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Analysis and Prediction of Patient Falls from Beds Using an Infrared Depth Sensor

Fumiya Ishizu,[1*] Takuya Tajima,[2] Takehiko Abe[3]

[1]System Management Engineering, Graduate School of Engineering, Fukuoka Institute of Technology, 3-30-1, Wajirihigashi, Higashi-ku, Fukuoka-shi, Fukuoka 811-0295, Japan
[2]Department of System Management, Faculty of Information Engineering, Fukuoka Institute of Technology, 3-30-1, Wajirihigashi, Higashi-ku, Fukuoka-shi, Fukuoka 811-0295, Japan
[3]Aichi University, 4-60-6 Hiraike-cho, Nakamura-ku, Nagoya, Aichi 453-8777 Japan

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Falling down is a common symptom of geriatric syndromes, and fractures and intracranial hemorrhages triggered by falling down lead to serious problems and impair life functioning. Moreover, it sometimes leads to a higher risk of death. In Japan in recent years, the number of fatalities from traffic accidents has been declining, whereas the number of fatalities from falls has been leveling off. In 2020, 8851 people died from falls, whereas the number of fatalities from traffic accidents was 2199. The number of fatalities among the elderly due to falls is approximately four times the number of fatalities from traffic accidents. Therefore, in this paper, we propose a system that analyzes the body by using Kinect, an infrared depth sensor for tracking a skeletal model of a user. In this study, the goal is for the predicted fall values from Kinect-measured data and the predicted fall values from motion-capture-measured data to be close to the predicted values, so that this technology can eventually be used in clinical practice. On the basis of information from the skeletal model, the system analyzes element indices such as the center of gravity and body tilt of people in need of nursing care when falling down. Then, it predicts the risk factor for falling down. This information is used for detecting warning signs for falling down in the early stages. Finally, this study will contribute to decreasing number of falls from the bed.

1. Introduction

While Japan's total population has been in a long-term decline, the number of elderly people aged 65 and over in Japan reached a record high of 36.21 million in 2021 (36.02 million in the previous year), and the ratio of this population to the total population (aging rate) was 28.9% (28.6% in the previous year). This data indicates that Japan has become a super-aged society.

It is predicted that the population aged 65 and over will continue to increase, peaking at 39.35 million in 2060, after which it is predicted to begin declining. However, even as the population aged 65 and over begins to decline after 2060, the percentage of elderly will continue to climb,

*Corresponding author: e-mail: mjm22101@bene.fit.ac.jp
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reaching 38.4% in 2065, when one out of every 2.6 people will be aged 65 and over (12.8% of the total population) and one out of every 3.9 people will be aged 75 and over (25.5% of the total population). Falls from the bed in the elderly are a major cause of clinical accidents. Falls can lead to fractures, becoming bedridden, and even death, and are a factor that cannot be overlooked.[1,2]

According to accident statistics, there were 8,851 deaths due to falls in the year 2020 among people aged 65 and over, about four times the number of deaths due to traffic accidents among the same age group. In addition, falls are a particular problem in clinical nursing care settings. In 2021, falls accounted for 44% (1732 cases) of all types of accident in nursing care settings, with bedside falls accounting for more than half of these.[3]

In light of the above, there is demand for fall prediction and prevention by quantitatively identifying fall risks and analyzing fall characteristics, and it is essential to establish a support system for fall prevention for the elderly and to disseminate the system as soon as possible. In this study, I will estimate and predict user falls using Kinect, an infrared depth sensor that tracks the user's skeletal model.

2. Importance of Fall Prevention

2.1 Background of falls in the elderly

As Japan's elderly population continues to grow, so does the demand for nursing care, and the shortage of nursing care personnel has become an urgent issue. This issue is having a significant impact on the nursing care field, and there are many accidents that are caused by nursing care work being performed with a personnel shortage.[4] In addition, owing to the urgent need to secure nursing care personnel, the number of inexperienced caregivers and personnel from other industries performing nursing care work has been increasing every year.[5] Additionally, the sheer variety of circumstances providers work under, including the nature of the services provided, the condition of the patient, and the site where the services are provided, makes it difficult to predict the occurrence of nursing care accidents even for experienced care workers. The risk of accidents is even greater for less experienced workers.[4,6]

In particular, the type of fall accident discussed in this study is different in nature from a medication accident and is not directly related to medical or nursing care activities. In clinical practice, this is referred to as a nonprocess accident. This means that process improvement from the medical or nursing care provider side alone cannot be expected to be effective in preventing accidents. To reduce the number of accidents involving falls as much as possible, it is important to identify the risk factors that trigger falls.

