Gaze analysis of a walker user for the development of a gaze-based interface to operate a robotic walker

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Abstract

As populations in advanced economies continue to age and birth rates decline, a growing shortage of caregivers has emerged. This shortage has led to an inability to meet the demand for rehabilitation through human caregivers, prompting research into the automation of rehabilitation, such as robotic walkers. Estimating the user's intent in a robotic walker can improve safety and provide intuitive control, as well as personalized assistance, thus reducing the psychological barriers users may face when interacting with the robot. This study aims to investigate the intention of direction change based on head orientation by analyzing gaze patterns during turning and while checking the surroundings. Gaze analysis was performed using the Tobii Pro Glasses 3. Participants were asked to perform a task involving both turning while navigating a specific route and checking numbers placed around them, allowing for the collection of gaze data. The collected gaze data were analyzed using three machine learning models: Random Forest, LightGBM, and SVM—which are capable of handling high-dimensional datasets and are expected to achieve high classification performance. Using gaze data collected during surrounding check tasks and direction change tasks, a classification model was trained to distinguish between surrounding check behavior (Class 0) and direction change behavior (Class 1). As a result, the Random Forest model achieved a classification accuracy of 99.5%, the LightGBM model 99.8%, and the SVM model 99.4% for healthy participants, consistently demonstrating high accuracy. For patients with Parkinson's disease (PD), the model trained on healthy participants could not be directly applied. Still, an attempt to improve SVM classification accuracy by adjusting the threshold using the decision function resulted in a classification accuracy of 64% at a threshold of 0.5.

Contribution of the Paper: This study's main contribution is verifying the effectiveness of gaze-based classification for distinguishing between turning and checking the surroundings in healthy individuals and PD patients, concerning head orientation.

Keywords: rehabilitation system, gaze analysis, intent estimation, machine learning

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1. INTRODUCTION

In recent years, Japan and many other countries have faced a rapid increase in the aging population, leading to a significant shortage of caregivers. This demographic shift has created a growing need for assistive robots and rehabilitation technologies to support daily activities [1]. Age-related diseases also present serious challenges in aging societies. Reduced walking ability is particularly critical, as it lowers a person's ability to perform activities of daily living (ADLs) and directly affects their quality of life (QoL). Parkinson's disease (PD), a progressive neurodegenerative disorder, is one of the most common conditions affecting mobility in older adults, with more than 10 million people affected worldwide [2]. PD is characterized by motor symptoms such as tremors, gait disturbances, and impaired

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postural reflexes, as well as non-motor symptoms including cognitive decline and depression [3]. A typical motor symptom in PD patients is freezing of gait (FoG), which has been reported in approximately 54% of patients [4].

FoG is often described as the sensation of being "glued to the floor" and is difficult to predict [5]. This unpredictability increases the risk of falls, significantly impacting both ADLs and QoL for those living with PD.

Long-term physical therapy rehabilitation for Parkinson's disease (PD) patients has been shown to be effective in improving motor symptoms [6]. Additionally, it may have a beneficial effect on non-motor symptoms, such as improving cognitive function, mood, and reducing daytime sleepiness [7].

In the gait rehabilitation of Parkinson's disease (PD) patients, the use of various assistive devices is anticipated. Härdi et al. compared the effectiveness of a cane, crutches, and a four-wheeled walker, demonstrating that the use of any of these devices improves gait quality compared to when no assistive device is used [8].

Additionally, Kegelmeyer et al. investigated the impact of walking assistive devices on the gait patterns of Parkinson's disease (PD) patients. They demonstrated that the four-wheeled walker consistently improved gait variables compared to other devices and resulted in less variability [9].

These studies suggest that the four-wheeled walker is effective in gait rehabilitation for PD patients.

In the past, gait rehabilitation was typically conducted by specialists with expert knowledge. However, with the ongoing aging population and shortage of caregiving staff, it has become increasingly difficult to rely solely on traditional one-on-one rehabilitation. Therefore, the automation of rehabilitation using robotic technology is increasingly seen as essential.

As a response to these challenges, there has been active development of smart walkers that integrate various digital technologies into the functionality of traditional walkers.

In particular, regarding intent estimation, it is expected that users will not only be able to operate the smart walker intuitively, enabling more adaptive control, but also that it will reduce the psychological barriers associated with the use of the smart walker.

