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Fatigue Detection Using Computer Mouse Operation Patterns

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Abstract. With the spread of the Internet, the number of users utilizing digital devices has increased. Consequently, the proportion of users who use these devices for extended periods has also risen. While the widespread adoption of digital devices enhances users' daily lives, it has also introduced new issues, such as eye strain, shoulder stiffness, and wrist fatigue due to prolonged use. To address these issues, fatigue detection methods have been researched. However, many conventional methods require specialized sensors or external devices, limiting their practicality for everyday use. Therefore, this study proposes a fatigue detection method that does not require additional equipment, utilizing computer mouse operation patterns. This method focuses on the correlation coefficient between vertical mouse movement and the frequency of left clicks to determine fatigue states. Evaluation experiments showed that the proposed method achieved a higher precision value in detecting fatigue states compared to conventional machine learning models, such as Random Forest and Logistic Regression.

Keywords: Data analysis, Fatigue detection, Machine learning, Computer mouse

1. Introduction

With the spread of the Internet and advancements in information and communication technology (ICT), the use of digital devices in daily life and work environments has increased. In particular, work involving visual display terminals (VDTs) has become widespread, making prolonged digital device usage a common occurrence [1]. As a result, health issues such as eye strain and mental fatigue have become more prominent. Therefore, optimizing the work environment and introducing regular breaks for workers engaged in VDT tasks are recommended. Additionally, measures such as ensuring proper lighting conditions, maintaining appropriate working postures, and managing working hours are crucial for reducing health risks associated with prolonged use. These measures contribute not only to workers' health but also to improved productivity and work efficiency.

However, if these countermeasures are not adequately implemented, accumulated eye strain and mental fatigue may lead to decreased attention and concentration, potentially increasing the likelihood of human errors. Early detection of fatigue and appropriate countermeasures are essential not only for mitigating health risks but also for establishing a safe and efficient working environment.

Fatigue assessment methods have traditionally focused on physiological indicators and behavioral data analysis. Physiological indicators include brain waves, heart rate variability, and eye movements, which directly reflect an individual’s physical and mental state, allowing for high-accuracy fatigue detection [2][3][4]. However, methods based on physiological indicators require sensor-based measuring devices, which present several challenges for practical implementation in everyday work environments. Devices such as electroencephalograms (EEG), heart rate sensors, and eye-tracking systems require setup and wearing time, and they are often expensive. Additionally, the presence of such devices may impose psychological burdens on workers and disrupt their natural working state. These factors particularly limit the practical application of continuous monitoring in real-world work settings.

Furthermore, while non-contact measurement methods, such as analyzing eye movements and blinking patterns, have been explored in behavioral data analysis, they also face challenges. For instance, external factors such as lighting conditions and the precision of measurement devices may affect results, necessitating careful validation outside laboratory settings.

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This paper aims to clarify a new fatigue detection method that utilizes naturally obtainable data in everyday work environments. It focuses on the operation of a computer mouse used in VDT tasks and proposes a method for detecting user fatigue from that information, discussing its effectiveness.

2. Related Works

Fatigue detection methods using eye movements and blinking frequency have been widely applied in car driver monitoring. Devi et al. [5] and Chen et al. [6] proposed systems that detect fatigue states by analyzing real-time eye opening and closing conditions. However, these methods are susceptible to environmental factors such as lighting conditions and camera positioning. Additionally, while Luo et al. [7] introduced a deep learning-based approach for evaluating human fatigue conditions, which achieves high accuracy, its high computational cost poses challenges for real-time processing.

For fatigue detection in VDT work, Hachiya et al. [8] proposed a method that analyzes heart rate and skin electrical activity, while Mitsui et al. [9] developed a real-time fatigue detection system based on cumulative blink count and head movement. These methods enable highly accurate fatigue assessment but require dedicated devices, limiting their applicability in everyday work environments.

On the other hand, studies on behavioral analysis using computer mouse operation patterns have shown promising results. Cepeda et al. [10] analyzed computer mouse movements and click positions to assess users' decision-making processes. However, these studies primarily focus on user psychological states and operational efficiency rather than direct fatigue detection.