2.2 Facts about fall accidents

According to a survey report at Musashino Red Cross Hospital, the behavior of patients and people in need of nursing care seems to show that fall accidents are most likely to occur before and after defecation, but about 60% of the fall accidents occurred at the bedside (Fig. 1).[6]

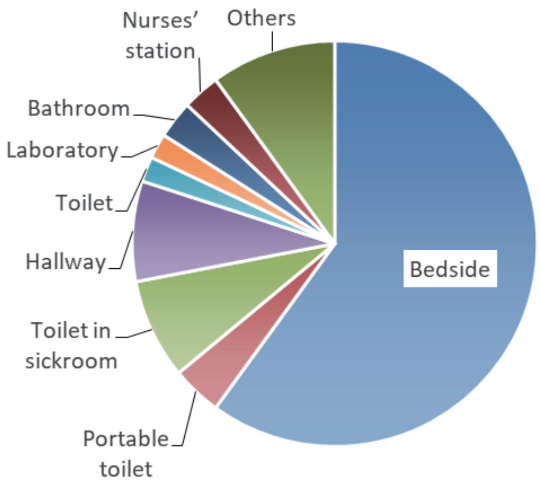

Fig. 1. (Color online) Location of fall accidents.

Recently, low-floor beds have become the norm in order to prevent falls. However, in places where the action of standing up is required, such as beside beds and toilets, the risk of fall accidents occurring is overwhelmingly higher.[7–9]

In addition, in today's nursing homes, bedrooms are often relatively spacious, and depending on the location of the beds, there are often no walls or furniture to provide support in the event of a fall. We believe that this makes the accident rate after falls higher. In contrast, toilets are closed private rooms and are covered from all angles by walls, so the walls most likely act as a safety device. In addition to the above, because most falls are nonprocess accidents, and it is very rare that a medical professional or caregiver directly witnesses the moment of the fall, it is necessary to examine in detail the factors that lead to the fall accident.

2.3 Cases of falls in clinical settings for people in need of nursing care

[Case 1] A patient requiring short-term nursing care/Time: Early morning
The patient fell down when leaving the bed to go to the toilet. The bed was designed to be used from the right side at home, but owing to the bed specifications in the facility, the patient fell when leaving the bed from the left side, which was unfamiliar to her. The patient's left leg was fractured.[10]
[Case 2] Nursing home for the elderly/Time: Midnight
The patient fell when she was getting out of her bed. Although the patient needed assistance when moving, she was very independent and stood up by herself without pushing and fell. The patient's right hand was fractured.[10]
[Case 3] Elderly care facility/Time: Daytime
The patient fell when she tried to stand up from a chair in the dining room of the facility. The

patient was incontinent at the time of the fall and may have been trying to go to the toilet on her own.[10]

3. Effective Approaches to Fall Prevention

In the previous section, it was noted that most falls are nonprocess accidents. It is true that, unlike falls caused by physical impact, it is not easy to prevent falls in the process leading up to an accident. However, we believe that medical professionals and caregivers working in clinical care settings can contribute to the reduction and prevention of falls by recognizing the tendencies and warning signs of potential falls of the people in their care. We believe that preventing fall accidents and their recurrence will become possible by incorporating research on falls, including this study, into clinical algorithms.

4. Purpose of the Experiment

In this experiment, the body's center-of-gravity sway data will be calculated from the 3D coordinate data obtained from the skeletal information, and the data will be trained. On the basis of the learned training data, we estimated the posture and center of gravity sway of bodies that are likely to fall, and verified from experiments whether using the estimation from the skeletal information and center of gravity sway data is a valid method for estimating the likelihood of falls.