2. RELATED WORKS

2.1. Studies on smart walkers with intent estimation functionality

Examples of research on smart walkers with intent estimation functionality include intent recognition using pressure sensors [10], a fusion method of forearm reaction force and gait kinematics using a laser rangefinder [11], control using force-acceleration features [12], and a monitoring walker utilizing IoT [13]. However, many of these studies still face challenges related to the accuracy of intent estimation and the control of the walker, and the realization of accurate intent estimation and corresponding walker control is required.

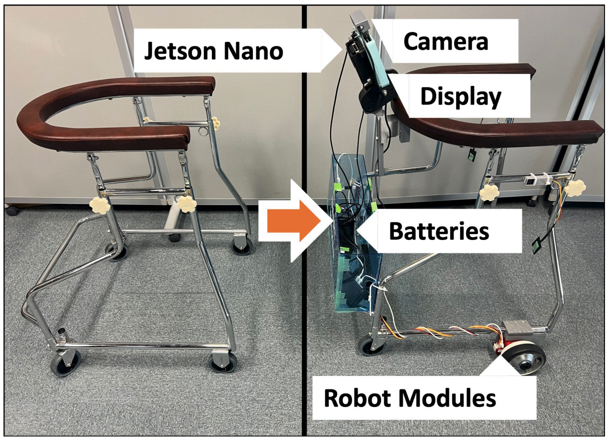

Figure 1: Smart Walker Outfit

2.2. Previous research

Against this background, we have developed a four-wheeled walker-type assistive robot, the "Smart Walker," for gait assistance and rehabilitation of Parkinson's Disease (PD) patients. The appearance of the Smart Walker is shown in Figure 1.

The Smart Walker is a robot designed to promote rehabilitation and reduce FoG by recognizing the user's gait and physical condition through the installation of motors and various sensors (including cameras) on an existing four-wheeled walker, and providing appropriate interventions.

This robot detects the natural action of the user pushing the walker during walking through a torque sensor in the motor attached to the bottom of the walker and starts the assistance by recognizing the intent to walk.

Additionally, by using MediaPipe, an open-source machine learning library provided by Google [14], for face recognition, the Smart Walker recognizes the user's intent to turn by detecting when the user turns their face towards the direction of the turn and assists with the direction change.

However, in the direction change assistance feature of the Smart Walker, it was also confirmed that the system sometimes misinterprets the user's intent, such as recognizing a surrounding check as a direction change trigger, leading to unintended actions like turning when the user does not actually intend to do so.

This issue is common with the challenge mentioned earlier in the research on smart walkers, which is "the realization of accurate user intent estimation and corresponding walker control."

From the research background, we confirmed the importance of automating rehabilitation for Parkinson's disease (PD) patients and relieving freezing of gait (FoG) to improve the quality of life (QoL) of PD patients. Additionally, we confirmed that smart walkers are useful for these purposes, and we proposed controlling assistive walkers based on face orientation, verifying their effectiveness. However, while face orientation-based control is effective in improving the operability of PD patients, there is a challenge: when the user does not intend to turn, especially during a surrounding check, unintended actions occur. Such malfunctions can amplify the user's anxiety and pose a safety risk.

In this study, to address this issue, we focus on gaze data, which has been shown to be effective in intent estimation tasks in prior research. We collected and analyzed face orientation and gaze data during direction changes and surrounding checks, comparing their characteristics. In particular, by performing data analysis using machine learning, we aim to construct a model that accurately estimates the intent to turn, thereby reducing the Smart Walker's malfunctions and improving both safety and operability. In other words, this study focuses on "accurate user intent estimation" within the broader challenge of "realizing accurate user intent estimation and corresponding walker control."

2.3. Studies of the relationship between gaze information and head

The relationship between gaze information and head movement has been extensively studied. Early research focusing on the coordinated movement of the head and eyes revealed that the body tends to follow the direction of gaze [15]. Doshi et al. studied driving tasks and found that in the case of a sudden visual stimulus appearing at the edge of the field of view, the gaze moves first and the head follows. In contrast, during a conscious shift in attention, the head moves first and the gaze follows [16]. Imai et al. investigated the relationship between head movement and gaze during walking and turning [17]. Their research showed that during straight walking, the head is adjusted to maintain a forward direction. Additionally, during a direction change, the head rotates ahead of the body, predicting the direction of movement. Durant et al. [18] demonstrated that gaze movement contributes to improving the accuracy of visual motion information during walking and stabilizing head-centered motion, revealing how visual processing during direction changes and surrounding checks is made more efficient.

