Materials Research Proceedings 27 (2023) 127-134 https://doi.org/10.21741/9781644902455-16

Effects of architectural space design on predicting turning in daily life

Yurie Matsunami[1, a *], Ryosuke Motoyama[1, b], Mikita Miyaguchi[2, c], Masayoshi Kondou[2, d] and Ami Ogawa [3, e]

[1]School of Science for Open and Environmental Systems, Keio University, 3-14-1 Hiyoshi, Kohoku, Yokohama 223-8522, Japan

[2]Research and Development Institute, Takenaka Corporation, 1-5-1 Otsuka, Inzai, Chiba 270-1395, Japan

[3]Department of System Design Engineering, Keio University, 3-14-1 Hiyoshi, Kohoku, Yokohama 223-8522, Japan

[a]yurie.john825@keio.jp, [b]r.motoyama@keio.jp, [c]miyaguchi.mikita@takenaka.co.jp, [d]kondou.masayoshi@takenaka.co.jp, [e]ogawa@sd.keio.ac.jp

Keywords: Motion Prediction, Turning, Architectural Space Design, Motion Capture System, Azure Kinect DK

Abstract. In recent years, the diversification of lifestyles and the increase in the number of elderly single-person households have increased the need to introduce robots and sensors into living spaces to control living spaces appropriately for individuals. To realize these goals, it is necessary to predict people's non-steady motions which is one of the challenges in introducing robots into living spaces. In response, we have conducted research on motion prediction systems using robots and sensors. These studies will contribute to the realization of safe and comfortable architectural spaces by introducing robots into living spaces and collaborating with various space controls such as automatic doors and lighting. In this study, we focused on turning related to walking, which is the most basic motion in activities of daily living. As turning is a non-steady motion greatly affected by aging and disease, it is difficult to predict while is highly useful as a health indicator. Previous studies have suggested that architectural space design can influence the prediction of turning, but the actual effects are not clear because these studies were conducted only under highly constrained conditions in a laboratory environment. Thus, existing systems for predicting turning have not been validated in daily living environments due to issues such as instructions of motions to participants, limitations of natural motions because of contact sensors, and validation in experimental environments that are specially prepared to ensure reproducibility. Therefore, the purpose of this study was to introduce our sensing systems into actual living spaces and to validate our turning prediction system using acquired data on participants' natural motion. In addition, the influence of architectural space design on predicting turning was clarified by conducting an experiment at a T-junction with an open space and a crossroad with poor visibility. In this study, an office space was selected as the experimental field as a living space to verify the feasibility of our turning prediction system.

Introduction

In recent years, the increase in the number of single elderly people and the diversification of lifestyles due to the super-aging society have increased the need to control living spaces appropriately for individuals by introducing robots and sensors into living spaces. In order to realize spatial control based on human positions and motions in real-time, it is necessary to predict people's non-steady motions which is one of the challenges in introducing robots into living spaces. In response, we have conducted research on motion prediction systems using robots and

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 license. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI. Published under license by Materials Research Forum LLC.

Materials Research Proceedings **27** (2023) 127-134 https://doi.org/10.21741/9781644902455-16

sensors. Among the prediction of the motion in activities of daily living, this study focused on the prediction of the turning motions during walking.

The turning motions are frequently occurring movements during walking in daily life [1]. On the other hand, the turning motions are movements to slow down the speed of motions in the direction of travel when walking straight ahead and to shift the center of gravity in the new direction of travel [2], and they are known as challenging movements that modify the periodic motion of the lower limbs by asymmetrically adjusting the stride length and ground reaction force of both feet [3]. It is said to increase the risk of falls, especially for the elderly with reduced mobility and cognitive function [4]. In addition, the risk of falling due to turning is known to be influenced by dual tasks [5] and the architectural factors [6], such as increased turning angles, inadequate lighting [7], and opening and closing doors during turning. Therefore, by predicting the turning motions in advance, appropriate real-time space control such as automatic door opening/closing and lighting control can be realized, aiming to improve safety and comfort during motions.

