Cognitive Robotics 2 (2022) 50–59

Contents lists available at ScienceDirect

Cognitive Robotics

journal homepage: http://www.keaipublishing.com/en/journals/cognitive-robotics/

Eye fatigue estimation using blink detection based on Eye Aspect Ratio Mapping(EARM)

Akihiro Kuwahara, Kazu Nishikawa, Rin Hirakawa, Hideaki Kawano, Yoshihisa Nakatoh*

Kyushu Institute of Technology, 1 1-1 Sensuicho, Tobata Ward, Kitakyushu City, Fukuoka Prefecture, Fukuoka, Japan

ARTICLE INFO

Keywords:
Eye Fatigue
VDT syndrome
Digital eye strain
Blink detection
Eye Aspect Ratio

ABSTRACT

With the advent of the information society, the eyes' health is threatened all over the world. Rules and systems have been proposed to avoid these problems, but most users do not use them due to the physical and time constraints and costs involved and the lack of awareness of eye health. In this paper, we estimate the eye fatigue sensitivity by detecting spontaneous blinks with high accuracy. The experimental results show that the proposed Eye Aspect Ratio Mapping can classify blinks with high accuracy at a low cost. We also found a strong correlation between the median SBR (Spontaneous Blink Rate) and the time between the objective estimation of eye fatigue and the subject's awareness of eye fatigue.

1. Introduction

Prolonged use of display devices (Visual Display Terminals) such as smartphones and computers will have various adverse effects on users' health [1]. Various symptoms such as eye fatigue, blurred vision, dry eyes, redness, headache, and stiff shoulders are signs of VDT syndrome (Visual Display Terminal Syndrome) or Digital Eye Strain (DES) [2,3]. These are also known as computer vision syndromes or IT ophthalmopathy and are caused by dryness of the cornea due to reduced blinking and tension of the ciliary muscles due to prolonged staring at short distances [4].

According to a WHO report, more than 2.2 billion people worldwide have various visual impairments ranging from visual impairment to blindness [5,6]. Furthermore, by 2050, the number is expected to increase to nearly 5 billion, half of the world's population at that time. It has also been reported that approximately 80% of millennials experience symptoms of eye strain caused by these factors when using display devices [7].

This problem can be avoided by taking appropriate precautions, such as taking proper breaks, paying attention to distance regularly, and blinking consciously. There is a 20–20–20 rule proposed by Professor Jack Dennerlin and a 15-minute break for every hour of VDT work proposed by the Japanese Ministry of Health, Labor, and Welfare, both of which are considered highly valid [8,9]. However, unfortunately, most users are not aware of this problem, and even among those who are aware, very few are taking appropriate preventive measures. We believe that this situation is caused by the discrepancy between the user's perception of eye fatigue and the actual eye fatigue, the user's feeling that they are not yet tired, and a lax perception of eye overuse. In order to improve this situation, it is necessary for users to objectively understand their eye health condition and suggest the most appropriate rest. Currently, there are several methods to manage users' eye health. The MHealth system is an application that identifies patients with eye problems by

* Corresponding author.
E-mail addresses: kuwahara.akihiro135@mail.kyutech.jp (A. Kuwahara), nishikawa.kazu615@mail.kyutech.jp (K. Nishikawa), hirakawa.rin151@mail.kyutech.jp (R. Hirakawa), kawano@ecs.kyutech.ac.jp (H. Kawano), nakatoh@ecs.kyutech.ac.jp (Y. Nakatoh).

https://doi.org/10.1016/j.cogr.2022.01.003
Received 19 January 2022; Received in revised form 29 January 2022; Accepted 29 January 2022
Available online 30 January 2022

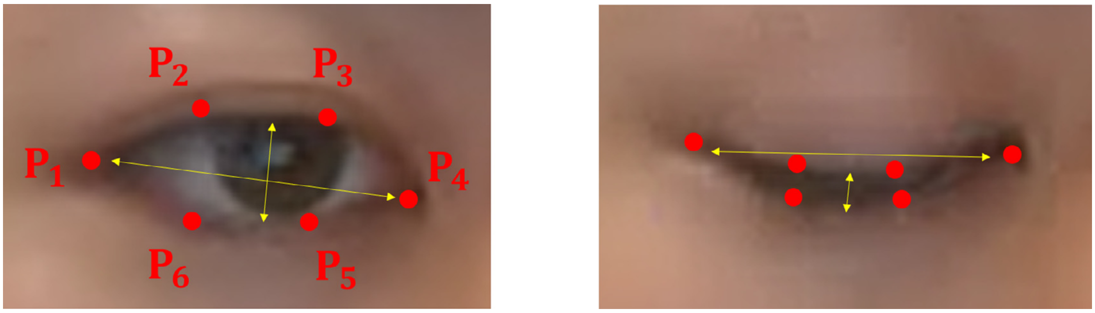

Fig. 1. Open and closed eyes with landmarks automatically detected by dlib [26,31].

testing their vision and assessing their distance vision [10]. This application has the disadvantage of being time-consuming and physically restrictive, as the patient must use a smartphone to perform the vision test and questionnaire-based distance vision assessment. Another example is ZINS MEME, proposed by ZINS [11]. This is a wearable device in the form of eyeglasses that collects and analyzes various data such as angle, number of steps, blink, etc., to monitor the state of the body and mind. However, the disadvantages are that it forces the wearer to wear glasses and requires regular costs for operation. On the other hand, teleophthalmology has been proposed, but it requires specialized equipment such as optical coherence tomography (SD-OCT) and a pulse air tonometer and is not practical at all in terms of cost [12].