Gaze information has been reported to be related to intent determination and action planning in various fields. In the following, we will specifically discuss visual information, methods of visual information analysis, and their applications.

Gaze is considered an important indicator for estimating a person's behavioral intentions, and it has been shown in many studies to be particularly involved in direction changes during walking [19], [20]. Generally, people tend to direct their gaze toward the direction they intend to turn before making the turn [21]. Research on gaze behavior during walking has reported that gaze movements precede foot movements, indicating the intention to turn [22]. Furthermore, studies analyzing pedestrian gaze patterns have shown that, in situations where a change in direction is required, the user's gaze tends to move toward the new direction in advance [23]. Regarding gaze studies in Parkinson's disease (PD) patients, Gibbs et al. [24] highlighted the importance of evaluating eye movements in natural environments, revealing that PD patients have longer fixation times and smaller saccade amplitudes.

From this, it can be understood that there is a relationship between gaze information and head movement, and that this relationship can change depending on the situation or task. However, while many of these studies focus on walking tasks, they do not clarify the relationship between the two during the use of a smart walker, and the subjects involved are not PD patients, but healthy individuals. Therefore, in this study, we focus on the "direction change task" and the "surrounding check task" during the use of the Smart Walker, and aim to achieve "accurate user intent estimation" by clarifying the relationship between head movement and gaze during these tasks.

3. PROPOSED METHOD

3.1. How to obtain gaze data

This study collected gaze data using the Tobii Pro Glasses 3, a wearable eye-tracking device developed by Tobii Corp. The device employs the pupil center corneal reflection (PCCR) method, which enables highly accurate estimation of gaze points. The field of view is 106° diagonally, 95° horizontally, and 63° vertically. Eye movements and fixation points were recorded in real time while participants wore the device. The horseshoe-shaped walker used in this study is thought to reduce wobble while walking. It also leads to label bias since the majority of the data is collected while walking during the experiment. Therefore, data during walking is not used for training. The procedure for data collection was as follows:

1. Calibration was performed by asking the participant to fixate on a central point on a calibration card held 0.5 to 1 meter away.
2. The device's built-in sensors continuously recorded gaze positions and trajectories during the experiment.
3. The recorded data were analyzed as time series data using Tobii Pro Lab, software provided by Tobii Corp.

3.2. Method for obtaining head orientation data

In this study, multiple methods were tested to obtain accurate head orientation data, and the accuracy of each method was verified. After evaluating several approaches, we concluded that the methods tested for acquiring head orientation data were unreliable due to poor recognition accuracy. Therefore, this study decided to perform intent estimation using only gaze data.

3.3. Method for classifying gaze data

In this study, gaze data obtained from the Tobii Glasses were classified into "surrounding check" and "direction change" using three machine learning methods: Random Forest, LightGBM, and SVM (Support Vector Machine), and their performance was compared.

3.4. Experiment with healthy participants

Before conducting the experiment with Parkinson's disease (PD) patients, a walking experiment using the Smart Walker was performed with four healthy participants.

A walking path was created as shown in Figure 2. The following is the procedure for the experiment:

1. The participants, wearing the Tobii Glasses, used the Smart Walker and stood at the "Start" position.
2. They walked straight for 2 meters from "Start" to point A, and at point A, they turned right.
3. After completing the turn, they walked straight for 1 meter and turned right at point B.
4. From point B, they walked straight for 2 meters to point C, where they were instructed to pause.
5. The participants were asked to look at the designated number (twice).
6. They then walked straight for 2 meters from point D to point E, and at point E, they turned left.
7. After completing the turn, they walked straight for 1 meter and turned left at point F.
8. After walking straight for 2 meters, they paused at the experimenter's instruction.
9. The participants were asked to look at the designated number (twice).
10. They then walked straight for 2 meters and paused for 3 seconds at the "Goal."

The entire experiment was conducted twice for each participant.