Recently, methods combining pattern recognition and machine learning, or Deep Learning have been used for motion prediction. Recurrent Neural Networks, which are Deep Learning using time series elements, are widely used for motion prediction [8][9]. However, while Deep Learning can derive highly accurate solutions from huge amounts of data, several issues have been pointed such as the obscuring of detailed algorithms, enormous computational costs, and the physical constraints of the human body are unconsidered. On the other hand, the method that combines pattern recognition and machine learning allows the selection of input features, which makes it possible to consider the physical constraints of the human body and create a simpler motion prediction system. In this study, we used only head rotation, shoulder rotation, and hip rotation as useful parameters for predicting turning which we extracted in the previous research [10],and applied machine learning.

The problem with existing systems for predicting turning is that the participants' motions are limited by the experimental conditions. Specifically, the systems have been verified in an experimental environment [11] specially prepared to ensure reproducibility [12],and have not been verified in daily living environments [13]. Moreover, few studies have focused on architectural space design and the prediction of turning motions. Takeda [12] compared the predictability of turning motions in a space with poor visibility and a large pillarless space, and they concluded that the prediction time was longer in a space with poor visibility and that head rotation was a parameter that depended on environmental factors. However, they used wearable sensors and did not measure natural motion.

Therefore, the purpose of this study was to validate the applicability of our turning prediction system by measuring participants' natural motions in actual living spaces, and to clarify the influence of architectural space design on the prediction of turning motion. In this study, only Azure Kinect DK (Microsoft, Redmond, WA, USA), a non-contact and marker-less RGB-D sensor, was used for data acquisition and only 3D depth data was analyzed for the applicability to daily living space. The position and timing of turning were not specified, and the participants' usual walking motions were measured.

Materials & Methods

・Experimental Setup & Subjects

The experiment was conducted in a corridor space at Takenaka Corporation's Technical Research Institute shown in Figure 1 on 12th July 2022. The plan of the experimental setup is shown in Figure 2. Two Azure Kinect DK (Kinect) units were positioned to measure a corridor between two intersections named "Crossroad" and "T-junction". The Kinect Body Tracking SDK was used to measure 32 points on the entire body at a frame rate of 30 fps. The height of both

Materials Research Proceedings **27** (2023) 127-134 https://doi.org/10.21741/9781644902455-16

Kinects was set at 1.1 m to enable data acquisition of the joint positions of only the upper body within 0.5m-1.0 m and the whole body at 2.0 m or more.

We measured unspecified numbers of employees passing through the corridor from 10:00 a.m. to 4:30 p.m. They were walking as usual, not in a specially prepared experimental environment. For the analysis, we selected 12 walking data of different employees who were able to walk independently (M:11, F:1), including six straight walking and six turning to left motions for which skeletal information within the predicted location could be obtained. People who walked from point 1 performed straight walking or turning motions at the "T-junction" with good visibility where there is an open space on the right side and captured by the Kinect at point 1, while people who walked from point 2 performed straight walking and turning motions at the "Crossroad" with poor visibility captured by the Kinect at point 2.

This experiment was approved by the ethical committee of Keio University (approval number: 2022-081). Due to the nature of the experiment, we obtained informed consent for participation in the experiment from all employees at once, and an announcement of the experiment was given by flyers at the site one week in advance. On the day of the experiment, flyers were posted in the vicinity of the measurement area stating that measurements were being taken. Whenever consent for the experiment was not obtained, or when a subject to exclusion was passing by, the measurement was temporarily stopped.

