Automatic Collection of Dual-task Human Behavior for Analysis of Cognitive Function

Fumio Okura †, Ikuhisa Mitsugami ††, Masataka Niwa †, Kota Aoki †, Chengju Zhou †, Yasushi Yagi †

Abstract The performance of dual task, simultaneously performing two tasks, is a useful measure of a person’s cognitive abilities because it creates a heavier load on the brain than single tasks. Large-scale datasets of dual-task behavior are required to quantitatively analyze the relationships among dual-task performance, cognitive functions, and personal attributes such as age. We present an automatic data collection system for dual-task behavior that can be installed in public spaces without an operator in attendance. The system is designed as an entertainment kiosk to attract participants. We used the system to collect a large-scale dataset consisting of more than 70,000 sessions of dual-task behavior, in conjunction with a long-running exhibition in a science museum. The resultant dataset, which includes sensor data such as RGB-D image sequences, can be used for learning- and vision-based investigations of human cognitive functions.

Key words: data collection, dual task, cognitive impairment, gait analysis.

1. Introduction

As population aging rapidly accelerates, achieving long healthy life years1, or disability-free life expectancy, is especially important for a high quality of life. Cognitive impairments caused by degenerative diseases such as dementia are known to be an important factor in reducing the number of healthy life years. Early detection during the early stage of mild cognitive impairment (MCI) is crucial.

For educational uses, monitoring the growth of children is also important. Understanding the development of children essentially contributes to the personalization of the primary education.

Performing a dual task2, i.e., simultaneously performing two tasks, puts a heavier cognitive load on the brain than single tasks, and thus reflects a person’s level of cognitive functioning. Such tasks are therefore commonly used for the evaluation of cognitive functions. It is generally known that performance on dual tasks that consist of a physical (e.g., walking) and a cognitive (e.g., calculation) task is an indication of the person’s level of cognitive functioning, particularly among children3 and elderly people4.

In the earlier dual-task studies, the performance was evaluated by limited measurements (e.g., walking speed and response time). Gait (i.e., walking style), for example, is considered to be an effective indicator of dual-task performance according to comparisons using walking speed5,6. However, to detect early signs of cognitive impairment or estimate the growth of children using various possibly-effective features beyond simple ones (e.g., walking speed), it is necessary to construct a dataset for employing machine learning and computer vision techniques.

Mainly for human identification tasks, large-scale gait datasets of thousands or even tens of thousands of participants are collected7,8. These gait databases capture the walking appearance of participants; dual-task behavior, however, is notably more complex than simply walking. Therefore, an important challenge in the creation of large-scale dual-task datasets is the need for an appropriate control of tasks. We first summarize the challenges for large-scale dual-task data acquisition:

Challenges:

- Need for an unmanned system: In large-scale data collection, it is difficult to arrange an operator to be present during the entire data collection period. Similarly, the security of the collected data is crucial because sensitive personal information, including videos of the participants, is collected.
- Difficulty of recruiting participants: Hiring
thousands of participants is unrealistic, and thus data collection must be performed in public. This requires motivating the public to become voluntary participants in the experiment.

- **Difficulty of controlling human behavior**: Participants’ behavior in a dual-task experiment needs to be well controlled because the behavior is more complex than simply walking, as in other gait datasets\[^9\]–\[^8\]. The basic challenge is in how to control participants' behavior without the presence of an operator who makes instructions.

- **Ethics issues**: We collect a sensitive personal information including appearances of participants. Proper agreement from each participant is needed if the data are to be used for research purposes.

To overcome the above challenges, we propose an automatic data collection system designed as an entertainment kiosk, which captures the behavior of participants playing a game involving dual-task behavior (stepping while calculating), according to the instructions displayed in the kiosk. The overview of the system is shown in Figure 1. This kiosk is designed as a game-like demonstration so that visitors of the museum would be interested in and like to experience it. The game-based data collection is intended to motivate them to follow the instructions carefully to earn a higher score. To maximize the exposure to potential participants, we installed the proposed system in the largest science museum in Japan. The data collection was performed with the informed consent of each participant. The resultant dataset includes the participants’ performance on cognitive tasks as well as their appearance and body skeleton acquired from an RGB-D camera for further analysis of gait and posture.

We summarize our concept for design the automatic data collection system, which are detailed in Section 3.

**Design concept** (Section 3):
- **Unmanned data collection** (3.1): We developed the data collection system so that it did not require an operator. The hardware and software configurations were designed to securely store participants’ personal data.

- **Attracting participants** (3.2): As an experiment, we installed a data collection system in the largest science museum in Japan. To attract participants, the proposed system was designed as an entertainment kiosk. The participants were asked to play an interactive game involving dual-task behavior. The game-based tasks were intended to motivate the participants to follow the instructions faithfully to obtain higher scores.

- **Consideration of privacy** (3.3): Participants provided consent for their data to be used for research purposes through the system, which was designed in accordance with the advice of a lawyer.