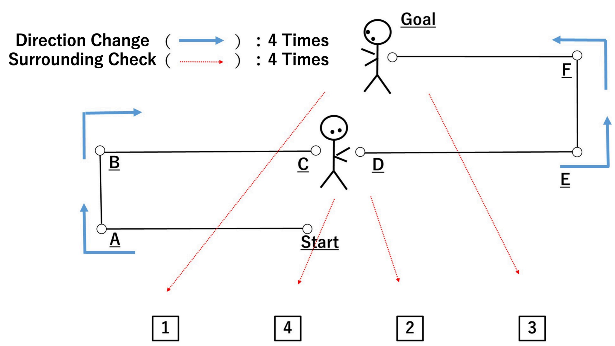

Figure 2: Walking Path

3.5. Evaluation Method

For the gaze data obtained from the preliminary experiment, machine learning was applied, and the performance of multiple models was compared to determine the optimal classification method. First, labeling was performed on the data collected from Tobii Pro Lab. Specifically, "0" was assigned for surrounding check tasks and "1" for direction change tasks. Manual labeling was done while referring to the video of the experiment recorded by Tobii.

The input variables are as follows:

- Gaze point X/Y : 2D coordinates of the gaze position on the screen
- Gaze point 3D X, Y, Z : 3D coordinates of the gaze position in space
- Gaze direction left X, Y, Z : Unit vector representing the gaze direction of the left eye
- Gaze direction right X, Y, Z : Unit vector representing the gaze direction of the right eye
- Pupil diameter left : Pupil diameter of the left eye (in mm)
- Pupil diameter right : Pupil diameter of the right eye (in mm)
- Fixation point X, Y : The 2D location where gaze fixation occurred on the screen

3.5.1. Random Forest

Classification of gaze data was performed using Random Forest (RF). The gaze data used were from experiments with healthy participants, and a model was created to classify surrounding check actions (Class 0) and direction change actions (Class 1).

The analysis procedure is as follows:

1. Data containing missing values were removed.
2. Label Cleaning: Label -1 (walking only) was excluded, and only data necessary for intent estimation were used.
3. The data were split into training (80%) and testing (20%) sets.
4. To address class imbalance, the parameter `class_weight="balanced"` was set.
5. Hyperparameters were optimized using Grid Search Cross-Validation(GridSearchCV) .
6. Stratified K-Fold Cross-Validation with 5 splits was performed to check the generalization performance.
7. The prediction results on the test data were evaluated, and accuracy, F1 score, and feature importance were calculated.

3.5.2. LightGBM

Next, a machine learning model using LightGBM was built, and its performance was evaluated. Based on the gaze features, classification was performed for surrounding check (Class 0) and direction change (Class 1). The data processing procedure is as follows:

1. Removal of Missing Values: To maintain data integrity, missing data were excluded.

2. Label Cleaning: Label -1 (walking only) was excluded, and only data necessary for intent estimation were used.
3. Data Splitting: 80% of the data was used for training, and 20% was used for testing.
4. Class Imbalance Correction: The sample count for each label was considered, and the `scale_pos_weight` was calculated.

The hyperparameters optimized using Optuna are as follows:

- `num_leaves`: From 20 to 100
- `learning_rate`: From 0.001 to 0.01
- `n_estimators`: From 100 to 500
- `min_data_in_leaf`: From 50 to 100
- `feature_fraction`: From 0.8 to 1.0

The optimization was performed by maximizing the F1-score of five-fold cross-validation during training.

3.5.3. SVM

Finally, SVM was applied using all the features. Data containing missing values were removed. Label -1 (walking only) was excluded, and only data necessary for intent estimation were used. To address class imbalance, `class_weight="balanced"` was applied, and hyperparameter optimization was performed using `GridSearchCV` to adjust the values of C (regularization parameter) and γ (kernel coefficient).

3.6. Experiment with PD Patients

Based on the data obtained from the preliminary experiment, an experiment was conducted with Parkinson's disease (PD) patients to evaluate the discriminant model. One PD patient participated as the subject, using the Smart Walker while walking along the path shown in Figure 3.