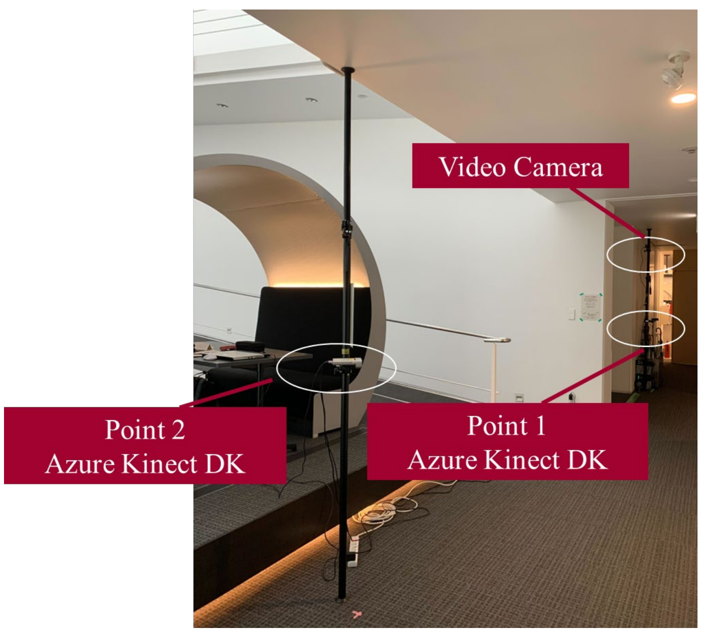


Fig. 1 experimental environment

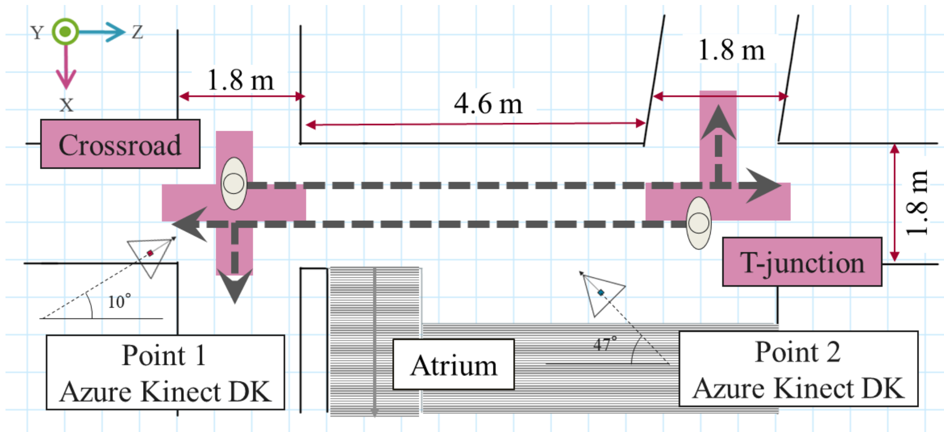


Fig. 2 the experimental plan and sensor placement

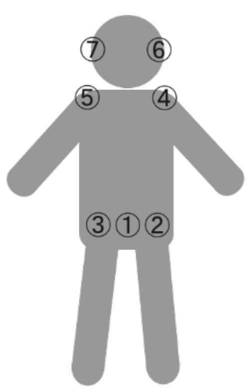
・**Caluculation of Prediction Parameters**

Experiments comparing straight walking and turning motions with specified start and end positions of walking suggest that the angles in the XZ plane of head rotation, shoulder rotation, and hip rotation are useful parameters for predicting turning motions [10]. Based on this, we used these three parameters for the same calculation method. Table 1 lists the predictive parameters. Figure 4 shows the 7 skeletal positions used to calculate these parameters. Figure 5 shows how the predictive parameters for head rotation were calculated. It was calculated using the following equation (1).

$$\theta = \tan^{-1}\frac{b}{a} \tag{1}$$

Table. 1 List of Prediction Parameters

Parameter θ (°)		**Positions of sensors**
Head rotation	θ (XZ plane)	Ear_Right — Ear_Left
Shoulder rotation	θ (XZ plane)	Shoulder_Right — Shoulder_Left
Hip rotation	θ (XZ plane)	Hip_Right — Hip_Left