**Contributions**: The main contributions of this study are twofold. First, this paper provides a hands-on example for acquiring large human behavior data from public participants using a game-based unmanned system. Our framework and ideas can easily be extended for other data collection purposes assisted by media technology. Second, this study enables the automatic collection of dual-task behavior data, where the datasets collected by the proposed framework will be an important standard of dual-task studies. The system, so far, allowed us to construct a large-scale dataset comprising over 70,000 sessions of dual-task behavior, including RGB-D image sequences of the participants performing tasks, together with their personal information.

2. Related Work

2.1 Analysis of Dual-task Performance

Traditionally, cognitive ability is quantitatively evaluated using cognitive measures based on oral examinations such as the Mini-Mental State Examination (MMSE)\[^9\] and the Revised Hasegawa’s Dementia Scale (HDS-R)\[^10\], which consists of questions related to calculation, short-term memory, and comprehension. Written examinations such as Intelligence Quotient (IQ) test\[^11\] are utilized particularly for measuring the de-
Development of children. Especially, MMSE is a de-facto standard measurement for the quick assessment of dementia, which is performed by face-to-face verbal testing. It consists of 30-point written questionnaires including the questions related to recognition, memory, attention, calculation and language abilities. An example question related to the calculation is “I would like you to count backward from 100 by sevens.” (The answer should be 93, 86, 79, 72, 65.)

Dual-task performance is a quick way to evaluate human cognitive functions. Dual tasks require more cognitive resources than single tasks, even when the tasks are simple, such as walking while chatting; thus, they provide a better assessment of cognitive abilities than performing only a single task. Dual-task studies usually use a combination of walking (or stepping) behavior and cognitive tasks (e.g. calculation) because walking behavior is a daily motor task. Performance on such dual tasks can be assessed in terms of gait (i.e. walking style) and cognitive task performance. Doi et al. found a relationship between level of cognitive functioning and dual-task walking speed.

According to the interference theory, the cognitive load exerted by a dual task interferes with short-term memory, which makes it difficult for people with low cognitive ability to perform either or both tasks. Dual-task performance therefore decreases in people with cognitive impairments due to conditions such as stroke and Parkinson’s disease. Age is also a major factor affecting dual-task performance, particularly among children and elderly people. Performing dual tasks on a daily basis is reported to contribute to the prevention of MCI.

2.2 Collection of Behavioral Data

In earlier dual-task studies, the performance was evaluated by only a few measurements, such as walking speed and response times. However, obtaining reliable results using machine learning techniques requires utilizing beyond such simple features, it is required to construct a large dataset with rich information (e.g. videos). A common way to acquire such large-scale datasets is to use videos captured by surveillance cameras and webcams around the world. However, it is hard to control people’s behavior according to the aims of the study. From an ethical viewpoint, it can also be difficult to use these datasets for human behavior research if they are acquired without the informed consent of the subjects.

We designed a data collection system for installing in public spaces to capture data during experience-based exhibitions similar to dataset collection of human gait. However, dual-task behavior is notably more complex than simply walking. In addition, the data collection is intended for people to contribute their data voluntarily, it is important to design it so that it was attractive to increase participation. Therefore, our data collection system was designed as an entertainment kiosk to motivate the participants to follow the instructions faithfully, while providing them with a fun and interesting task.

3. Dual-task Behavior Collection System

The system acquires behavioral data while participants perform physical and cognitive tasks. Participants are presented with instructions displayed on the system asking them to perform calculation (single cognitive task) and stepping (single physical task) tasks individually, and both tasks together (dual task).

Cognitive ability and dual-task performance are known to vary with age, particularly among children and elderly people. Our investigation therefore focused on the relationship between age and dual-task performance. The following attributes were collected through the proposed data collection system:

- Age and gender.
- Answers to and response times for calculation questions.
- RGB-D image sequences and body skeletons while performing the tasks.

While we collected a dual-task behavior involving stepping and calculation, our data collection framework can easily be extended for other task combinations. We will discuss the extendability of our framework in Section 5.1.

3.1 Unmanned Data Collection: Hardware Design

An important issue for the system design is to achieve data collection without an operator present. The system is shown in Figure 2. We achieved automatic ticket-based management of participants’ ID and attributes (age and gender). We developed a kiosk-type data collection environment (cf. Figure 2(b)) and a ticket issuing machine. Participants played the game in accordance with the instructions automatically presented in the kiosk while the behavioral data were captured by attached sensors.

(a) Entrance.

Before starting the experimental session, participants
input their age, gender, and preferred language for the experimental instructions (Japanese or English) using a touchscreen tablet, as shown in Figure 2(a). A ticket with a QR code is issued for each participant and the inputted information (age, gender, and language) is associated with the participant’s ID.

(b) Data collection kiosk.