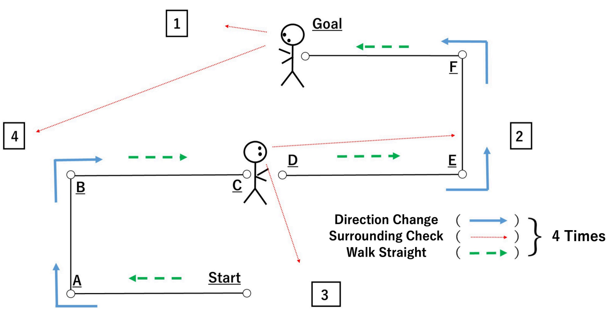

Figure 3: Walking Path Used in the PD Patient Experiment

Based on the results of the preliminary experiment, changes were made to the experimental environment to induce more natural surrounding check actions. Specifically, in the preliminary experiment, four sheets of paper with numbers were placed on the same wall. In this experiment, the numbers were randomly placed at a height of 120 cm on all four walls. Additionally, to avoid the subject memorizing the positions of the numbers, the numbers were randomly rearranged before the second trial. Other than the above changes, the experimental procedure is the same as for the healthy subjects.

4. RESULT

4.1. Experiment with healthy participants

4.1.1. Random Forest

The classification results using Random Forest are summarized in Table 1. Five-fold cross-validation on the training data yielded an average accuracy of 99.3% (standard deviation: 0.3%). After training with the optimized hyperparameters, the model was evaluated using the test set.

Table 1: Classification Results Using Random Forest

Class	Precision	Recall	F1-score
0 (Surrounding Check)	1.00	0.99	0.99
1 (Direction Change)	0.99	1.00	1.00
Accuracy		0.995	
Macro Avg	1.00	0.99	1.00
Weighted Avg	1.00	1.00	1.00

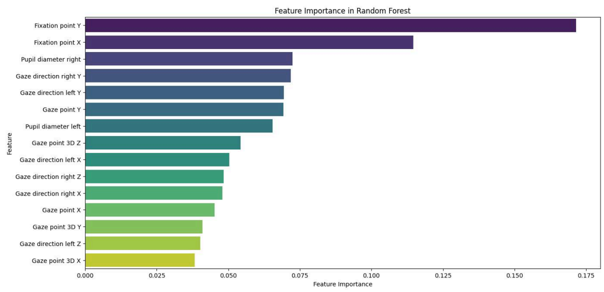

Figure 4: Feature Importance in Random Forest

Table 1 presents the precision, recall, and F1-score for each class, with an overall accuracy of 99.5%. The model demonstrated excellent performance in distinguishing between "Surrounding Check" and "Direction Change".

Feature importance analysis (Figure 4) indicated that "Pupil diameter right," "Fixation point Y," and "Fixation point X" were among the most influential features. These variables reflect key differences in gaze behavior between the two tasks.

4.1.2. LightGBM

The performance of the optimized model is shown in Table 2.

The feature importance of LightGBM was analyzed, and the main factors for intent estimation in gaze data are shown in Figure 5.

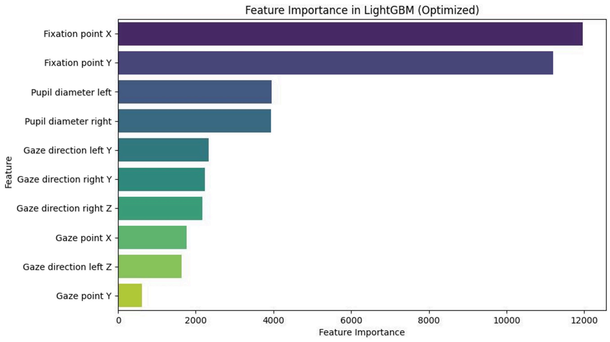

Figure 5: Feature Importance in LightGBM

4.1.3. SVM

During training, the model was trained using gaze data from healthy participants, and five-fold cross-validation was performed. As a result, the optimal hyperparameters were found to be $C = 100$, $\gamma = 1$, with an RBF kernel. The average accuracy in the cross-validation was 99.4% (standard deviation 0.0013), showing a high value.

Furthermore, in the test using the training data, the accuracy reached 99.4%, and the precision, recall, and F1-score for each class all recorded over 99%. This result confirmed that the model built based on healthy participant data has very high classification performance.

The feature importance for each feature is shown in Figure 6.

Since SVM cannot directly visualize feature importance, Permutation Importance was used to evaluate the importance of features. Permutation Importance is a method that estimates the relative importance of each feature by randomly shuffling the values of each feature and measuring the impact on the model's prediction accuracy.