5. Experiment Summary

5.1 Infrared depth sensor

In this study, an infrared depth sensor is used to acquire skeletal information. The infrared depth sensor used in this study is Microsoft's Kinect™.

Kinect has x, y, and z coordinate systems as shown in Fig. 2. When the infrared depth sensor is attached parallel to the floor, the horizontal plane is represented by the x and z planes, and the vertical direction by the y-axis. Kinect is equipped with a near-infrared projector, an infrared camera, an RGB camera, and a built-in microphone. In this system, the near-infrared projector and near-infrared camera are used as depth sensors. In this study, data acquisition was conducted at a shooting speed of 30 fps.[11,12]

Furthermore, the Kinect v2 used in this study can track significantly more bodies and joints at the same time than the Kinect v1. Six people at a time can be tracked, and the number of detectable joints is 25 (Fig. 3). [11–13]

5.2 Equipment location

The infrared depth sensor used in this study is oriented so that the z-axis direction is in front of the person. The height of the sensor is set at a distance of 0.9 m from the floor to provide the

Fig. 2. (Color online) Infrared depth sensor coordinate system.

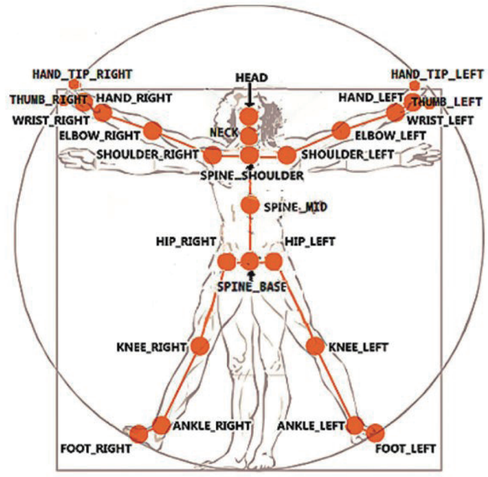

Fig. 3. (Color online) Kinect joint.

widest measurement range. This height is about 10 cm longer than half the height of an average Japanese male adult (1.8 m). In addition to the aforementioned installation position, the theoretical measurable range of Kinect is shown in Fig. 4 when measurements are taken in consideration of bed placement and other factors.

In addition, the environmental design of the laboratory is also mentioned. To mimic an actual clinical site of nursing care, no furniture or objects were placed near the bed, and the measurable range was marked with plastic tape. Subjects were asked to leave their beds within this range, and their condition was measured and recorded using Kinect.

5.3 Development environments

The experimental equipment used included Kinect v2 (Microsoft Corporation) and a notebook PC (Panasonic). To detect and retrieve the data obtained by Kinect, the programming language was C# and the programming environment was Visual Studio. To extract the center-of-gravity sway graph, we built a form to create the center-of-gravity sway graph using Microsoft Macro in Excel.

5.4 Learning environment

NVIDIA's Deep Learning GPU Training System (commonly known as DIGITS) was used as the learning environment from the extracted center-of-gravity motion graphs.

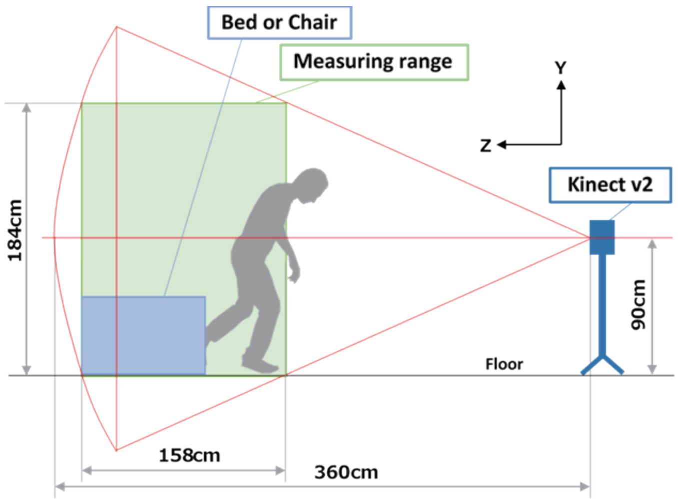

Fig. 4. (Color online) Design diagram of measurement range.