The participants are then asked to move to the entertainment kiosk to play the game, as shown in Figure 2(b). The kiosk is equipped with a QR code reader for acquiring the participant’s ID; the experimental session starts once the QR code is presented to the reader. The participant then follows the instructions presented visually on the display and vocally through a speaker.

The system is equipped with sensors to collect the behavioral information. We particularly focus on the acquisition of gait information while performing tasks, which can be used for vision-based analysis. Accordingly, the participant’s appearance while performing the tasks is recorded in RGB images, depth images, and body skeletons captured by an RGB-D sensor (Kinect v2, Microsoft Corp.) mounted at the top of the display in front of the participant. The participant answers the calculation questions by selecting the correct answer from two alternatives using a push button in each hand. All of the captured data are encrypted and stored automatically in storage devices in a locked cabinet to ensure the security of the participants’ personal information.

3.2 Attracting Participants: Game-based Behavior Control

As noted above, an important point for large-scale data collection in a public space is to motivate public participants to contribute to the data collection. To attract participants, the proposed system is designed as an entertainment kiosk. The participants play an interactive game involving calculation and stepping tasks. The system displays the single- and dual-task performances as a score for the game, as shown in Figure 3. The results include scores for several intuitive factors related to dual-task performance such as stepping speed, stability, response accuracy, and response time. The system also presents an average score and a synthesized picture using depth-based chroma key to increase participants’ interest. A printed version of the score sheet is given to participants who agree to their behavioral data being used for research uses.

During the game, participants are asked to perform three tasks: a single physical task, a single cognitive task, and a dual task. Instructions for the tasks are presented to the participants through the display. To attract the participants, the system provides interactive feedback, such as whether the calculations are correct, and the participant’s silhouette while stepping is also projected on the display. Figure 4 illustrates the typical flow for each task. Before starting each task, the system provides the participant with instructions, as listed in Table 1. Note we designed the system to flex-
Fig. 4  Tasks for participants and corresponding instructions on the display. Before starting each task, participants are presented with both spoken and written instructions (cf. Table 1), with the option of either Japanese or English instructions.

1) Instructions

2) Tasks (single physical, single cognitive, and dual tasks)

(a) Single physical task.
We chose to measure stepping behavior for the physical task. We used stepping instead of walking, which is often used as the physical task in dual-task studies because the area available for the experiment was much reduced. Participants are asked to continually step on the same spot until the next instruction is given. The system provides visual feedback by displaying a silhouette of the participant acquired from the RGB-D camera during the task.

(b) Single cognitive task.
A key challenge of task design is the selection of appropriate cognitive tasks that are effective for dual-task analysis. Following discussions with psychiatrists, we designed a cognitive task that involves calculation and short-term memory, both of which are fundamental cognitive abilities.

The cognitive task is performed according to the flow on the right of Figure 4. Calculation questions consist of the addition or subtraction of two numbers. Each question is briefly displayed then replaced by two candidate answers: correct and incorrect ones. The question and answer candidates are not shown simultaneously to load the participant’s short-term memory. The incorrect responses are generated by randomly simulating common mistakes in calculation: mistakes in carrying and borrowing, unit place, and adding instead of subtracting. Participants hold a button in each hand for selecting the correct answer. Accuracy and response time are recorded, and the participant receives immediate feedback. While collecting the data described in Section 4.2, we used the timings listed in Table 2 to show and hide the questions and answers (corresponding to $t_1$, $t_2$, $t_3$ shown in Figure 4).

The proposed system can be used by participants of all ages and education levels. Standard criteria (such as MMSE cut-off scores) are occasionally inefficient for diagnosing cognitive impairments because performance differs with education level. Similarly, the difficulty of the cognitive tasks in the proposed system differs among individuals. We thus allowed participants to select the level of difficulty of the calculation questions in the cognitive task, as listed in Table 3. The level is selected before the start of the experiment, as shown in Figure 5.

(c) Dual task.
During a dual-task session, participants are asked

---

**Table 1** Instructions provided before the task. Japanese instructions are also available.

| Task                | Instruction (display and voice)          |
|---------------------|------------------------------------------|
| Single cognitive task | “Answer questions without walking.”       |
| Single physical task | “Please step on the spot.”               |
| Dual task           | “Answer questions while stepping.”        |

**Table 2** Timings for cognitive tasks. Corresponding symbols ($t_1$, $t_2$, $t_3$) are shown in a flow in Figure 4.

| Timings                      | Duration [ms] |
|------------------------------|---------------|
| Duration of question display ($t_1$) | 300           |
| Delay until the answer is displayed ($t_2$) | 100           |
| Delay until the next question is displayed ($t_3$) | 100           |

**Table 3** Difficulty levels of calculation questions for the cognitive task.

| Level       | Calculation questions | Example question | Example candidates |
|-------------|-----------------------|------------------|-------------------|
| Easy        | 1 digit ± 1 digit     | $9 + 8 = ?$      | 17, 15            |
| Middle      | 2 digits ± 1 digit    | $98 - 7 = ?$     | 105, 91           |
| Difficult   | 2 digits ± 2 digits   | $98 + 76 = ?$    | 174, 184          |
to perform the physical and cognitive tasks simultaneously; i.e., they answer the calculation questions while stepping. According to the interference theory\(^{13}\), performance on the dual task is expected to be worse than on each single task, particularly for those with cognitive impairment. In addition to investigating the relationship between dual-task performance and cognitive functions, the resultant dataset enables the comparison of dual- and single-task performance.

