

A Study on Gathering Staircase Information for Active Staircase Entry of Wheelchair Stair Climbing Assistive Devices

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Abstract: Wheelchairs are the most commonly used auxiliary devices by people with mobility impairments, and autonomous driving technology has recently been applied to these wheelchairs using robot technology. However, in an autonomous driving environment, most stairs are recognized as obstacles. For autonomous driving on stairs, recognition of stairs information must be preceded. Currently, the classification of stairs into stairs and non-stairs is performed based on vision sensors and can be determined by a high recognition rate. However, the measurement and estimation of the riser height value, tread depth value, and angle of pitch value of stairs are not. Therefore, this study proposes a method of obtaining the shape information of stairs using 2D LiDAR. The proposed method measured the riser height and tread depth of stairs using the K-Means and RANSAC algorithm after obtaining the raw data by rotating the 2D LiDAR by 90 degrees, and based on this, the angle of pitch value was calculated. The riser height and tread depth values were determined by about $\pm 13\text{mm}$ on average, and the angle of pitch value showed the accuracy of $\pm 1^\circ$ accuracy through applying a quantitative verification method for the proposed method.

1 INTRODUCTION

It is paying attention to the rapid increase in the elderly group (aged people) since COVID-19 throughout the world. According to the "World Social Report 2023" published by the UN, the number of elderly people aged 65 or older is expected to reach 1.6 billion by 2050 (United Nations, 2023). It is analyzed that this increase trend is progressing faster in developing countries than in developed countries.

Such elderly people have difficulty walking due to physical aging, and the frequency of outdoor activities decreases compared to the younger age, making it worse as they have disabilities (Miodrag Počuč et al., 2021). These activity constraints become passive in voluntary social participation and can lead to psychological depression or lack of self-esteem (AH Taylor et al., 2004).


People who have difficulty walking due to physical ageing and disability are referred to as mobility impairments, and most of them use cars with


guardians for convenience of their movement (Miodrag Počuč et al., 2021; United Nations, 2022). However, this situation suggests that more caregivers are needed in the future society, but it is currently expected that supply versus demand will not be kept up due to a severe drop in fertility rates (United Nations, 2023).


Currently, the elderly and the disabled people, who are facing mobility impairments, use wheelchairs as a means of mobility assistance after cars, but they do not meet their mobility independence. Therefore, the intelligence of wheelchairs using robot technology is being actively studied.


In the past, the study of intelligent wheelchairs was mainly aimed at manipulating interfaces, posture change, and obstacle recognition and avoidance for the purpose of use by various disabled groups (Jesse Leaman et al., 2017; Amiel Hartman et al., 2019).

In recent research on intelligent wheelchairs, autonomous driving technology using robot

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technology has become a hot topic to solve the social problems raised above. Since wheelchairs are not much different from mobile robots due to their mechanical characteristics, studies based on the AMR (Autonomous Mobile Robot) technology are being attempted (André R. Baltazar et al., 2019). However, since the use environment of wheelchairs is used in daily life, unlike AMR, further studies on the detection and avoidance of various obstacles are needed. Among them, countermeasures against stairs are a must-resolve challenge. The reason for this is that wheelchair users refer the environment as the biggest travel restriction in their daily lives as mound and stairs driving (Korean Consumer Agency, 2011).

Currently, the platform for wheelchairs to move on stairs adopts an orbital wheel structure, but the technology to automatically recognize and move on stairs is insignificant (Weijun Tao et al., 2017; Bibhu Sharma et al., 2022). A vision-based study is a representative technology for recognizing stairs. However, these technologies were developed for the purpose of AMR or mobile robots to recognize stairs as obstacles rather than driving environments, and the problems and approaches raised in this study are different (M Basavanna et al., 2021).

With the development of vision-based AI technology after the 4th industry, the recognition rate of stairs environments is more than 90% based on the technology of image matching and pattern comparison, but the rate in this technology for estimating the stairs shape information, riser height and tread depth, which are necessary for moving on stairs, is not high (Chen Wang et al., 2023).