6. Experimental Flow and Results

6.1 Learning environment

As shown in Fig. 5, the environment is designed so that the front of the subject who has left the bed is facing the *z*-axis direction of Kinect's sensor. The sequence of events is from just before the subject leaves the bedside until the subject stands up or falls down. This movement is performed multiple times and each is recorded. Each time the sequence is completed, a CSV file containing the skeletal coordinate data is extracted.

The acquired data in the CSV file includes the "skeletal data acquisition time" at each joint site, the acquired data in the CSV file named the "acquisition time of skeletal data", "numerical values of 3D coordinates", and "numerical values of movement direction of joints (adopting quaternion as rotation angle)" for each joint site.

Furthermore, fall movements were divided into three categories: "fell over", "almost fell over but did not", and "did not fall over (stood up normally)". The CSV data files extracted after the completion of the operation are stored and classified according to these categories.

6.2 Creation of center-of-gravity sway graphs

To calculate the center-of-gravity motion graphs, the CSV files extracted in Sect. 6.1 are imported into a format created by ourselves using an Excel macro (Fig. 6).

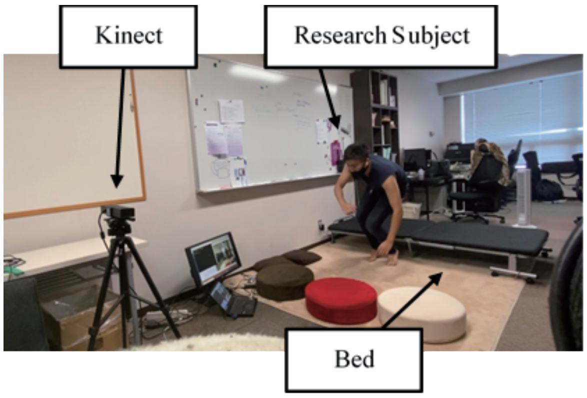

Fig. 5. (Color online) Experimental environment.

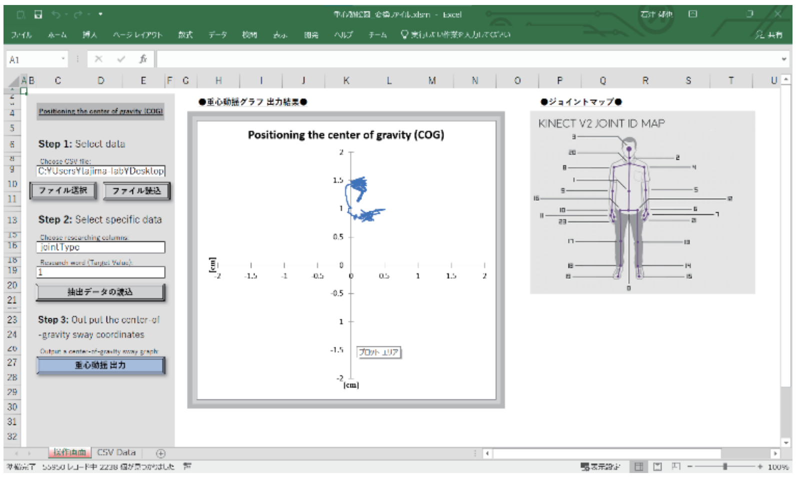

Fig. 6. (Color online) Format created using Excel macro.

6.3 Learning about fall features using a CNN

The center-of-gravity sway graph calculated in Sect. 6.2 was replaced with image data, and then, feature analysis and deep learning on the center-of-gravity image data were conducted. In the feature analysis of the center-of-gravity sway, we analyzed the trend features among the three categories of fall movement that we just described above. For deep learning, a convolutional neural network (CNN) was used to estimate the trend discrimination among the three categories of fall movements, given the test data [14].