1	Pelvis
2	Hip_Left
3	Hip_Right
4	Shoulder_Left
5	Shoulder_Right
6	Ear_Left
7	Ear_Right

Fig. 3 Skeletal data used for analysis

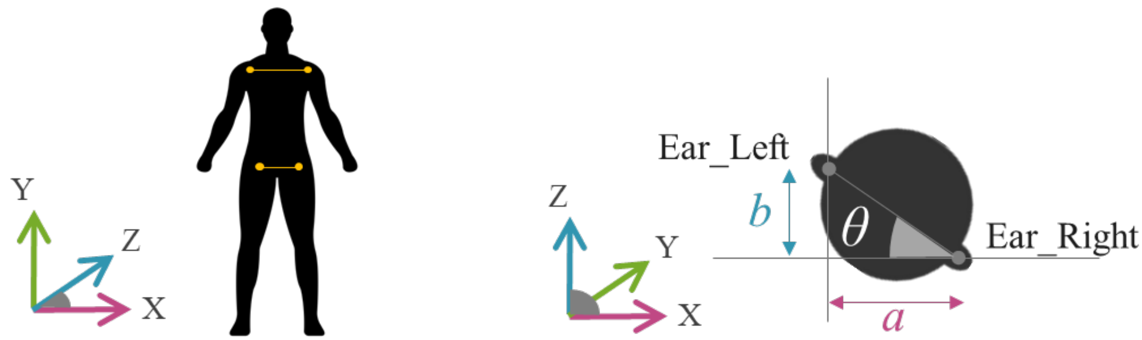


Fig. 4 Calculation of Predicted Parameters (Ex1: head rotation)

・**Data Analysis**

Based on the previous studies' judgment criterion, we predicted targets' turning motions if the predictive parameters exceeded the thresholds pre-calculated. Previous studies adopted the predicted time to evaluate their prediction system of turning motion [11][12]. The predicted time is defined as the time from when the predictive parameters exceeded the threshold value to the start time of the turning motion. However, the predicted time is likely not to work for actual use as it depends on the targets' walking speed. Also, the predicted positions to the intersection are not considered which should be evaluated to clarify the effect of the spatial characteristics. Therefore, we adopted the predicted positions which were calculated as the distance from the intersection to the targets' positions when the turning motions were predicted. The positions of the intersections were defined as the midpoints of diagonal lines connecting corners of the intersecting roads shown as blue and red rectangles in Figure 5. The predicted positions of turning were determined by comparing the three straight and the respective turning motion . 4 walking data were compared, and the threshold was set as the position where three straight and turning motion could be distinguished. Furthermore, the average of the calculated predicted positions of turning motions was calculated.