In order to solve these problems, we focused on image processing technology, which is also used in the diagnosis of many diseases [13–15]. We then proposed a blink detection system that accurately captures the blink of an eye using only camera images without requiring physical restraint of the user or special equipment [16,17]. In this paper, we re-evaluate the system by preparing a new dataset that is more appropriate for evaluation, clarify the relationship among blink, subjective eye strain time, and objective eye strain time, and propose a system to estimate eye strain sensitivity based on the obtained data.

2. Related works

2.1. Eye blink

There are three types of blinking: voluntary eyeblink, reflexive eyeblink, and voluntary eyeblink [18]. While the first two types are unconscious eyeblinks, the latter one depends solely on the subject's will, and each has a different function. Blinking has been used as a physiological indicator of drowsiness and concentration, as well as eye fatigue and dry eyes [19,20]. In this paper, the spontaneous blink, which is closely related to eye fatigue, is defined as blink below.

Spontaneous Eyeblink Spontaneous Eyeblink refers to the closing of both upper eyelids that occurs unconsciously, transiently, or briefly, in a very similar and coordinated manner, without any apparent stimulus. Such eyelid movements are essential for clarifying the user's vision, distributing tear fluid over the ocular surface, and maintaining the stability of the tear fluid. Dry eye patients have been reported to have faster tear evaporation and an increased number of spontaneous blinks [3,21].

2.2. Blink detection method

From the past to the present, various methods based on various features related to blinking have been proposed. In this section, we will discuss these related studies.

Electrooculogram (EOG) is derived from the electrical potential recorded from electrodes placed above and below the eye during the blink of an eye [22]. This technique takes advantage of the fact that the cornea has a positive potential for the eye. The natural eyelid movements during the blink affect the potential between the two electrodes located above and below the eye. Blink detection is based on the high correlation between the waveform of the obtained potential difference and the standardized EOG of the blink. This method does not limit the position of the head and has high blink detection accuracy. This method is mainly used to track the blink changes of drivers [23–25].

Eye Aspect Ratio Eye Aspect Ratio is proposed by the Czech Technical University [26,27]. It is a scalar quantity obtained by detecting a face from an image, finding the Euclidean distance of the corresponding eye coordinates, and substituting it into the following formula.

$$EAR = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|} \tag{1}$$

where p1, . . ., p6 are the 2D landmark locations, depicted in Fig. 1. When the eye is open, the value is almost constant, but it approaches zero when the eye is closed. This value does not depend on head posture or distance, and there are small individual differences when the eyes are open. Since eye blinking is performed by both eyes synchronously, the EAR of both eyes is averaged. Due to the simplicity of the calculation formula, it has excellent real-time performance and shows high robustness. However, although we are trying to classify irregular movements such as eye thinning, absent stretching, or only eyes looking down, detection is difficult at the threshold. Also, although it is claimed to have high and straightforward detection accuracy, it causes a loss of accuracy when there is a sudden movement of the face or when the face is exceptionally far away from the camera. The resolution degradation due to distance could be solved by converting face images to higher resolution using super-resolution techniques, but this has not been investigated [28].

In addition to the above two methods, various other methods have been proposed, such as predicting blinks based on changes around the eye and binary classification of eye-opening and closing based on template matching [19,29,30].

However, most of these existing methods have some limitations. They are susceptible to various external factors such as image resolution, illumination, and head pose, require specialized equipment and are computationally expensive. It should also be noted that many blink detectors only distinguish between open and closed eyes and do not detect temporal blinks at all.

2.3. Relationship between eye fatigue and visual system indices

The relationship between eye fatigue and visual system indices has been studied extensively. Eye fatigue consists of two types: the functional decline of the optical regulatory system, including muscle fatigue of the ciliary muscle and other muscles that affect the focusing function, and central fatigue of visual information processing that concerns the cognitive process. This section will introduce research on the relationship between eye fatigue and optical system indices.

2.3.1. Eye fatigue and pupillary movement

Hoshino et al. [32] test with quantifying ocular fatigue using the dynamic characteristics of the pupil-to-photoreceptor response as a physiological index and reported that a decrease in the pupil reaction speed was predominant. Furthermore, Kondo et al. [33] extend the work of Hoshino et al. [32] They reported dominant changes in pupillary contraction velocity, pupillary reaction velocity, and pupillary re-dilation velocity and that these changes are effective as objective indicators.

In addition, Kondo et al. [33] considered that the fatigue of the pupillary sphincter caused these fatigues due to its continuous contraction.

2.3.2. Eye fatigue and critical fusion frequency of flicker

The flicker frequency per unit time is called the flicker value (Hz). The critical fusion frequency (CFF) is the flicker value at the boundary between what is perceived as continuous light and what is perceived as flickering light. The smaller the CFF, the higher the level of fatigue. According to Takahashi et al. [34] research, it has been confirmed that the flicker value measuring device can be used to evaluate the eye fatigue of subjects objectively.

2.3.3. Eye fatigue and blinking

Since ancient times, many studies have examined the relationship between eye fatigue and blinking. According to the literature, it has been reported that the number of blinks per minute decreases drastically during VDT (Visual Display Terminal) work compared to regular work and increases with the accumulation of eye fatigue [35]. In addition, Takizawa et al. [36] reported that it is possible to quantify fatigue by adding up the number of blinks is a certain percentage less than the usual number of blinks. Furthermore, Asagai et al. [37] reported a strong negative correlation (r=-0.92) between IBLI (Inter-Blink Interval) and the perceived time of eye fatigue. Both studies examined subjective eye fatigue, but the link to objective eye fatigue values was weak. They were unable to quantify the degree of fatigue.