3. Proposed System

3.1. Relation between Computer Mouse Operations and Fatigue

Since the relation between computer mouse operation patterns and fatigue states has not been fully elucidated in existing research, a preliminary experiment was conducted to verify this correlation. Specifically, mouse operation patterns, such as vertical and horizontal movement distance, the number of clicks, and the number of scrolls, were extracted as features. Based on these data, the operation patterns during fatigued and non-fatigue states were analyzed. Participants were monitored for approximately 5 hours, with mouse operation data sampled every 0.5 seconds. The participants' fatigue levels were assessed once per hour, and this information served as the ground truth data. Table 1 shows the average results of the experiment with three participants. The experimental results revealed that the correlation coefficient between vertical mouse movement and the number of left clicks increased during fatigue**.** A statistical test was conducted to determine whether the increase in correlation occurred by chance. As a result, the p-value was less than 0.05, indicating statistical significance.

Table 1: Results of Preliminary Experiment (Average values of Three Participants)

	X-coordinate	Y-coordinate	Left Click	Scroll
X-coordinate	0	0.11	0.12	0.01
Y-coordinate	0.11	0	0.18	-0.07
Left Click	0.12	0.18	0	-0.05
Scroll	0.01	-0.07	-0.05	0

3.2. Fatigue Detection Method Using Mouse Operation Patterns

From the findings in Section 3.1, it is hypothesized that the correlation between vertical mouse movement and the number of left clicks increases in fatigued states. Based on this hypothesis, a new fatigue detection system that utilizes this correlation as its foundation is proposed in this paper. Specifically, the system incorporates vertical mouse movement and left-click frequency as key features to accurately detect fatigue states using changes in their correlation as an indicator.

The processing flow of the proposed system is structured as follows:

First, mouse operation data from users engaged in Visual Display Terminal (VDT) work is collected at 0.5-second intervals. This involves capturing the mouse movement distance, number of clicks, and number of scrolls within a 0.5-second interval. This approach ensures the potential applicability of the collected data for future research.

Next, the collected mouse operation data is aggregated into 10-second intervals and further organized into 10-minute units. The reason for this 10-second data aggregation is threefold:

- Noise Reduction – Smoothing the data helps mitigate sudden short-term changes and outliers, leading to more stable analysis.
- Computational Efficiency – Reducing the overall data volume lowers computational load and enhances processing efficiency.
- Comparative Analysis – Aggregated data facilitates comparisons across different time periods, aiding in the detection of long-term trends and patterns.

Following data aggregation, the coefficient correlation between vertical mouse movement and the number of left clicks is calculated. This correlation coefficient serves as a quantitative measure of the impact of fatigue on user mouse operation patterns. Furthermore, the correlation coefficient for the current period is compared with that of the initial usage period. If the correlation coefficient has increased and statistical testing confirms that this increase is unlikely to be due to random variation, the user is classified as being in a fatigued state. To verify the validity of this classification, Fisher’s z-transformation is employed, and a one-tailed test is conducted at a 5% significance level. By continuously monitoring changes in correlation over time, the system dynamically assesses the progression of fatigue.

Finally, when fatigue is detected, the system notifies the user of their current state. This notification feature allows users to be aware of their fatigue levels in real-time and provides them with the necessary information to take appropriate breaks or adjust their work schedule. Figure 1 shows the flowchart of the proposed system.