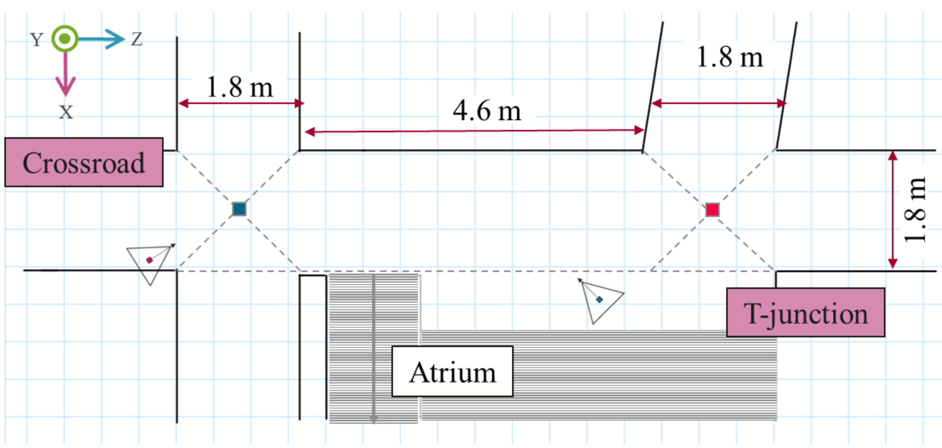


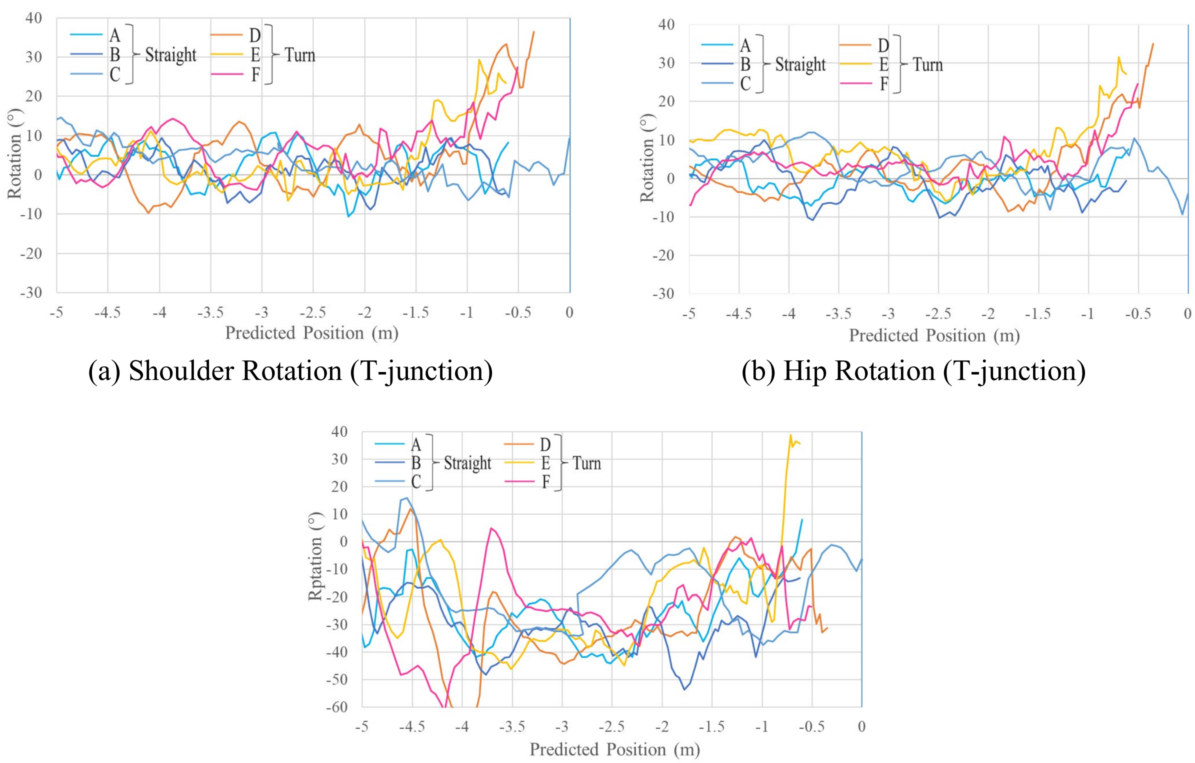
Fig. 5 Predicted position 0m at each location

Results & Discussions

Figure 6 shows the results of three subjects (A~C) walking straight and three subjects (D~F) with turning motions ahead with shoulder rotation, hip rotation, and head rotation at the "T-junction". Figure 7 shows the results of 3 subjects (A~C) walking straight and 3 subjects (D~F) with turning motions ahead with shoulder rotation, hip rotation, and head rotation at the "Crossroad". A comparison of the three predictive parameters for straight walking and left turning motions revealed that shoulder rotation and hip rotation were highly useful. Head rotation, which was considered to be a useful parameter for predicting turning, was found to be significantly affected by the surrounding environment in the natural walking condition. At the “Crossroad”, the head rotation angle was found to be very unstable and inaccurate, since most of the subjects were seen to move to check their surroundings due to poor visibility of where they were going. The “T-junction” had many subjects walking while checking the right side of the road because there were experimenters on the right side during the experiment.

Table 2 shows the predicted distances for the three predictive parameters. Regarding the shoulder rotation, at the “T-junction” the straight walking and turning motions were discriminated at an average of 1.41m before the intersection while the predictable distance was an average of 1.31m at the “Crossroad”. About hip rotation, at the “T-junction” straight walking and turning motions were discriminated at an average of 1.23m before while the predictive accuracy was an average of 1.28m at the “Crossroad”.

Regarding the placement of the Kinect, further study is needed. According to the acquired data, the average distance which Kinect at point 1 recognized subjects and detected joint positions was 6.1 m before the intersection position of the “T-junction” On the other hand, for the Kinect at point 2, the average distance was 2.8 m before the intersection position of the “Crossroad”. That is the average distance of the Kinect at point 2 for the acquisition of joint positions was the average 3.3 m shorter than the Kinect at point 1. This suggests that Kinect at point 2 would be able to recognize the subjects and detect the joint positions from 6.0 m before by moving 3.0 m in the positive direction of the *Z*-axis, then a more accurate prediction of turning movements would be possible.