In addition, Mark et al. [38] reported that the rate of incomplete blinks increased in computers versus printed materials, even when the task is the same. Incomplete blinking, defined as blinking that covers less than two-thirds of the cornea, leads to tearing evaporation and has been cited as a cause of dry eye. However, its causal relationship to ocular fatigue is unknown. This paper does not measure incomplete blinks but complete spontaneous blinks in which the upper eyelid margin and lower eyelid touch.

3. Proposed method

In this section, we describe our proposed blink detection method and the objective measure of eye fatigue we use.

3.1. Blink detection method

We assume that our video source is a camera attached to a monitor or the front camera of a smartphone, tablet, or PC to make a full image of the face available. The system diagram of our proposed system for blink detection using a whole face image is shown in Fig. 2.

Our proposed method is partially based on the work of Tereza et al. [26,27] with the addition of normalization of the face image and the difference in the blink classification method. The system consists of the following steps.

1 Detecting and cropping the face region from the input image using OpenCV, and normalizing the image size.
2 Detecting and cropping the face region from the input image using OpenCV and normalizing the image size. Calculate the coordinates of 68 face organ points from the normalized face image using HOG features and SVM [31]. We also need a dataset to use this library. iBUG 300-W has a trained dataset "shape_predictor_68_face_landmarks.dat" [39–41].

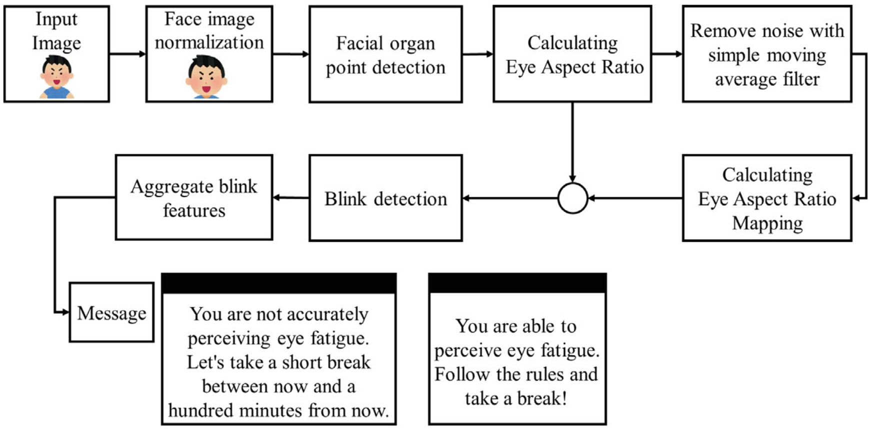

Fig. 2. An overview of the proposed method.

3 The EAR is calculated from the coordinates of 12 points around the eye. The time-series data is corrected by applying a simple moving average filter to remove noise. In order to preserve the features, the width of the simple moving average is set to 5.
4 Convert the time series data into a time series that shows a response to spontaneous blinking only, using our formula EARM.
5 Compare the EARM time series data with the original data to detect blinks.

3.1.1. EARM (Eye aspect ratio mapping)

In the case of blink classification using only EAR, we believe that the risk of false positives is high. This is because the noise caused by irregular movements, such as stretching or looking down, maybe mistakenly detected as a blink. In this study, we propose a new calculation formula, Eq. (2), which focuses on the blink time having a slight variation of 100∼150 ms and draws a characteristic graph [16].

$$\mathrm{EARM(t)} = \mathrm{EAR}\left(\mathrm{t} - \frac{\mathrm{X}+1}{2}\right) + \mathrm{EAR}\left(\mathrm{t} - \frac{\mathrm{X}-1}{2}\right) + \mathrm{EAR}\left(\mathrm{t} + \frac{\mathrm{X}-1}{2}\right) + \mathrm{EAR}\left(\mathrm{t} + \frac{\mathrm{X}+1}{2}\right) - 4 * \mathrm{EAR(t)} \tag{2}$$

Where, X is the number that satisfies the number of frames and the odd number of frames per eye blink, which is defined as 11 in this experiment. Also, t is the number of frames since the start.

The merit of the proposed system is the lightness of processing by Dlib and OpenCV, which does not depend on the high performance of information terminals. OpenCV uses cascade classification for fast face detection, while Dlib uses a combination of SVM and HOG features to detect facial organ points. By using such a combination, we can achieve fast processing.

3.1.2. Face image normalization

According to et al. [26] study, the EAR equation is independent of the face distance. Indeed, even if the face distance changes, the EAR should not change because the Euclidean distance of the coordinates is universal. However, because of our preliminary experiments, we found that the EAR is determined by the number of pixels in the input image. When the face is small, the noise in the EAR becomes large, which is one of the causes of the decrease in blink detection accuracy. Therefore, we used OpenCV's cascade classifier to detect the face, cropped the face image, and normalized it to a size of 300 × 300 pixels [17].

3.2. Methods of objective testing for eye fatigue

In general, eye fatigue has been quantified using various physiological indices such as critical fusion frequency (CFF) of flicker, eye movement, and pupil contrast reaction [19,38,42]. However, they all have problems in terms of simplicity and implementation cost. EOG is used to measure eye movements, but electrodes are attached around the eyes, which creates a sense of physical restraint and may produce unusual data. In addition, pupillary photoreceptor response requires specialized equipment and high installation cost, making it universally unavailable.