The reason why such information is needed is that the angle of pitch value of the pitch line derived from the shape of stairs is required for the orbital wheel platform to ensure safe driving on stairs. If this information is not recognized, a large impact occurs due to the change in the center of gravity of the platform in the landing section at the beginning and end of stairs (Daisuke Endo et al., 2017).

The following two types of research on the stairs information estimation are representative. The first is a method of estimating stairs based on a number of single distance detection sensors, and the recognition rate is not high in the form of estimating the approximate height of stairs and inferring the pitch line, and it may not be applicable depending on the stairs driving platform (Su-Hong Eom et al., 2020; Hyun-Chang Hwang et al., 2021).

The second method uses a depth camera, which has an excellent effect on straight line detection of stairs through an algorithm such as the Hough transform method for edge detection after

preprocessing image information, but has a problem of varying accuracy due to a relatively low recognition rate and some external environmental factors such as light exposure (Jia sheng Liu et al., 2020; Haruka Matsumura et al., 2022).

Therefore, this study proposes a method of estimating the riser height and tread depth of stairs, and the angle of pitch value of the pitch line using 2D LiDAR in order to solve the problems of the existing method.

Inferring the information of stairs based on the information from LiDAR causes an increase in the cost of the system compared to the method mentioned above. However, the purpose of this study is that wheelchair users autonomously drive on stairs using an infinite orbit platform, and it is assume that the platform is already equipped with a LiDAR sensor system.

The proposed method is a little more intuitive when using 3D LiDAR, but in an autonomous driving system in mobile robots, 2D LiDAR is generally used to solve the increase in the cost of operating its system. For this reason, the stairs were vertically scanned by rotating the LiDAR by 90° to estimate the stairs information.

2 METHOD

The riser height and tread depth of stairs vary depending on the manufacturing and installation environment, and the angle of pitch value of the general walkable stairs is about 45° (HM Government, 2013). as shown in Figure 1. However, the mechanical characteristics of stairs are the same. In addition, the shape measured may differ depending on the operating principle or operation method of the applied sensor. In this study, since 2D LiDAR is applied to vertical plane measurement rather than horizontal plane measurement, it is necessary to convert the measurement data into the same form as seen with the human eye through a coordinate transformation process, and to adjust the sensing range to be measured.

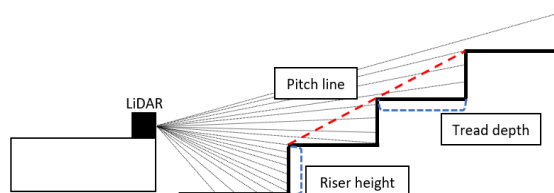


Figure 1: Schematic of stairs measurement limitations using LiDAR.

The riser height and tread depth measurements of stairs require the separation of data for measuring stairs information from the LiDAR raw data and the data unnecessary for measurement. This is because the tread depth cannot be measured depending on the location of stairs viewed from LiDAR. Therefore, this section describes the method of calculating the angle of pitch value based on the riser height and tread depth of stairs together with the above-mentioned parts.

In this paper, the wheelchair direction is straightforward to the staircase to scan the stairs vertically with 2D LiDAR, and only the ascending staircase is considered.

2.1 Limiting the Scan Area of the LiDAR Sensor and Transforming the Plane Coordinate System

2.1.1 Limiting the Scan Area of the Lidar Sensor

LiDAR has a different scan range depending on the product specifications. Therefore, it is necessary to limit the scope to measure stairs at an installation location, otherwise more information is measured together, which acts as a noise component. For example, in the case of the measurement situation as shown in Figure 1, the environmental information with the stairs is measured together, and there is a trouble of performing an additional preprocessing process to estimate the stairs information. Therefore, this study attempts to limit the scan area when measuring by LiDAR to prevent such problems from occurring.

In this paper, the LiDAR scan area aims to set a scan range of 15° upward (left) and 40° downward (right) from the center of the scan range. This may vary depending on the location of the LiDAR installation. The effect of this setting is shown in Figure 2.

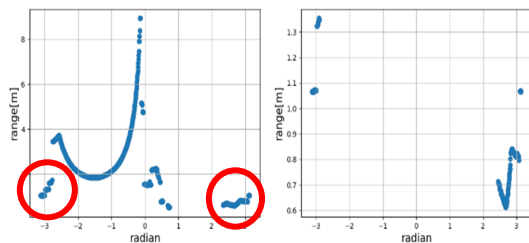


Figure 2: LiDAR raw data before and after the scan range limit.