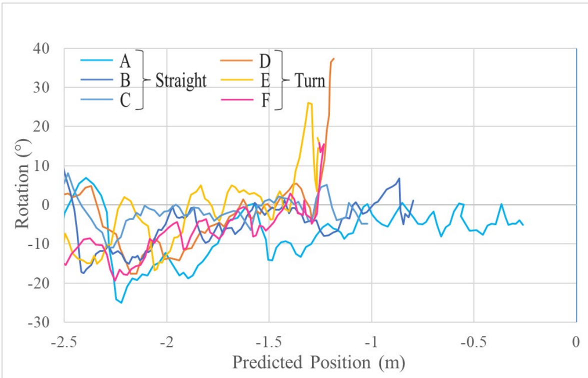
(a) Shoulder Rotation (T-junction)

(b) Hip Rotation (T-junction)

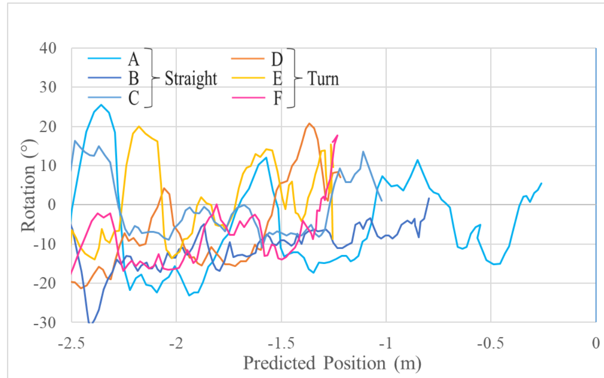
(c) Head Rotation (T-junction)

Fig. 6 Six subjects’(A to F) shoulder rotation,hip rotation, and head rotation at the “T-junction”

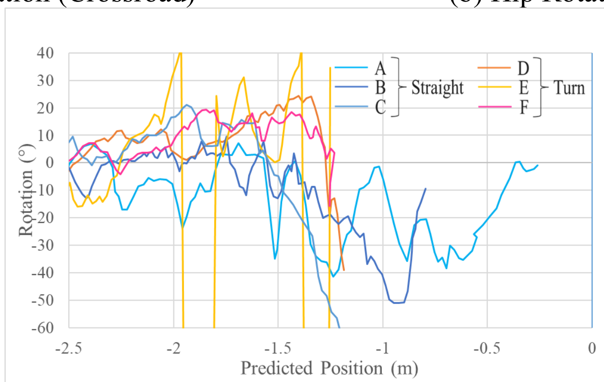
Materials Research Proceedings **27** (2023) 127-134
https://doi.org/10.21741/9781644902455-16



(a) Shoulder Rotation (Crossroad)



(b) Hip Rotation (Crossroad)



(c) Head Rotation (Crossraod)

Fig. 7 Six subjects'(A to F) shoulder rotation,hip rotation, and head rotation at the "Crossroad"

Table. 2 Validation of usefulness of forecasting parameters

Location	Predictive parameter	D	E	F	Mean predicted position (m)
T-junction Data acquired from point 1	Head rotation				
	Shoulder rotation	-1.38	-1.62	-1.23	-1.41
	Hip rotation	-0.99	-1.57	-1.13	-1.23
Crossroad Data acquired from point 2	Head rotation				
	Shoulder rotation	-1.26	-1.40	-1.26	-1.31
	Hip rotation	-1.23	-1.26	-1.34	-1.28

Conclusions

In this study, we quantitatively evaluated the applicability of the turning prediction system in actual living spaces and compared prediction accuracy between two different intersections aiming to create a motion prediction system using robots and sensors. Azure Kinect DK was used as a non-contact sensor to measure natural motions, and three prediction parameters such as head rotation, shoulder rotation, and hip rotation were calculated. The results suggest that hip rotation and shoulder rotation are highly useful as predictive parameters. The turning motions with good visibility in open space were predicted at the point of average of 1.41 m before the intersection, while turning motions at the "Crossroad" with poor visibility were predicted at the point of average of 1.31 m before. Head rotation, which has been considered useful in previous studies, was found to be inaccurate as a prediction parameter in natural walking conditions.