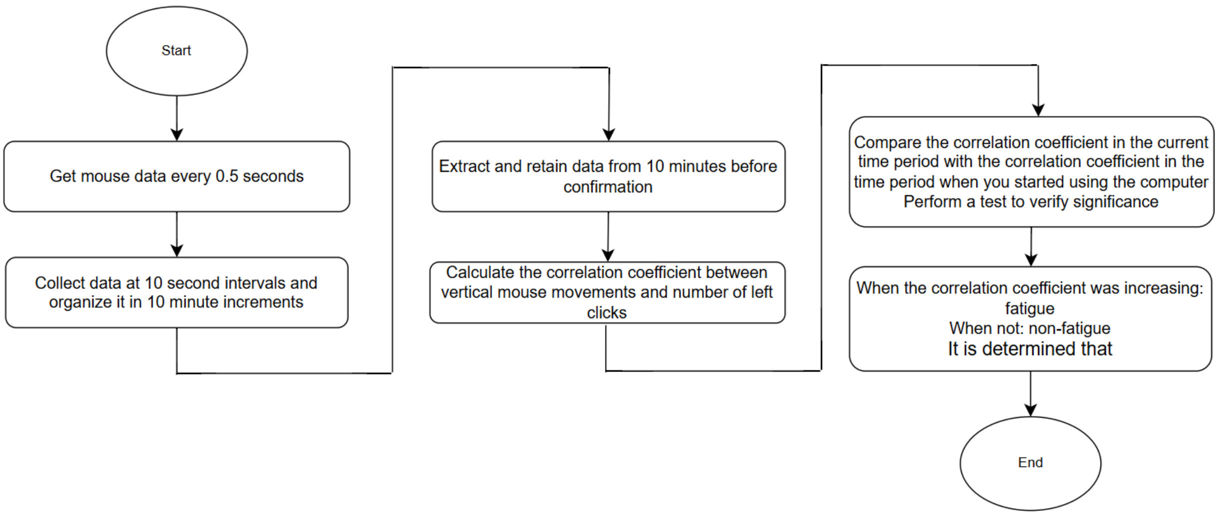

Fig. 1: Flowchart of Proposed System

4. Evaluation Experiment

To verify the effectiveness of the proposed fatigue detection method using computer mouse operation patterns, which determines a fatigued state when the correlation coefficient between vertical mouse movement and the number of left clicks significantly increases, an evaluation experiment was conducted.

4.1. Experimental Method

The experiment was conducted with 10 university students in their 20s, both male and female. To conduct the experiment in a realistic environment, the participants performed unrestricted computer tasks without being assigned specific tasks.

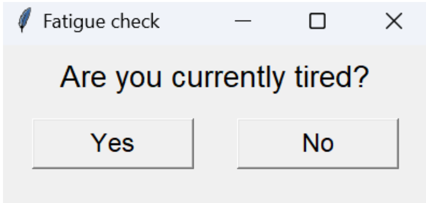

Fig. 2: Confirmation Window

First, as shown in Figure 2, a confirmation window was displayed on the computer monitors used by the participants every hour, prompting them to subjectively evaluate whether they were fatigued or not. At the same time, mouse operation data from 10 minutes immediately preceding the subjective evaluation was recorded. From the recorded data, the correlation coefficient between vertical mouse movement and the number of left clicks was calculated. The correlation coefficient was then compared with the one from the non-fatigue period. In this experiment, the data from a 10-minute period within the first hour after the computer was started, considered to be non-fatigue, was used as the non-fatigue period data. The fatigue evaluation and correlation coefficient calculations were conducted repeatedly throughout the experiment. If the calculated correlation coefficient increased compared to the one in the non-fatigue period, the participant was regarded as in a fatigued state during the period.

In this experiment, the self-reported fatigue states provided by the participants were used as ground truth data, and the performance of the results determined as fatigued by the proposed method was evaluated. As performance evaluation metrics, Precision, Recall, and F-measure were used. Additionally, for comparative verification, Random Forest and Logistic Regression models were employed to analyse the participants' true fatigue data, and the results were compared with the performance of the proposed system. In machine learning, the data from 10 minutes before the participants' self-reported fatigue state was used, totaling 180 data points. The dataset was then split into 80% for training and 20% for testing.

4.2. Experimental Results

Table 2 presents the confusion matrix for fatigue state classification using the proposed system, while Figure 2 shows a comparison graph between the proposed system and machine learning models (Random Forest and Logistic Regression models)

Table 2: Fatigue State Classification Results by Proposed System

	Predicted: Fatigue	Predicted: Non-Fatigue
Actual: Fatigue	27	24
Actual: Non-Fatigue	23	56

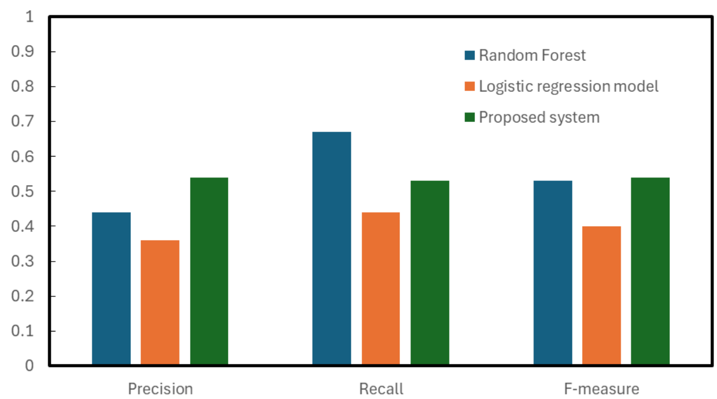

Fig. 3: Comparison of Results between Proposed System and Machine Learning Models

As seen in Figure 3, the proposed system achieved precision, recall, and F-measure values of 0.54, 0.53, and 0.54, respectively. Compared to machine learning models, the proposed system demonstrated superior precision in fatigue detection and slightly outperformed machine learning models in terms of F-measure.