6.4 Structure of CNN

The CNN is a type of neural network that can be trained by stacking layers called convolutional and pooling layers. In recent years, the CNN has been used in most of the deep learning of images and is often used in image processing. It achieves high discrimination rates without the need to extract features from the image in advance and only requires pixel value information as input. The architecture of the CNN is AlexNet (Zhang, 2023), which has been used in similar studies on falls, and this study is an attempt to follow this architecture [14, 15].

6.5 Evaluation methods

The validity of the algorithm for finding fall features and propensities from center-of-gravity sway data was evaluated by feeding test data to a trained model of center-of-gravity sway data and comparing the estimated and true values.

6.6 Creation of center-of-gravity sway graphs

First, the tendency to fall, which was analyzed from the center-of-gravity sway calculated by Kinect, is as follows.

In most cases, the center-of-gravity sway at the time of fall (Fig. 7) showed a linear motion, indicating that the subject was unable to raise his/her body during the fall. The center-of-gravity sway (Fig.8) at the time of almost but not falling showed a temporary linear movement, but the center-of-gravity coordinate system eventually tended to take a U-turn trajectory. We believe that this is due to the behavior of the body trying to recover its state of physical balance by raising the body after falling downward once.

The center-of-gravity sway when the subject did not fall over (normal standing) (Fig. 9) showed extremely short movements compared with other movements in terms of the range of movement of the center of gravity. This indicates that it was possible to analyze the tendency to fall and the characteristics of body movements during falls from the data acquired from Kinect.

The next result of the fall estimation performed using the CNN is shown below. Figure 10 shows the identification rate of the overall model when trained, and Table 1 shows the prediction results for each movement type when we validated it on the test data. The results in Table 1 show that the predicted values were calculated to be one step short of those in the test data. In particular, the prediction result for the "center-of-gravity system when almost falling but not falling" was calculated to be almost the same as that of falling.

We believe the reason for this is that the trends of the two center-of-gravity shifts are very similar, but the major difference between the two is that the final body center-of-gravity coordinate system when a person falls over is completely different from when they do not. When a person falls, the body's final center-of-gravity coordinate system drifts significantly outward. However, if a person is about to fall but does not fall, the final coordinate system of the body's center of gravity can easily take a U-turn trajectory because the person needs to make a movement to raise the body. We believe that more accurate prediction results can be obtained by conducting more experiments focusing on this motion feature.

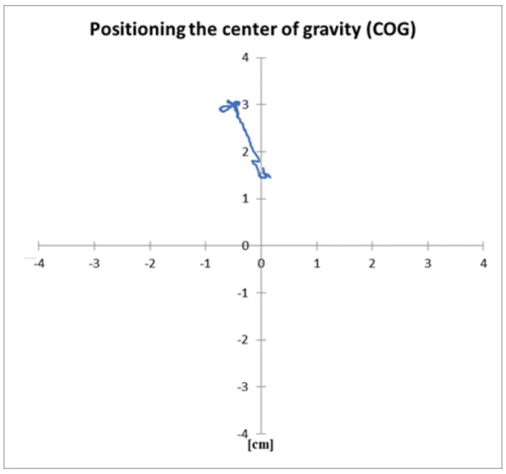

Fig. 7. (Color online) Center of gravity sway during a fall down.

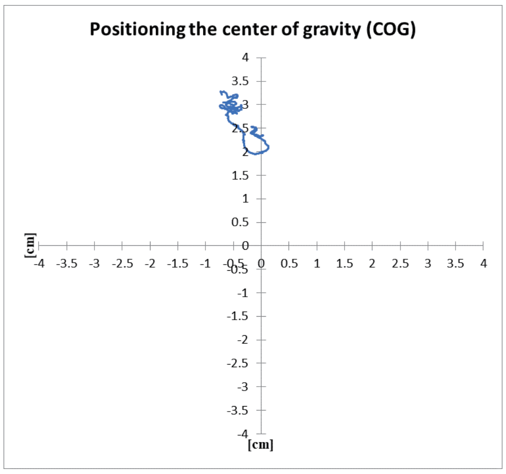

Fig. 8. (Color online) Gravity sway when user almost fell but did not.