2.1.2 Coordinate Transformation of the LiDAR Sensor

LiDAR raw data is generally output as an angle value and a distance value located on the target object around the LiDAR. As these data are polar coordinate, it is necessary to transform it into a two-dimensional planar coordinate system in order to estimate information on stairs. This coordinate system transformation is performed by Equation (1) and (2). In Equation (1) and (2), the negative multiplication is based on the direction of the LiDAR installation and may be omitted depending on the situation.

$$x = (-1) \times \gamma \times \cos(\theta) \quad (1)$$

$$y = (-1) \times \gamma \times \sin(\theta) \quad (2)$$

2.2 Preprocessing Methods for Measuring Stairs Information from LiDAR Data

2.2.1 Data Clustering

Since the object information data of LiDAR consists of distance information and angle information by irradiating a laser in a fan shape at the center of LiDAR, there are measurable and unmeasurable parts depending on the location of the object and LiDAR. In a data collection environment as shown in Figure 1, the first tread depth of the stairs may be measurable, but depending on the height of the LiDAR position, the tread depth of the second step may not be measured. Therefore, it is necessary to separate segments for measuring stairs information from the LiDAR raw data.

The segment separation means the separation of valid data and ineffective data. This process is possible using a machine learning method. In the machine learning method, the data separation is performed as a way of classification or clustering, and SVM (Support Vector Machine), KNN (K-Nearest Neighbors), K-Means, and Hierarchical Clustering are representative (Shweta Mittal et al., 2019; Abiodun M. Ikotun et al., 2022). Among them, this study aims to perform clustering through the K-Means algorithm because the purpose is to implement clustering based on the location similarity of data.

The reason for choosing clustering by the K-Means algorithm is that the hierarchical clustering algorithm goes through a hierarchical clustering process and has the disadvantage of considering the distance and similarity of cluster data in advance. In addition, this is because the computational

complexity is higher than that of the K-Means algorithm in real-time reflection of this system. Although it cannot be concluded that the K-Means algorithm has a shorter calculation time than the Hierarchical Clustering algorithm, the method proposed in this study is possible because the area was limited when collecting the LiDAR raw data.

2.2.2 Data Linearization

In calculating the riser height and tread depth length of the stairs from the clustered data, it is necessary to linearize the data in order to calculate the angle of pitch of the stairs from the clustered data showed in 2.2.1. This is because the LiDAR raw data results in shape errors caused by foreign substances present in the stairs and errors due to damages of the edge of the stairs. the data linearization can be performed by simply using a moving average filter, but it causes data errors when unexpected noise components are introduced. Therefore, in this study, the RANSAC (Random Sample Consensus) algorithm is used. The LSM (Least Square Method) algorithm is also applicable, but the RANSAC algorithm is effective in this case because it needs to be linearized into a straight component of non-damaged stairs from the previously mentioned data such as edge breakage (Sunglok Choi et al., 2009).

**2.2.3 Stairs Entry Angle Calculation
Algorithm for Stable Stairs Driving of
Orbital Wheels**

As shown in Figure 1, the pitch line of the stairs connects the end points of the stairs tread and becomes a driving path when the track-type wheel drives on the stairs. Here, the angle of the driving path can be calculated as a trigonometric function with the riser height value and the tread depth value as shown in Equation (3), (4), and (5). The riser height value selects a cluster with a large area value among clusters derived through the K-Means algorithm, linearizes the selected cluster through the RANSAC algorithm, and segments continuous Y-axis data. Based on the segmented data, the coordinates of both end points of riser-1 and riser-2 are obtained as shown in Figure 3, and the tread depth is calculated based on this. Figure 4 shows its schematic diagram.

$$\text{stair depth} = |P_0x - P_1x| \tag{3}$$

$$\text{stair height} = |P_1y - P_2y| \tag{4}$$

$$\text{stair angle} = \tan^{-1}\left(\frac{\text{stair height}}{\text{stair width}}\right) \tag{5}$$

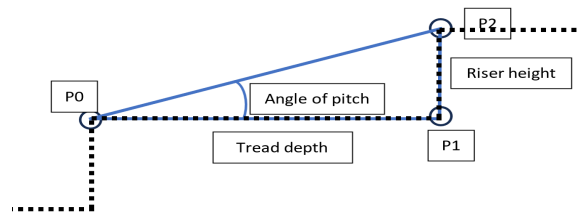


Figure 3: Schematic diagram for calculating the entrance angle of stairs.