However, the recall value of the proposed system was lower than that of the Random Forest model, indicating that some fatigue states were not detected. This suggests that further improvements are needed to enhance the system's sensitivity.

There exists a trade-off relation between precision and recall. In the proposed fatigue classification process, statistical testing was performed to determine whether the difference in correlation coefficients was significant or not, and fatigue was detected accordingly. Specifically, if the p-value was less than 0.05, the difference was considered statistically significant. It was also observed that changing the p-value affected both precision and recall, confirming their trade-off relation. By optimizing the p-value depending on the user's preference, it may be possible for the proposed system to achieve better performance than traditional machine learning models.

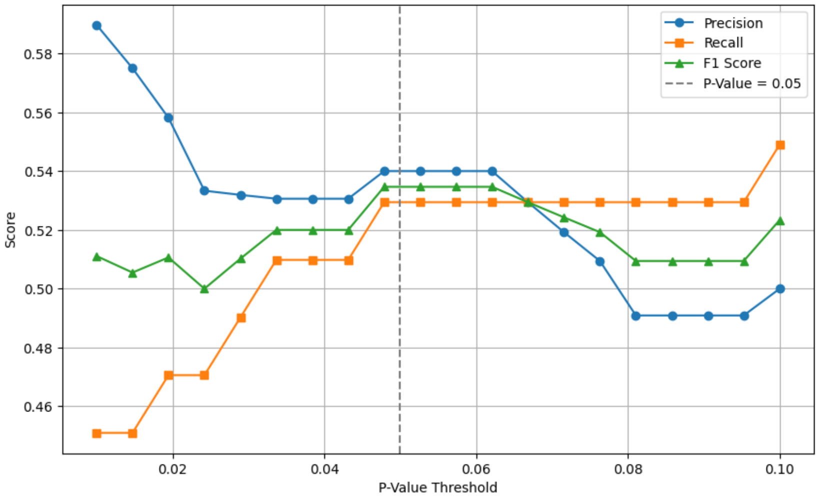

Fig.4: Trade-off Curves between Precision and Recall, Including F1 Score Curve

Figure 4 illustrates the trade-off curves between precision and recall as the p-value changes. The F1 Score curve is also shown in the figure as a reference, and the dotted line at p-value = 0.05 represents the threshold set by the proposed system. From this graph, if the goal is to balance both metrics (precision and recall), the p-value at the intersection of the two curves should be selected. Additionally, and importantly, the proposed system can dynamically change the p-value, allowing adjustments to the extent to which false positives or false negatives are prioritized for reduction. This flexibility enables customized fatigue detection tailored to different work environments and user needs.

5. Conclusions

In this paper, a fatigue detection method utilizing computer mouse operations, which are widely used by many PC users, has been discussed. Conventional fatigue detection methods often require specialized sensors or external devices, making them impractical for daily use. To address this issue, a new system that estimates fatigue states without additional hardware was proposed, based on the hypothesis that the correlation between vertical mouse movement and the number of left clicks increases during fatigue.

To evaluate the effectiveness of the proposed system, an experiment was conducted with 10 participants. The results were assessed using the metrics of precision, recall, and F-measure. Additionally, these results were then compared to those obtained from machine learning models such as Random Forest and Logistic Regression. The evaluation results showed that the proposed system outperformed the machine learning models in terms of precision and F-measure, thereby confirming its effectiveness in fatigue detection. However, the recall was lower than that of Random Forest, indicating a potential risk of missing some fatigued states.

Furthermore, precision and recall exhibited a trade-off relation, and this study confirmed that the fatigue detection criteria varied depending on the p-value threshold. Future improvements should focus on optimizing p-value selection and model refinement to reduce undetected cases and enhance detection accuracy.

The findings of this study demonstrated the feasibility of fatigue detection using mouse operation data without requiring specialized sensors or additional hardware. This method is highly applicable to daily work environments and has the potential to contribute to the creation of safer and more efficient work conditions. Future challenges include diversifying data and conducting long-term monitoring to develop a more accurate and reliable fatigue detection system.

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