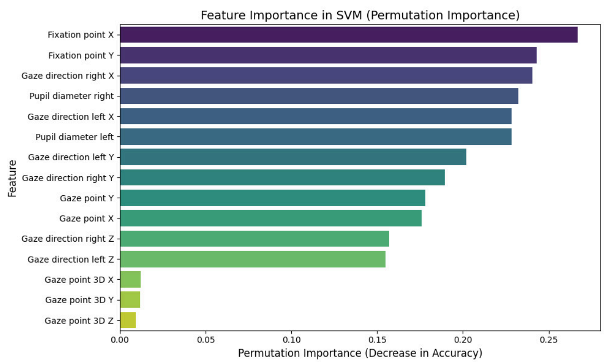

Figure 6: Permutation Importance Importance in SVM

Table 2: Optimization Results of LightGBM

Metric	Score
Best Cross-Validation F1-score	0.9974
Test Accuracy	0.9984
Test F1-score	0.9986

As a result of comparing three methods—Random Forest, LightGBM, and SVM—LightGBM showed the highest classification accuracy in intent estimation using gaze data. Specifically, in cross-validation with healthy participant data, test accuracy of 99.8% was achieved, with classification accuracy (precision, recall, and F1-score) for each class also exceeding 99%. However, SVM demonstrated stable performance with relatively small amounts of data, and due to its ability to suppress overfitting while appropriately learning decision boundaries, it was determined to be suitable for the dataset used in this study. In addition, since the classification threshold in the SVM decision function can be flexibly adjusted, it is possible to improve classification performance even when the distribution of PD patient data differs from that of healthy participants. Therefore, SVM was adopted as the method for evaluating classification performance on PD patient data.

4.2. Experiment with PD Patients

Using the SVM model identified as optimal in the previous experiments, we evaluated classification performance on data collected from a PD patient.

The results are presented in Table 3. While the model showed high recall (76.5%) for "Direction Change," recall for "Surrounding Check" remained low (32.5%), yielding an overall accuracy of 53.7%.

The confusion matrix (Figure 7) highlights this imbalance.

To improve performance, we adjusted the decision threshold of the SVM decision function.

The Precision for Class 0 was 0.60, and for Class 1 it was 0.51, indicating that the Precision for Class 0 was not particularly low. While a portion of the predicted Class 0 instances were correct, the overall classification performance remained limited due to the low Recall. Since the model tended to overpredict Class 1, there is room for improvement by adjusting the classification threshold in the SVM decision function. By modifying the threshold, it is possible to introduce a bias in the prediction, allowing the model to be adjusted to classify more readily into either Class 0 or Class 1.

At a threshold of 0.5, recall for "Surrounding Check" improved to 70.0%, and the F1-score rose from 0.42 to 0.66, demonstrating that threshold tuning significantly enhances model performance for PD patients.

5. DISCUSSION

5.1. Performance Comparison: Healthy Participants vs. PD Patients

In this study, we developed a gaze-based classification model using Support Vector Machine (SVM), trained on data from healthy participants. The model achieved high performance, with a classification accuracy of 99.4% and an F1-score of 0.994 on the training dataset.

Table 3: Classification Results for PD Patient Data

Class	Precision	Recall	F1-score
0	0.60	0.33	0.42
1	0.51	0.76	0.61
Accuracy		0.54	
Balanced Accuracy		0.54	
Macro Avg	0.56	0.54	0.52
Weighted Avg	0.56	0.54	0.51