On the other hand, measuring the critical fusion frequency of flicker is simple and does not require much time to learn. Furthermore, it is highly versatile and has a low implementation cost, as it can be measured in some applications. However, since the value of CFF differs from person to person, it is necessary to normalize the value.

Therefore, this paper introduces EFL (Eye Fatigue Level), a new normalized version of CFF, and evaluates the relationship between objective eye fatigue and blink rate using both SBR and EFL.

Spontaneous Blink Rate SBR is obtained by observing a subject for a period of time and dividing the total number of blinks performed by the observation time [18]. The following is obtained by Eq. (3), and the unit is bl/sec.

$$Spontaneous\ Blink\ Rate = \frac{Spontaneous\ Blink\ count\ (bl)}{Time\ (min)} \tag{3}$$

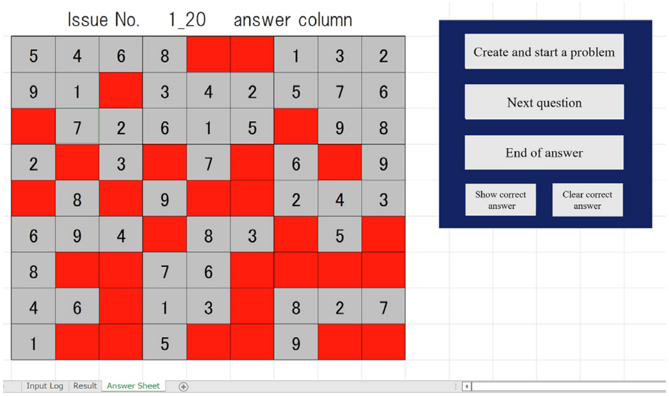

Fig. 3. Sudoku puzzle used in the experiment.

EFL(Eye Fatigue Level) EFL is an objective quantification index of ocular fatigue introduced in this paper and is defined by the following Eq. (4).

$$EFL = 1 - \frac{CFF_t}{CFF_0} \tag{4}$$

Where CFF_0 is the CFF value before the experiment and CFF_t is the CFF value at time t seconds after the VDT task is started.

As a result of preliminary experiments, it was estimated that eye fatigue was accumulated when EFL≥0.034. Therefore, the elapsed time of VDT work when EFL = 0.034 was defined as the time when eye fatigue was objectively accumulated.

4. Experiments

4.1. Dataset

A serious problem exists in evaluating the performance of blink detection systems. There are no standardized evaluation videos with which researchers can compare their results. For this reason, most of the research to date has generally been conducted by evaluating algorithms on videos that have not been standardized and taken by individuals. In this paper, to evaluate the performance of the blink detection system under conditions closer to the actual usage environment, we shot videos for evaluation under the following conditions.

Evaluation Videos All videos were shot using the front camera on the surface pro5 at a resolution of 640 × 480 pixels at 30fps with a length of about 11k frames per person. The images show the upper part of the body almost facing the camera, allowing us to see the appropriate body movements during VDT work. Also, those with bangs over their eyes had their hair trimmed to ensure face detection. In addition, the correct labels of SBR were counted manually after we visually checked all the videos. Furthermore, only complete spontaneous blinks were counted, so incomplete blinks were ignored.

Subject The subjects were four subjects in their 20 s who handled information equipment daily. In order to keep the experimental conditions the same, the experiment was conducted within 5 hours of waking up with the minimal accumulation of eye fatigue.

Experimental environment In this experiment, we worked indoors, shutting out the outside light to not depend on the weather conditions of the day. The room temperature was set at 26 ° Celsius, and the air conditioning was turned off before the start of the experiment in order to prevent the eyes from drying out. The luminous intensity of the display was set to the highest luminance that could be set. All the subjects were tested one by one in the same room, and no outsiders were allowed in the room while they were working to elicit their concentration.

4.2. VDT task

There is no standardized VDT task that induces eye fatigue. As a VDT task, Takizawa et al. imposed an English letter search task [36]. Participants were asked to count the number of specific alphabets within a time limit. Kondo et al. imposed a number search task [33]. The participants had to click on randomly arranged numbers from 1 to 99 in order within a time limit. Although the VDT tasks that induce eye fatigue vary from author to author, they have in common that they are easy to master, require concentration and short-term memory, and cause frequent shifts in viewpoint.

In this paper, as shown in Fig. 3, a Sudoku puzzle was assigned as a VDT task that meets these requirements. A Sudoku puzzle is a pencil puzzle in which a grid of nine rows and nine columns is divided into blocks of three rows and three columns [43]. The numbers 1 to 9 are placed in each column, row, and block without overlapping. In order to shorten the thinking time and make the eye movement more active, the difficulty level was set to beginner.

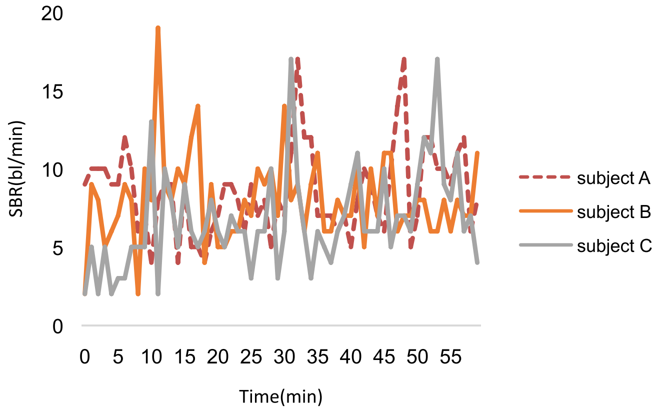

Fig. 4. Time trends of SBR of subject A, subject B, and subject C.
Time trend of SBR of subject D.