3.3 Consideration of Privacy: Automatic Agreement Collection

A challenge when collecting research data is to acquire participants’ agreement for their collected data to be used for research purposes. The proposed system acquire participants’ agreement based on informed consent according to suggestions from a lawyer. According to the laws, the most important thing is that we should clarify what kind of personal information is actually collected. Therefore we showed images actually collected from the participants after the demonstration. Also, it is important to describe the purpose and policies of the research. We avoided to let the participants read the long sentences during or after the game, instead we presented the research purposes before experimenting at the entrance terminal.

During the long-running exhibition, therefore, we checked the participants’ agreement both before and after the experiment, which is a unique aspect of our framework:

**Before experiment:** A signboard was installed at the entrance of the exhibition area. The signboard indicates that we capture videos in the area of the exhibition, and are stored for a research purpose. We expressly collected participants’ agreement at the entrance terminal (i.e., before experimenting). The terminal presented the purpose and policies of the research, and required agreement from participants to issue a QR code ticket, as shown in Figure 6. Each display is presented in several seconds (i.e., the “next” button is not enabled during several seconds) to let them read the sentences.

**After experiment:** In addition to the agreement at the entrance, a unique aspect of our method of obtaining informed consent is that after the experimental session ended, the proposed system presents the terms of the agreement as well as images (RGB and depth) actually captured in the session, as shown in Figure 7. Participants need to select push buttons to indicate whether they agreed with the use of the collected data. By performing these tasks, participants understand what kind of personal information have actually been recorded, thus providing them with an opportunity to refuse the data collection at the end of the session. If the participant agrees, the system prints a score sheet (see Figure 3) from the printer; otherwise, the system immediately deletes all of the data related to the session.

Note the long-running exhibition has originally been performed from July 2015 to June 2016 in Japan. Therefore it is possible that the specific requirements and sentences presented to participants do not fit the current standards for data collection in Japan or other countries due to the difference of laws and social situations. Meanwhile, the idea of our approach, collecting participants’ agreement both before and after an experiment while showing information actually collected from the participant, should be valuable for future data collection studies.

4. Experiments and Datasets

4.1 Data Collection in a Large Public Space

The number of participants in dual-task studies is normally in the order of tens or hundreds. However, with the growth of recent data-driven machine learning approaches, a larger dataset is required. To increase the exposure to the public, we collected the data in the National Museum of Emerging Science and Innovation (Miraikan), the largest science museum in Japan with approximately one million visitors per year, over a period of approximately 11 months. This was considered a good location to attract participants because we expected science museum visitors to be interested in providing their data for research purposes.

Through the experiment, we collected the following dataset:

(1) Large-scale dataset from public participants: One important application of dual-
Agreement collection w/ descriptions of the purpose and overview of the exhibition

1. Input gender and age

2. Issue QR code ticket

More than 12 yrs

0 – 5 yrs old

7 – 12 yrs old

More than 17 yrs old

Yes

Parent is here

No parent

Agreement collection is required to issue a QR code ticket.

Flow for the agreement collection in the entrance terminal:

A ticket is not issued if the agreement is not collected. Please input your gender and age on the terminal. After that, the QR code ticket will be issued. If you understand and agree, then the data is collected.

Do you agree that the data is collected?

Agreement collection with descriptions of the purpose and overview of the exhibition.

- If you agree, then the agreement is recorded.
- If you disagree, then the agreement is not recorded.

If there is no parent, then the agreement is completed.

Fig. 6
task analysis is the development analysis of young people. We collected dual-task behavioral data associated with age and gender information, which consists of 70,513 sessions completed by 66,177 individuals—mainly children and young adults—participants.

(2) Dataset with traditional cognitive score:
For comparison with existing cognitive measures, we also collected MMSE data from 187 elderly participants by face-to-face testing. We conducted a pilot study to investigate the relationship between cognitive scores and dual-task performance.

4.2 Large-Scale Dataset from Public Participants
The data collection took place between July 15, 2015 and June 27, 2016, in conjunction with a long-running exhibition in Miraikan, the 15th media lab “Arukudake—Just from walking—”. The dataset consists of single- and dual-task performance data collected during 70,513 sessions, contributed by 66,177 individuals∗. Overall, 93.4% of participants agreed to their data being included in the dataset, through the interface described in Section 3.3.

