure 9 shows the compassion of all participants during their first 15 minutes of reading online materials and the last 15 minutes of reading. The slope gradient for linear regression for the participant in the first 15 minutes is m=40.1, b=0.00051 compared to last 15 minutes gradient m=2.012, b=0.0091.

3.1.1 Evaluating the Goodness of Fit

The linear relationship between SD of blink duration and frequency was evaluated for its goodness of fit and method of residual plots are used to test the goodness of fit. The residuals from a fitted model are defined as the differences between the response data and the fit to the response data at each predictor value with the following equation:

$$residual = data - fit$$



(a) (b)

Figure 9. Correlation analysis: measure of linear relationship strength between SD-AVEBLKDU and SD-AVEBLKFR for all participants in the first 15mints (a) and last 15mints (b) of the online reading.

Figure 10 shows the residual plot for randomly selected participant data in the first 15 minutes of reading with predicted SD-AVEBLKDU. The results show the residuals appear randomly scattered around zero indicating that the model describes the data well.

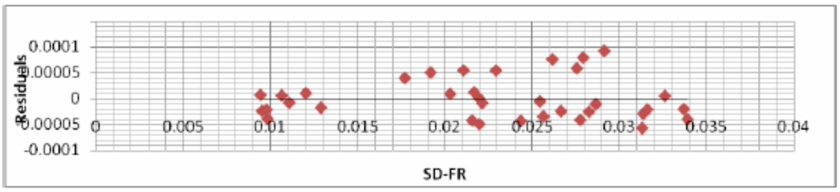


Figure 10. The residual plot for randomly selected participant data in the first 15mints of reading

Most of the participants showed some increase in their blink duration and frequency in the last 15mints of their online reading compared to the first 15mints. The reason for this behaviour suggested that they were not fully concentrating on the reading or were bored.

4 CONCLUSIONS

An important possibility of non-verbal feedback concerning the interest of a person towards an E-learning content is the degree of engagement or interest in the materials presented. The data collected from the system that measured eye blink indicates the person's interest level and their focus of attention in relation to the E-learning content. The eye blink frequency and blink duration measure system could be used to monitor users' interactivity responsiveness on online materials in real-time and level of alertness to the learning activities because these eye blink parameters is a possible predictor of interest and interaction with E-learning materials. The blink detection system can be embedded into the E-learning tools by activating user webcam to monitor readers' interaction experience and will provide factual feedback, so the educators get a better picture of appraising or modifying the online contents. In this article, the authors addressed the dependent variable of reaction time measure. This parameter can be used for the system and may contribute to finding new ways of making more interactive and adaptive environments for E-learning content.

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