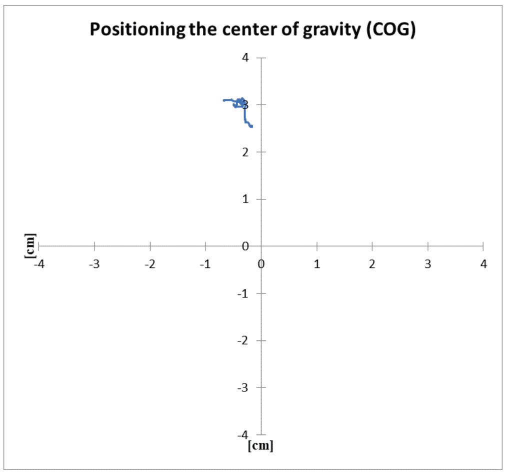

Fig. 9. (Color online) Center of gravity sway when user did not fall over.

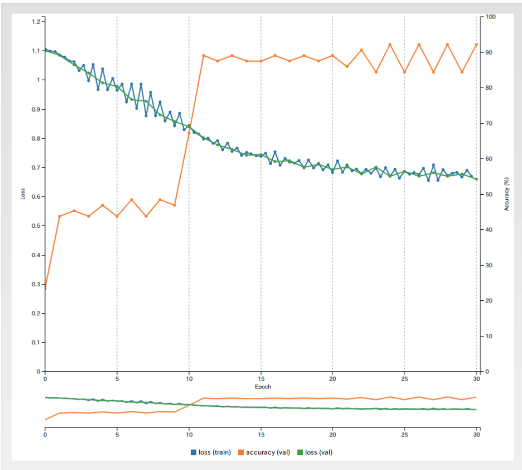

Fig. 10. (Color online) Identification rate.

Table 1
Prediction results.

Type of movement	Prediction					
	No. 1		No. 2		No. 3	
Fell over	Fell over	59.35%	Almost fell over but...	20.75%	Did not fell over	19.90%
Almost fell over but did not	Almost fell over but...	41.92%	Fell over	40.03%	Did not fell over	18.05%
Did not fell over	Did not fell over	48.14%	Fell over	32.63%	Almost fell over but...	19.23%

7. Conclusion

In this study, we have conducted fall estimation and analysis using an infrared depth sensor with the goal of fall prevention for people in need of nursing care.

In the experiments of this study, Kinect, which is an inexpensive infrared depth sensor that is capable of nonconstrained 3D measurement, was used for implementation, and as a preliminary step in the demonstration experiment targeting people in need of nursing care, data from young people getting out of beds were obtained.

In fact, many falls of people in need of nursing care are due not only to the way of falling considered in this study, but also internal factors such as sensory impairment and muscle weakness in many cases. We would like to measure in the demonstration experiment what type of fall estimation is possible after taking these factors into account.

Acknowledgments

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About the Authors

Fumiya Ishizu received his B.S. degree in management systems engineering from Fukuoka Institute of Technology, Faculty of Information Engineering, Department of Systems Management, in 2021. He is currently a member of the Graduate School of Engineering, Fukuoka Institute of Technology. He is engaged in research on optimizing management and production control. (mjm22101@bene.fit.ac.jp)

Takuya Tajima received his master's degree from the Graduate School of Managerial Engineering, Kanazawa Institute of Technology, in 2003. In 2008, he received his Ph.D. degree in engineering from the Graduate School of Natural Science and Technology, Kanazawa University, Japan. He is currently a professor at Fukuoka Institute of Technology, Japan. He is a member of the Japanese Society for Artificial Intelligence (JSAI), Japan Industrial Management Association (JIMA), and so forth.

Takehiko Abe received his B.A. and Ph.D. degrees from Kanazawa University, Japan, in 1988 and 1997, respectively. He joined Daiwa Institute of Research Ltd. in 1988. He is currently a professor at Aichi University, Japan. His research interests include data mining and management information. He is a member of the Institute of Electronics, Information and Communication Engineers (IEICE), JSAI, JSPM and the Japan Society for Management Information (JASMIN).