Our future works are to reexamine the placement of sensors to predict turning motions, to consider new prediction parameters, and to build a real-time prediction system that takes environmental factors into account.

References

[1] Glaister, B.C., Bernatz, G.C., Klute, G.K., Orendurff, M.S.: Video task analysis of turning during activities of daily living, Gait & posture, 2007, 25.2: 289-294. https://doi.org/10.1016/j.gaitpost.2006.04.003

[2] AKRAM, Sakineh B.; FRANK, James S.; CHENOURI, Shojaeddin. Turning behavior in healthy older adults: is there a preference for step versus spin turns?. Gait & posture, 2010, 31.1: 23-26. https://doi.org/10.1016/j.gaitpost.2009.08.238

[3] Hase K, Stein RB.: Turning strategies during human walking, Journal of neurophysiology, 1999, 81.6: 2914-2922. https://doi.org/10.1152/jn.1999.81.6.2914

[4] Lamontagne, Anouk, Caroline Paquette, and Joyce Fung.: Stroke Affects the Coordination of Gaze and Posture During Preplanned Turns While Walking. Neurorehabil Neural Repair 2007; 21: 62-67. https://doi.org/10.1177/1545968306290822

[5] Silsupadol, P., Siu, K. C., Shumway-Cook, A., & Woollacott, M. H.: Training of balance under single-and dual-task conditions in older adults with balance impairment. Physical therapy, 2006, 86.2: 269-281. https://doi.org/10.1093/ptj/86.2.269

[6] IMAEDA, S., SON, B., UCHIYAMA, E., TANAKA, T., SUTHUTVORAVUT, U., SUMIKAWA, U., BABA, A., IIJIMA, K., and OTSUKI, T.: The Measures Against Fall Prevention at Home By Multidisciplinary Specialists For Elderly People Who experienced Fall And Femoral Fractures Based On Their Environmental Changes ＜Part 1＞： To Clarify the Architectural Factors On Reasons Of Falls At Home, Journal of Architecture and Planning (Transactions of AIJ), 2020, 85.773: 1387-1395.(in Japanese). https://doi.org/10.3130/aija.85.1387

[7] CLARK, David J., Rose, D. K., Ring, S. A., & Porges, E. C.: Utilization of central nervous system resources for preparation and performance of complex walking tasks in older adults. Frontiers in aging neuroscience, 2014, 6: 217. https://doi.org/10.3389/fnagi.2014.00217

[8] J. Martinez, M.J. Black, J. Romero, On human motion prediction using recurrent neural networks, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 2891-2900. https://doi.org/10.1109/CVPR.2017.497

[9] Fragkiadaki, K., Levine, S., Felsen, P., Malik, J.: Recurrent network models for human dynamics, In: Proceedings of the IEEE international conference on computer vision, 2015. P. 4346-4354. https://doi.org/10.1109/ICCV.2015.494

[10] Motoyama, R., Matsunami, Y., Miyaguchi, M., Kondo, M., Ogawa, A., Mita, A.: Analysis and real-time prediction of turning movements during walking assuming activities of daily living, Summaries of Technical Papers of Annual Meeting, Architectural Institute of Japan, Information Systems Technology, 2022, 11111 (in Japanese)

[11] Sugimoto, N., Ogawa, A., Mita, A.: Prediction of walking turns focusing on the center of gravity, AIJ Journal of Technology and Design, 2022, 28.68: 510-514. (in Japanese). https://doi.org/10.3130/aijt.28.510

[12] Takeda, K., Ogawa, A., Mita, A.: Prediction of 90-degree turn using kinematic parameters for implementation of home robot, Journal of Environmental Engineering (Transactions of AIJ) , 2020, 85.778: 1027-1036. (in Japanese). https://doi.org/10.3130/aije.85.1027

[13] Ulrich, B., Santos, A. N., Jolles, B. M., Benninger, D. H., & Favre, J.: Gait events during turning can be detected using kinematic features originally proposed for the analysis of straight-line walking, Journal of biomechanics, 2019, 91: 69-78. https://doi.org/10.1016/j.jbiomech.2019.05.006