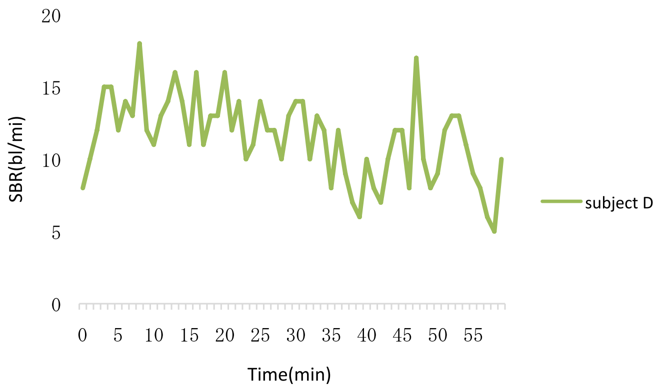

Fig. 4. Continued

4.3. Measuring the critical fusion frequency of flicker

There are various methods of measuring flicker value. A typical method is an ascending method, in which the flicker value is recorded when the subject begins to perceive the light source as fused light, and the descending method, in which the flicker value is recorded when the subject begins to perceive flickering by gradually decreasing the flickering frequency of the light source from fused light. Oikawa et al. found no statistically significant difference between these two methods [44]. Therefore, in this paper, we performed two measurements, one by the ascending method and the other by the descending method, and used the average of the two as the CFF value. Flicker value measuring instrument type II (automatic type) was used for flicker value measurement.

4.4. Experimental results and discussion

4.4.1. Time trends of SBR

The variations in SBR are summarized in Figs. 4 and 5. From Fig. 4, it appears that the SBR of subject ABC decreased and then gradually increased after the VDT task started, although there are individual differences. This indicates that SBR decreases during the VDT task and increases with fatigue, as seen in previous studies. On the other hand, as shown in Fig. 5 only subject D showed a tendency for SBR to decrease with time. We believe that this event is due to an eye disease. We know that subject D had strabismus surgery in his childhood. Since the median number of blinks was higher than the other subjects in Fig. 6, we inferred that he blinked more on his own even during VDT work due to eye diseases such as dry eyes.

4.4.2. Bkink detection

MAE is the average of the absolute values of the predicted and actual values and is calculated using Eq. (5) below [45].

It is one of the methods to quantitatively grasp the error between the predicted value and the actual value, and the closer it is to zero, the higher the accuracy of the prediction model. The unit is bl/min.

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|x_t - \hat{x}_t| \quad (5)$$

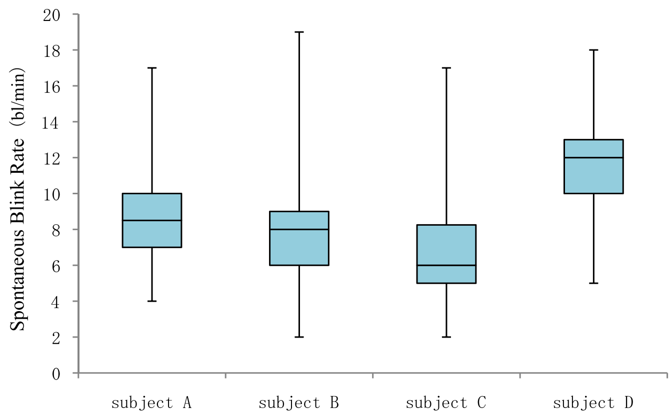

Fig. 5. Median SBR for each subject.

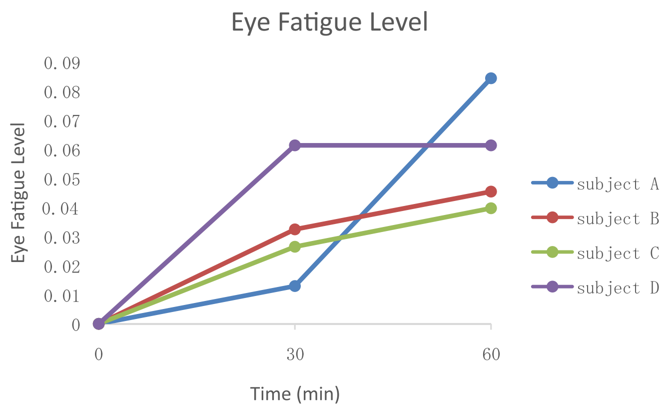

Fig. 6. Median SBR for each subject.

Table 1
Performance Evaluation of Blink Detection Method by MAE.

MAE	Blink detection methods (bl/min)			
	EAR	EARM	EAR+ normalized face image	EARM+ normalized face image
Subject A	1.43	0.69	0.94	0.35
Subject B	1.32	0.51	0.48	0.35
Subject C	0.90	0.18	0.27	0.07
Subject D	1.32	0.42	0.74	0.18
Average	1.24	0.45	0.61	0.24

where x_t is the actual value of SBR, $\hat{x}_t$ is the predicted value of SBR, N is the number of data and t is the time.

RMSE is the square root of the average squares of the predicted and actual values and is calculated using Eq. (6) below [45]. It is one of the methods to quantitatively grasp the error between the predicted value and the actual value, and like MAE, the closer it is to zero, the higher the accuracy of the prediction model. The difference between RMSE and MAE is that RMSE is less tolerant of outliers, so it is used to indicate how accurate the prediction model is.