Figure 8 shows examples of acquired images and body skeletons corresponding to their age and gender. In the dataset, RGB and depth images are respectively captured in 1920 × 1024 and 512 × 424 resolutions at 15 fps. The RGB-D sensor can capture up to 30 fps image sequences, while we dropped half of the frames due to the bandwidth of storage devices. We compressed RGB data as JPEG images, while 32-bit depth images are stored using LZ4 lossless compression. Consequently, body skeletons are extracted from each 15 fps depth images. Each skeleton contains 3D locations of 25 joints, which rely on the specifications of the sensor. The sensor acquires body skeletons up to six persons in the same frame; we store all skeletons in a single text file, associated with person indices in the frame.

The statistics of ages and genders are shown in Figure 9. Most of the participants were children and young adults, consistent with the profile of science museum visitors. Whilst, every age band under 80 years includes more than 200 participants. According to other statistical standards for cognitive analysis, our dataset includes the sufficient numbers of subjects to construct a statistical standard for age-related dual-task analysis; for example, standardization of the Wechsler Adult Intelligence Scale-Fourth Edition (WAIS–IV), a popular IQ test, was based on 2,200 samples (200 examinees for each 5-year age band)11).

4.3 Dataset with Traditional Cognitive Score
An important use of the dual-task paradigm is to investigate the relationship between performance and existing cognitive measurements, for the diagnosis of cognitive impairments. In addition to creating the large-scale dual-task dataset with associated age information, we conducted additional sessions to collect MMSE data9), as this is a commonly used measure for evaluating cognitive functions.

We invited 187 older participants (average age 65.5, standard deviation 13.4) to complete the MMSE. They first answered a Japanese version of the MMSE by face-to-face verbal testing. They then performed the single and dual tasks using the proposed system. They performed the calculation tasks at all three levels of difficulty (easy, medium, and difficult), with the order of the tasks and difficulty levels randomized. Their single- and dual-task behavioral data are associated with age, gender, and MMSE score (from 0 to 30).

Figure 10 presents the statistics for the 187 invited participants. The associated MMSE scores range from 21 to 30. The figure also shows two cut-off scores, proposed by two studies22)23), which are often used as rough standards for medical diagnosis of cognitive impairment (dementia and MCI). According to the cut-off score proposed by O’Bryant et al.22), our dataset includes 49 participants with possible cognitive impairment. The dataset can be used in future research to investigate differences in dual-task performance between cognitively impaired and non-impaired subjects, as well as to esti-

∗ Participants were allowed to perform the experiments multiple times.
| Age | Gender | Single cognitive task | Single physical task | Dual task |
|-----|--------|-----------------------|----------------------|----------|
| 76  | Male   | RGB                  | Depth                | Body skeleton (side, front) |
| 39  | Female | RGB                  | Depth                | Body skeleton (side, front) |
| 17  | Female | RGB                  | Depth                | Body skeleton (side, front) |
| 7   | Male   | RGB                  | Depth                | Body skeleton (side, front) |

Fig. 8 Example images from the dataset during each task. Note black rectangles are overlaid onto RGB images for anonymization.
Fig. 9  Age and gender statistics of participants who agreed to their behavioral data being included in the dataset. Overall, 50.4% of participants were male.

(a) Age and gender of participants.

(b) Distribution of MMSE scores.

Fig. 10  MMSE dataset. The dataset includes 187 participants with an average age of 65.5 years (standard deviation 13.4). Figure (b) shows cut-off scores for identifying cognitively impaired participants based on O’Bryant et al. and Tombaugh et al.; a variety of criteria are used among studies.

5. Discussions

As described in Section 1, the design concept of our data collection framework is categorized as 1) unmanned data collection, 2) attracting participants, and 3) consideration of privacy. To investigate our concepts were successfully achieved by the proposed system, we here discuss each topic via qualitative and quantitative evaluations.

5.1 Discussions about Unmanned Data Collection

(1) Validity of Collected Data

We achieved a data collection system that is designed to operate without the supervision of an operator, apart from for machine maintenance (e.g., consumables replacement for printers). Meanwhile, a common problem in automatic data collection is the validity of collected data, which depends on the faithfulness of participants in our case. In particular, main concerns in our study was if they input their age and gender correctly. There are some possibilities of inputting wrong personal information: some participants may not be faithful, or some QR code tickets of children could be used by their parents. Therefore, we manually screened each captured RGB videos to check if age and gender information inputted by the participants are correct. Although the screening was performed subjective manner, age and gender information associated with 97.5% of sequences were judged as correctly inputted. The ratio of correctness indicates that our game-based interfaces can collect personal data with a certain validity.
(2) Estimating Cognitive Function from a Dual-task Dataset

We performed a pilot experiment to confirm that the dual-task dataset with MMSE scores can be used to estimate cognitive function from dual-task performance. We implemented a simple classification system based on the dataset described in Section 4.3. We first extracted four features related to cognitive functions: the number of calculation questions answered correctly, the number of questions answered, and the means and standard deviations of the response time intervals. For the single cognitive and dual tasks, we used the four features to train a linear support vector machine to predict possible cognitive impairment. We selected the cut-off score of 25 (i.e., <25 and ≥25) for the classification; this is selected according to a middle cut-off score among previous studies related to MMSE.