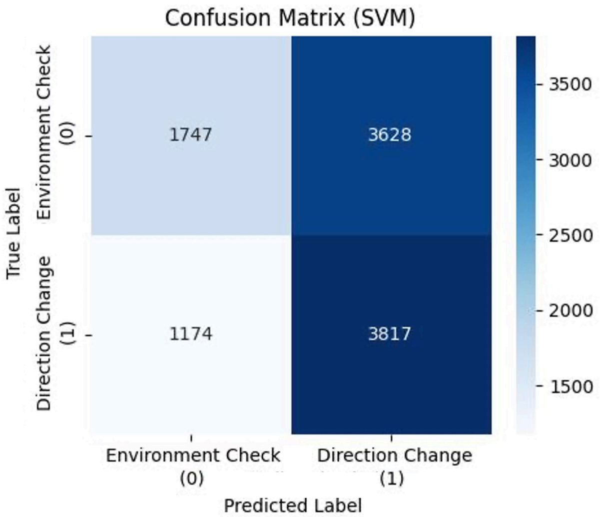

Figure 7: Confusion Matrix for PD Patient Data

However, when applied to gaze data from a participant with Parkinson's disease (PD), the classification accuracy dropped significantly to 53.7%. In particular, the recall for "Direction Change" remained relatively high (76.5%), while the recall for "Surrounding Check" was considerably lower (32.5%), suggesting an imbalance in model recognition.

This discrepancy is likely due to differences in gaze behavior between healthy individuals and PD patients.

By comparing the fixation point coordinates during surrounding check behavior (Class 0) and direction change behavior (Class 1) while using the walker between healthy participants and patients with Parkinson's disease (PD), the following observations were made:

1. PD patients tend to exhibit a wider distribution of gaze during surrounding check behavior (Label 0) compared to healthy participants.
2. During direction change behavior (Class 1), healthy participants move their gaze across a wider area.
3. Healthy participants show a greater number of gaze clusters than PD patients, indicating a tendency for more fine-grained gaze shifts.
4. Notably, differences in gaze patterns between healthy participants and PD patients were most prominent during direction changes.

Because SVM constructs decision boundaries strictly based on the distribution of training data, it may fail to generalize effectively to populations with different gaze characteristics.

To address this issue, we adjusted the decision threshold of the SVM's `decision_function`. This function outputs a confidence score for class membership, and the classification outcome can be controlled by varying the threshold.

By increasing the threshold to 0.5, recall for "Surrounding Check" improved substantially—from 32.5% to 70.0% and the F1-score rose from 0.42 to 0.66. This result demonstrates that threshold tuning is an effective strategy for adapting models to data with different distributions.

6. CONCLUSIONS

This study proposed an intent estimation model based on gaze data and evaluated its performance using SVM for both healthy participants and PD patients.

The model achieved high accuracy on the training data from healthy participants, with a classification accuracy of 99.4% and an F1-score of 0.994. However, when applied to PD patient data, the accuracy dropped significantly to 53.7%, likely due to differences in gaze patterns between the two populations.

To address this issue, we applied threshold tuning to the SVM decision function. By optimizing the threshold, we improved the classification accuracy for PD data to 64.0%. This adjustment mitigated the model's bias toward predicting the "Direction Change" class and improved its ability to detect "Surrounding Check" behavior. These results demonstrate that even with models trained on healthy individuals, adaptation strategies such as threshold adjustment can significantly enhance performance when applied to different user groups.

6.1. Future Challenges

Improvement of the model considering the gaze characteristics of PD patients is necessary. Specifically, the following points are raised as future challenges.

- Collect additional data from PD patients and increase the variation in the training data
  A model trained only with healthy participant data may not be able to account for the variability in gaze behavior of PD patients. Therefore, by collecting sufficient data from PD patients and incorporating it into the model's training, the generalization performance can be improved.

- Introduction of new features to better capture gaze behavior during surrounding checks
  In this study, only gaze data were used. However, by adding features that consider the fixation stability and patterns of variation in the gaze, it is believed that more accurate intent estimation can be achieved.

- Optimization of data preprocessing considering outliers
  Since PD patient data often contains gaze deviations or irregular movements, applying outlier handling and smoothing techniques is expected to improve the model's accuracy.

Additionally, in this study, it was initially planned to incorporate head orientation data into the model, but due to insufficient data acquisition accuracy, the focus was placed solely on gaze information. In future research, the accuracy of head orientation data acquisition will be improved, and by integrating it with gaze information, the goal is to construct a higher-precision intent estimation model.

The results of this study demonstrate the potential of intent estimation using gaze data and provide important insights for future developments. In particular, the development of a model considering the adaptation for PD patients is expected to contribute to the advancement of walking assistive systems and rehabilitation support technologies. For example, this could lead to the development of gaze-guided assistive devices and systems that support stable walking by promoting appropriate gaze behavior during direction changes in PD patients, taking into account differences in gaze strategies between healthy individuals and those with PD.

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