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(x_t - \hat{x}_t\right)^2} \tag{6}$$

where x_t is the actual value of SBR, $\hat{x}_t$ is the predicted value of SBR, N is the number of data and t is the time.

Table 1 and Table 2 show the MAE and RMSE calculated for each subject. As shown from Table 1 and Table 2, the proposed method outperforms most of the existing methods, EAR, in terms of blink detection accuracy. In addition, the number of false blink detections is reduced from 1.51 bl/min to 0.24 bl/min, indicating that the performance is improved. Also, as can be seen from Table 2, the average value of RMSE is the smallest at 0.61 bl/min, indicating that there is no significant deviation from the actual value. This indicates that the proposed method can reduce the noise in the blink detection and achieve more accurate detection.

Table 2
Performance Evaluation of Blink Detection Method by RMSE.

RMSE	Blink detection methods (bl/min)			
	EAR	EARM	EAR+ normalized face image	EARM+ normalized face image
Subject A	2.41	1.12	2.68	0.89
Subject B	1.79	0.72	1.16	0.87
Subject C	1.00	0.32	0.97	0.26
Subject D	1.91	0.55	2.00	0.43
Average	1.78	0.68	1.70	0.61

Table 3
Performance Evaluation of Blink Detection Method by RMS.

Subject	Eye Fatigue Time (sec)		
	Time it took for subjects to feel eye fatigue.	Eye fatigue time predicted from EFL	gap
Subject A	3220	2329	891
Subject B	2800	2012	788
Subject C	2940	2821	119
Subject D	2882	998	1994

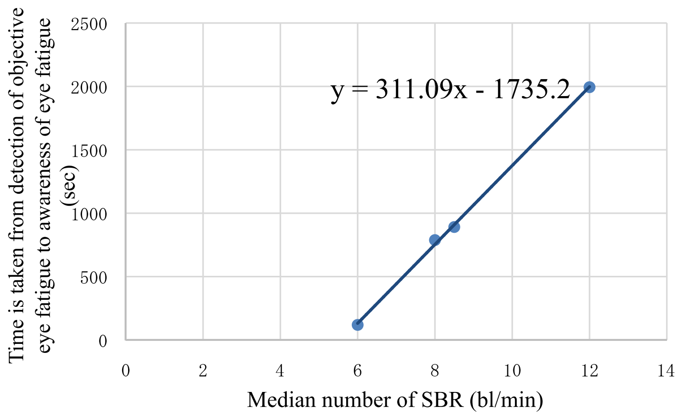

Fig. 7. Relationship between the median SBR and the time it taken from objective estimation of eye fatigue to the subject's awareness of eye fatigue.

However, when we checked the false positives of the proposed method, it was confirmed that the proposed method could not capture the continuous and fast blinks. This may be because the blink features were also smoothed using the simple moving average filter. Therefore, it was suggested that selecting a new filter that can retain the features while suppressing the noise is necessary.

4.4.3. Estimation of eye fatigue sensitivity

The time trends of EFL obtained by this experiment are shown in Fig. 6. According to Fig. 5, the movement of subject B and subject C had the same value, and it was confirmed that fatigue accumulated logarithmically by VDT work. In addition, it can be confirmed that subject D had already accumulated eye fatigue to the limit objectively 30 minutes after the VDT work started. On the other hand, subject A is expected to be relatively resistant to eye fatigue because of the rapid accumulation of eye fatigue between 30 and 60 minutes.

Next, Table 3 summarizes the difference in time from when eye fatigue was objectively estimated to when the subject became aware of eye fatigue. We believe that this difference in time indicates how accurately the subject grasps his eye fatigue, in other words, the sensitivity to eye fatigue.

As a result of the experiment, we found that subject D had the slightest accurate grasp of his eye fatigue, while subject C had the most accurate perception of eye fatigue.

Furthermore, when compared with SBR, there was a robust correlation (r=0.9995) between the median of SBR and the time taken from the time when eye fatigue was objectively estimated until the subject became aware of eye fatigue as shown in Fig. 7. This confirms that people who can accurately identify eye fatigue tend to have a lower SBR during VDT work. This suggests that it may be possible to measure the sensitivity to eye fatigue from the change in SBR.

5. Conclusion

In this paper, we propose a new spontaneous blink detection method based on face images and the possibility of estimating eye fatigue sensitivity. The experimental results show that the proposed blink detection method is simple, low cost, and highly accurate. We also found a robust correlation (r=0.9995) between the median SBR and the delay in the time when the subject became aware of eye fatigue from the objective estimated time of eye fatigue. Our experiments suggest the possibility of estimating the level of visual fatigue sensitivity and the onset of ocular fatigue by tracking the user's spontaneous blinks. We believe that such a prototype would help maintain eye health by providing users with appropriate breaks and awareness of eye fatigue during VDT work.

However, due to the small number of data and bias in the age and gender of the subjects, we would like to conduct additional experiments in the future to confirm the usefulness of the proposed approach.

Declaration of Competing Interest

We declare that we have no professional or other personal interests of any nature or kind with any products, services, or companies that could be construed to influence the position or peer review presented in the manuscript entitled "Eye fatigue estimation using blink detection based on Eye Aspect Ratio Mapping(EARM).