Figure 11 shows the receiver operating characteristic curves for the classification. According to the equal error rates of the estimation based on each task (0.325 for dual task and 0.364 for single task), dual-task performance better reflects performance on the existing measure of cognitive functioning. However, the classification accuracy is still insufficient for use in practical applications, such as for the diagnosis of cognitive impairment. This indicates the requirement of using rich information such as RGB-D sequences to further investigate the relationship between dual-task performance and cognitive functions.

(3) Extendability

The term dual task includes any of two combinations of behaviors. Our task combination (i.e., stepping and calculation) is determined via a discussion with a psychiatrist, while our kiosk-based framework can accept other combinations of physical and cognitive tasks by modifying the software or adding a few devices. An example of physical tasks other than stepping is making gestures. By using body skeletons acquired by the RGB-D sensor, combinations of gestures (e.g., like hand flag signals) and cognitive tasks are a simple extension of our framework. Regarding cognitive tasks other than calculation, quizzes to select correct colors or diagrams, are occasionally used for assessment of cognitive skills. By using microphones and speech recognition techniques, the proposed framework can be extended to more flexible cognitive tasks. Meanwhile, due to the space limitation of kiosk-based hardware configuration, it is difficult to acquire straight walking or other physical behaviors requiring a large space.

5.2 Discussions about Attracting Participants

To investigate the effectiveness of game-based data collection, we conducted user study of 69 elderly participants contributed to the MMSE datasets described in Section 4.3. We asked the following three factors using Likert scale value from 1 (no) to 5 (yes):

- Usability: Did you easily understand the usage of the system?
- Visualization in score sheet: Did the score sheet contribute to gain your interest for data collection?
- Periodic use: Are you willing to participate the data collection periodically?

Figure 12 shows the results of the usability study. Although it is difficult to compare the results with other data collection approaches, the participants highly satisfied the proposed system. These results indicate that our data collection paradigm indeed evoked the participants’ interest.

5.3 Discussions about Consideration of Privacy

An important interest of this study is the acceptability by participants for the data collection. While the 93.4% of public participants agreed to their data being included in the dataset described in Section 4.2, we investigated how they accept (or declined) the data collection. Through questionnaires, we asked participants the acceptability for the data collection by the proposed system:

Q: How do you feel to provide personal information, such as videos, age, and gender?

The participants selected one from the following answers:

- I willing to provide if it contributes to the society.
- I provide if the usage is limited (e.g. for academic research).
- I provide only if the information does not specify individuals (i.e. the data is anonymized).
6. Conclusions and Future Work

This paper proposes an automatic data collection system for cognition-related human behavior. The proposed system consists of an entertainment kiosk that provides participants with fun and is designed to be installed in public spaces. By installing the system in a long-running exhibition at a science museum, we captured over 70,000 sessions of dual-task behavior. The collected dataset consists of calculation performances and images captured by an RGB-D sensor, and each set of data is associated with the participant’s age and gender. We also acquired MMSE scores from 187 participants and created a dataset that combines dual-task and MMSE data. A pilot experiment showed that it is possible to estimate a cognitive function from the dual-task data.

These two datasets can be used for investigating dual-task performance, providing a novel approach to human cognition studies based on machine learning and computer vision. We plan to apply vision-based approaches to estimate cognitive functions and to investigate the relationship between age and dual-task performance.

As performing dual tasks may help to prevent cognitive impairment\(^{20}\), the proposed system could be used for daily monitoring of dual-task performance to facilitate the early detection and prevention of cognitive impairment. To confirm the effectiveness of the proposed system for the analysis and prevention of cognitive impairment, we plan to install it in facilities for the elderly.

Data collection is an important, yet challenging, aspect of studying human behavior. We firmly hope that the concept of the proposed system—large-scale data collection that is entertaining for participants—offers a practical solution to this problem.

Acknowledgements

This work was partly supported by a JST CREST project “Behavior Understanding based on Intention-Gait Model”. We thank the staff of Miraikan for giving us the opportunity to collect the data in conjunction with the exhibition. We also thank Mr. Masahiro Kobayashi from Hanamizuki Law Office for his advice on the agreement collection, and Prof. Hiroaki Kazui from Osaka University Graduate School of Medicine for the suggestions about the task design. We especially thank all of the exhibition participants who contributed their data.