Credit authorship contribution statement

Akihiro Kuwahara: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – Original Draft, Visualization. **Kazu Nisihkawa**: Conceptualization, Methodology. **Rin Hirakawa**: Resources, Writing –review & editing. **Hideaki Kawano**: Resources, Writing –review & editing. **Yoshihisa Nakatoh**: Writing –review & editiDeclaration of Competing Interestng, Supervision, Project administration.

References

[1] R. Gupta, L. Chauhan, A. Varshney, Impact of E-schooling on digital eye strain in Coronavirus Disease Era: A survey of 654 students, Journal of Current Ophthalmology 33 (2) (2021) 158–164 Wolters Kluwer Medknow PublicationsApr. 01, doi:10.4103/joco.joco_89_20.

[2] N. Hara, IT ophthalmopathy caused by brain fatigue [What is IT ophthalmopathy and smartphone presbyopia?], Japan for the Promotion of Medicine (2018) 31–39 Accessed: Dec. 23, 2021. [Online]. Available:https://www.idononippon.com/magazine/contents/2018/02/1803-1.html.

[3] U. Uchino, K. Tsubota, Dry eye and ocular fatigue, in: Symptoms and Conditions Commonly Observed in Daily Practice -Guidelines for Medical Treatment, Guidelines for Treatment-, 60, 2011, pp. 189–192.

[4] Y. Takahashi, IT eye disease and VDT syndrome, in: History of Medicine, 214, 2005, pp. 1029–1032.

[5] World Health Organization, "World report on vision," Oct. 2019.

[6] B.A. Holden, et al., Global Prevalence of Myopia and High Myopia and Temporal Trends from 2000 through 2050, Ophthalmology 123 (5) (May 2016) 1036–1042, doi:10.1016/j.ophtha.2016.01.006.

[7] "YouGov European Eye Fatigue Study," Apr. 2016.

[8] Ministry of Health Labour and Welfare, "Guidelines for Occupational Health Management in Information Equipment Operations," Dec. 2020.

[9] American Optometric Association, "Most Americans Experience Digital Eye Strain from Overexposure to Computers According to Survey," Feb. 29, 2016. https://www.prnewswire.com/news-releases/most-americans-experience-digital-eye-strain-from-overexposure-to-computers-according-to-survey-300227221.html (accessed Dec. 22, 2021).

[10] H. Rono, A. Bastawrous, D. MacLeod, E. Wanjala, S. Gichuhi, M. Burton, Peek Community Eye Health - MHealth system to increase access and efficiency of eye health services in Trans Nzoia County, Kenya: Study protocol for a cluster randomised controlled trial, Trials 20 (1) (Aug. 2019), doi:10.1186/s13063-019-3615-x.

[11] JINS, "JINS MEME," https://jinsmeme.com/, 2014.

[12] E. Grau, F. Horn, U. Nixdorff, G. Michelson, OCT and IOP findings in a healthy worker cohort: results from a teleophthalmic study in occupational medicine, Graefe's Archive for Clinical and Experimental Ophthalmology 257 (11) (Nov. 2019) 2571–2578, doi:10.1007/s00417-019-04457-1.

[13] S. Wang, et al., Pathological brain detection by artificial intelligence in magnetic resonance imaging scanning, Progress in Electromagnetics Research 156 (2016) 105–133 Electromagnetics Academy, doi:10.2528/PIER16070801.

[14] J. Wu, G. Li, H. Lu, T. Kamiya, A supervoxel classification based method for multi-organ segmentation from abdominal ct images, Journal of Image and Graphics(United Kingdom) 9 (1) (Mar. 2021) 9–14, doi:10.18178/joig.9.1.9-14.

[15] T. Aoki, et al., CT temporal subtraction: Techniques and clinical applications, Quantitative Imaging in Medicine and Surgery 11 (6) (2021) AME Publishing Company, Jun. 01, doi:10.21037/qims-20-1367.

[16] A. Kuwahara, R. Hirakawa, H. Kawano, K. Nakashi, Y. Nakatoh, Blink Detection Using Image Processing to Predict Eye Fatigue, in: International Conference on Human Interaction and Emerging Technologies, Jun. 2020, pp. 362–368, doi:10.1007/978-3-030-55307-4_55.

[17] A. Kuwahara, K. Nakashi, R. Hirakawa, Y. Nakatoh, H. Kawano, Eye Fatigue Prediction System Using Blink Detection Based on Eye Image, in: 2021 IEEE International Conference on Consumer Electronics (ICCE), 2021, pp. 1–3, doi:10.1109/ICCE50685.2021.94666.

[18] A.A. v Cruz, D.M. Garcia, C.T. Pinto, S.P. Cechetti, W.B. Jackson, Spontaneous Eyeblink Activity, Clin. Sci. (Colch) 9 (1) (Sep. 2011) 29–41.

[19] P.P. Caffier, U. Erdmann, P. Ullsperger, Experimental evaluation of eye-blink parameters as a drowsiness measure, Eur. J. Appl. Physiol. 89 (3–4) (2003) 319–325, doi:10.1007/s00421-003-0807-5.

[20] J.M. Cori, C. Anderson, S. Shekari Soleimanloo, M.L. Jackson, M.E. Howard, Do spontaneous eye blink parameters provide a useful assessment of state drowsiness? Sleep Med. Rev. 45 (2019) 95–104 W.B. Saunders LtdJun. 01, doi:10.1016/j.smrv.2019.03.004.

[21] Y. Su, Q. Liang, G. Su, N. Wang, C. Baudouin, A. Labbé, Spontaneous Eye Blink Patterns in Dry Eye: Clinical Correlations, Invest. Ophthalmol. Vis. Sci. 59 (12) (2018), doi:10.1167/iovs.18-24690.