References

1. A. A. Hyder, G. Rotllant, and R. H. Morrow, “Measuring the burden of disease: Healthy life-years,” *American Journal of Public Health*, vol. 88, no. 2, pp. 196–202, 1998.
2. H. Pashler, “Dual-task interference in simple tasks: Data and theory,” *Psychological Bulletin*, vol. 116, no. 2, pp. 220–244, 1994.
3. S. Boonyong, K.-C. Siu, P. van Donkelaar, L.-S. Chou, and M. H. Woollacott, “Development of postural control during gait in typically developing children: The effects of dual-task conditions,” *Gait & Posture*, vol. 35, no. 3, pp. 428–434, 2012.
4. H. Makizako, H. Shimada, D. Yoshida, Y. Takayama, T. Suzuki, et al., “Relationship between dual-task performance and neuropsychological measures in older adults with mild cognitive impairment,” *Geriatrics & Gerontology International*, vol. 13, no. 2, pp. 314–321, 2013.
5. P. Plummer-D’Amato, L. J. Altmann, D. Saracino, E. Fox, A. L. Behrmann, and M. Marsiske, “Interactions between cognitive tasks and gait after stroke: A dual task study,” *Gait & Posture*, vol. 27, no. 4, pp. 683–688, 2008.
6. T. Doi, H. Shimada, H. Makizako, K. Tsutsunimoto, K. Uemura, Y. Anan, and T. Suzuki, “Cognitive function and gait speed under normal and dual-task walking among older adults with mild cognitive impairment,” *BMC Neurology*, vol. 14, no. 1, pp. 1–8, 2014.
7. H. Iwama, M. Okumura, Y. Makihara, and Y. Yagi, “The OUISIR gait database comprising the large population dataset and performance evaluation of gait recognition,” *IEEE Trans. on Information Forensics and Security*, vol. 7, no. 5, pp. 1511–1521, 2012.
8. Y. Makihara, T. Kimura, F. Okura, I. Mitsugami, M. Niwa, C. Aoki, A. Suzuki, M. Muramatsu, and Y. Yagi, “Gait collector: An automatic gait data collection system in conjunction with an experience-based long-run exhibition,” in *Proc. 8th IAPR Int’l Conf. on Biometrics (ICB’16)*, Article No. 017, no. 017, pp. 1–8, 2016.
9. M. F. Folstein, S. E. Folstein, and P. R. McHugh, “‘Mini-mental state’: A practical method for grading the cognitive state of patients for the clinician,” *Journal of Psychiatric Research*, vol. 12, no. 3, pp. 189–198, 1975.
10. Y. Imai and K. Hasegawa, “The revised Hasegawa’s dementia scale (HDS-R):evaluation of its usefulness as a screening test for dementia,” *Hong Kong Journal of Psychiatry*, vol. 4, no. 2, p. 20, 1994.
11) D. Wechsler, Wechsler Adult Intelligence Scale—Fourth Edition: Technical and interpretive manual. San Antonio, TX: Pearson Assessment, 2008.
12) I. Brown, “Dual task methods of assessing work-load,” Ergonomics, vol. 21, no. 3, pp. 221–224, 1978.
13) D. Murray, “Research on human memory in the nineteenth century,” Canadian Journal of Psychology, vol. 30, no. 4, p. 201, 1976.
14) O. Beauchet, V. Dubost, K. Aminian, R. Gonthier, and R. W. Kressig, “Dual-task-related gait changes in the elderly: Does the type of cognitive task matter?,” Journal of Motor Behavior, vol. 37, no. 4, pp. 259–264, 2005.
15) Y.-R. Yang, Y.-C. Chen, C.-S. Lee, S.-J. Cheng, and R.-Y. Wang, “Dual-task-related gait changes in individuals with stroke,” Gait & Posture, vol. 25, no. 2, pp. 185–190, 2007.
16) S. O’Shea, M. E. Morris, and R. Iansek, “Dual task interference during gait in people with parkinson disease: Effects of motor versus cognitive secondary tasks,” Physical Therapy, vol. 82, no. 9, pp. 888–897, 2002.
17) L. Rochester, B. Galna, S. Lord, and D. Burn, “The nature of dual-task interference during gait in incident Parkinson’s disease.” Neurosciences, vol. 265, pp. 83–94, 2014.
18) O. Beauchet, R. W. Kressig, B. Najafi, K. Aminian, V. Dubost, and F. Mourey, “Age-related decline of gait control under a dual-task condition,” Journal of the American Geriatrics Society, vol. 51, no. 8, pp. 1187–1190, 2003.
19) H. Makizako, T. Furuna, H. Shimada, H. Ihira, M. Kimura, L. I. Oddsson, and T. Suzuki, “Age-related changes in attentional capacity and the ability to multi-task as a predictor for falls in adults aged 75 years and older,” Journal of Physical Therapy Science, vol. 22, no. 3, pp. 323–329, 2010.
20) T. Doi, H. Makizako, H. Shimada, H. Park, K. Tsutsumimoto, K. Uemura, and T. Suzuki, “Brain activation during dual-task walking and executive function among older adults with mild cognitive impairment: A fNIRS study,” Aging Clinical and Experimental Research, vol. 25, no. 5, pp. 539–544, 2013.
21) J.-F. Lalonde, A. A. Efros, and S. G. Narasimhan, “Webcam clip art: Appearance and illuminant transfer from time-lapse sequences,” ACM Trans. on Graphics (Proc. ACM SIGGRAPH Asia’09), vol. 28, no. 5, p. Article No. 131, 2009.
22) S. E. O’Bryant, J. D. Humphreys, G. E. Smith, R. J. Ivnik, N. R. Graff-Radford, R. C. Petersen, and J. A. Lucas, “Detecting dementia with the mini-mental state examination in highly educated individuals,” Archives of Neurology, vol. 65, no. 7, pp. 963–967, 2008.
23) T. N. Tombaugh and N. J. McIntyre, “The mini-mental state examination: a comprehensive review,” Journal of the American Geriatrics Society, vol. 40, no. 9, pp. 922–935, 1992.

Fumio Okura received his M.S. and Ph.D. degrees in engineering from Nara Institute of Science and Technology in 2011 and 2014, respectively. He is currently an assistant professor of the Institute of Information Science and Technology, Osaka University. His research interest lies in the boundary domain between computer vision and computer graphics. He is a member of IEEE, IEICE, IPSJ, and VRSJ.

Ikuhisa Mitsugami received his B.S. degree in engineering from Kyoto University in 2001, and M.S. and Ph.D. degrees in engineering from Nara Institute of Science and Technology in 2003 and 2007, respectively. He then started working for the Academic Center for Computing and Media Studies, Kyoto University, and in 2010 became an assistant professor of the Institute of Scientific and Industrial Research, Osaka University. He is currently an associate professor of the Graduate School of Information Sciences, Hiroshima City University. His research interests are computer vision, human interfaces, and human behavior analysis. He is a member of IEEE, IEICE, IPSJ, and VRSJ.

Masataka Niwa received the M.S. degree in information science and technology from Osaka Institute of Technology in 2006, and Ph.D. degrees in information science and technology from Osaka University in 2009, respectively. He was with the Advanced Telecommunications Research Institute International (ATR) during 2003-2006, the Graduate School of Information Science and Technology, Osaka University during 2009-2013, the National Institute of Advanced Industrial Science and Technology (AIST) in 2013, the National Institute of Information and Communications Technology (NICT) during 2013-2014, and the Institute of Scientific and Industrial Research, Osaka University during 2014-2017. He is currently a Specially Appointed Researcher of the Osaka University Institute for Datability Science. His research interests are virtual reality and human interface. He is a member of VRSJ.

Kota Aoki received the B.E. and Ph.D. degrees from Tokyo Institute of Technology in 2001 and in 2006, respectively. He was an assistant professor of the Imaging Science and Engineering Laboratory at Tokyo Tech. until 2016. He is now a specially appointed associate professor of the Institute of Scientific and Industrial Research at Osaka University. His research interests include computer vision, image processing, and pattern recognition. He is a member of IEICE, IEEE, and ITE.

Chengju Zhou received her B.S. degree in Electronic and Information Engineering and the M.S. degree in Signal and Information processing from Dalian University of technology, China, in 2008 and 2010, respectively. Since 2012, she has been pursuing the Ph.D. degree in Computer Science at Osaka University.

Yasushi Yagi has been the Executive Vice President of Osaka University in 2015. He received his Ph.D. degree from Osaka University in 1991. In 1992, he joined the Project Development Laboratory, Mitsubishi Electric Corporation, where he worked on robotics and inspections. He became a research associate in 1999, a lecturer in 1993, an associate professor in 1996, and a professor in 2003 at Osaka University. He was the Director of the Institute of Scientific and Industrial Research, Osaka University from 2012 to 2015. International conferences for which he has served as chair include: ROBIO2006 (PC), ACCV (2007PC,2009GC), PSIVT2009 (FC), and ACPR (2011FC, 2013GC). He has also served as the Editor of the IEEE ICRA Conference editorial board (2008-2011). He is a member of the editorial board of the International Journal of Computer Vision, Editor-in-Chief of IPSJ Transactions on Computer Vision & Applications, and Vice-President of the Asian Federation of Computer Vision Societies. He was awarded the ACM VRST2003 Honorable Mention Award, IEEE ROBIO2006 finalist of the T.I. Tan Best Paper in Robotics, IEEE ICRA2008 finalist for the Best Vision Paper, PSIVT2010 Best Paper Award, MIRU2008 Nagao Award, IEEE ICCP2013 Honorable Mention Award, MVA2015 Best Poster Award, IWBF2014 IAPR Best Paper Award, and IPSJ Transactions on Computer Vision and Applications Outstanding Paper Award (2011, 2013). His research interests are computer vision, pattern recognition, biometrics, human sensing, medical engineering, and robotics. He is a fellow of IPSJ and a member of IEICE, RSJ, and IEEE.