[22] K. Asakawa, H. Ishikawa, Clinical application and interpretation of electrooculogram, Rinsho Ganka 67 (2013) Accessed: Dec. 23, 2021. [Online]. Available:https://webview.isho.jp/journal/detail/abs/10.11477/mf.1410104595?englishFlg=1.

[23] T. Ito, S. Mita, K. Kozuka, T. Nakao, and S. Yamamoto, "Driver blink measurement by the motion picture processing and its application to drowsiness detection," Jul. 2003. doi: 10.1109/ITSC.2002.1041208.

[24] J. Schmidt, R. Laarousi, W. Stolzmann, K. Karrer-Gauß, Eye blink detection for different driver states in conditionally automated driving and manual driving using EOG and a driver camera, Behavior Research Methods 50 (3) (Jun. 2018) 1088–1101, doi:10.3758/s13428-017-0928-0.

[25] K. Adachi, T. Hamada, T. Nakano, S. Yamamoto, Blink Measurement to Detect a Driver's Drowsy State by Moving Image Processing, IEEJ Transactions on Electronics, Information and Systems 124 (3) (2004) 776–783, doi:10.1541/ieejeiss.124.776.

[26] T. Soukupová, Eye Blink Detection Using Facial Landmarks, Research Reports of CMP (5) (2016).

[27] T. Soukupová, “Real-Time Eye Blink Detection using Facial Landmarks.” 2016
[28] G. Gao, D. Zhu, H. Lu, Y. Yu, H. Chang, D. Yue, Robust Facial Image Super-Resolution by Kernel Locality-Constrained Coupled-Layer Regression, ACM Transactions on Internet Technology 21 (3) (Jun. 2021) 1–15, doi:10.1145/3418462.
[29] M. Divjak, H. Bischof, Eye blink based fatigue detection for prevention of Computer Vision Syndrome, Yokohama (May 2009).
[30] C. Talens-Estarelles, J.J. Esteve-Taboada, V. Sanchis-Jurado, Á.M. Pons, S. García-Lázaro, Blinking kinematics characterization during digital displays use, Graefe’s Archive for Clinical and Experimental Ophthalmology (2021), doi:10.1007/s00417-021-05490-9.
[31] D.E. King, “Dlib-ml: A Machine Learning Toolkit,” 2009.
[32] K. Hoshino, A. Watanabe, M. Saito, Estimation of Mental Fatigue through Analysis of Pupillary Light Response, Society of Television Engineers of Japan, Audio-Visual Technology Study Group (1995) 657–664.
[33] Y. Kondo, Y. Nishimura, H. Ishii, H. Shimoda, and H. Yoshikawa, “A study on an objective examination method of eye strain by using Eye-Sensing Display,” Aug. 2006.
[34] K. Takahashi, J. Morishita, H. Tashiro, Y. Nakamura, Objective Evaluation of Visual Fatigue for Reading of Radiographs Displayed on Medical-grade Liquid-crystal Displays, Japanese Journal of Radiological Technology (Jun. 2010) 1416–1422.
[35] T. Hukuda, *Biological Information Systems theory*. sangyo-tosyo, 1995.
[36] S. Takizawa, Proposal of a system to warn of eye fatigue in VDT work, life support 19 (2007) 30–31.
[37] T. Asagai, M. Kawasumi, Relation between Eyeblink and Eyestrain on VDT Work, in: Life Support Medical and Welfare Engineering Society Joint Conference 2010 Lecture Series, 2010, p. 112.
[38] M. Rosenfield and M.R. Mcoptom, “Computer vision syndrome (a.k.a. digital eye strain),” 2016. [Online]. Available: https://www.researchgate.net/publication/295902618.
[39] C. Sagonas, G. Tzimiropoulos, S. Zafeiriou, M. Pantic, 300 Faces in-the-Wild Challenge: The first facial landmark localization Challenge, Image Vision Comput. 47 (2016) 3–18 [Online]. Available:http://ibug.doc.ic.ac.uk/resources/300-W/.
[40] C. Sagonas, G. Tzimiropoulos, S. Zafeiriou, and M. Pantic, “A semi-automatic methodology for facial landmark annotation,” Jun. 2013. [Online]. Available: http://ibug.doc.ic.ac.uk/.
[41] C. Sagonas, E. Antonakos, G. Tzimiropoulos, S. Zafeiriou, M. Pantic, 300 Faces In-The-Wild Challenge: database and results, Image Vision Comput. 47 (Mar. 2016) 3–18, doi:10.1016/j.imavis.2016.01.002.
[42] M. Sakamoto, J. Imai, M. Omodani, Verification of Near Point Measurement as a Metrics of Eye Fatigue-An Approach to Getting Objective Scale for Readable Electronic Paper, The Imaging Society of Japan (2008) 142–146.
[43] K. Tsuboi and D. Watanabe, *A Study on Automatic Generation of 3D Sudoku Problems*. 2018.
[44] M. Oikawa, M. Ohtsuka, K. Mori, M. Satoh, M. Oguchi, Statistical Analysis for Critical Flicker Fusion Frequency (CFF), Illuminating Engineering Institute of Japan 79 (8) (Aug. 1995) 416–419.
[45] T. Chai, R.R. Draxler, Root mean square error (RMSE) or mean absolute error (MAE)? -Arguments against avoiding RMSE in the literature, Geoscientific Model Development 7 (3) (Jun. 2014) 1247–1250, doi:10.5194/gmd-7-1247-2014.