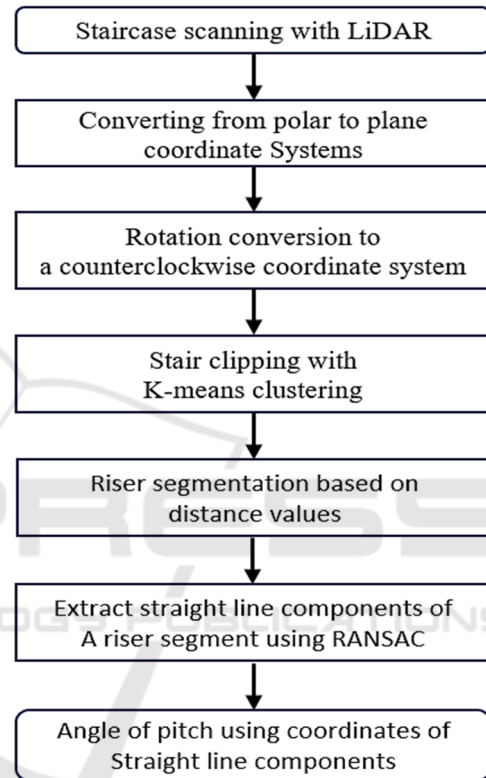


Figure 4: Block diagram for calculating the entrance angle of stairs.

3 EXPERIMENT AND RESULTS

3.1 Experimental Environment

For the theoretical verification of the method presented in this study, an experiment was conducted in a stairs environment as shown in Figure 5. The experiment was conducted by rotating the 2D LiDAR, which can measure the X-axis in a two-dimensional plane at a height of 55cm from the bottom of the stairs and 45cm from the front, by limiting the angle of the Y-axis to a scan angle of +15° to -40° based on 0°.

Table 1: Stairs specification.

Stair riser height	180mm
Stair tread depth	260mm
Stair angle of pitch	35°

Table 2: LiDAR sensor specification.

Manufacturer / Product Name	SLAMTEC / RPLiDAR S1
Scan rate	10Hz
Scan angle	180°
Angular Resolution	0.35°
Max Distance range	white object 40m, black object 10m



Figure 5: Experimental environment.

3.2 Experimental Results

3.2.1 Stairs Raw Data

For the theoretical verification of the method presented in this study, the stairs were measured as shown in Figure 1 in the experimental environment as presented in Figure 5. As a result, it was detected in three areas in the LiDAR scan area as shown in Figure 6.

Shape-1 means the shape of the first step, and Shape-2 and Shape-3 mean the riser of the second and third steps respectively. The reason why the tread was not measured from the second step is because of the LiDAR measurement height, as described in 2.1.

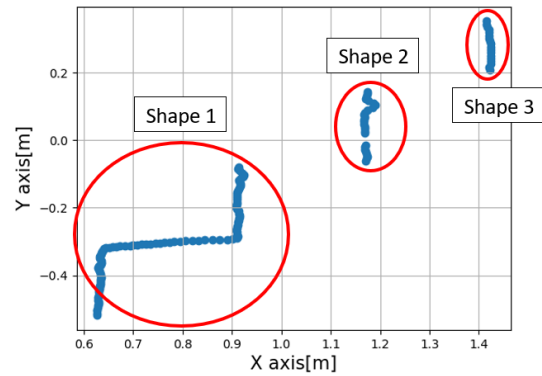


Figure 6: Scan results of the stairs using 2D LiDAR.

3.2.2 Stairs Raw Data

For clipping Shape-1 only from the measured raw data of the stairs (Figure 6), the clustering was performed using the K-Means algorithm, and the number of clustering for the cluster was determined by two. The initial value of the centroid was set to a random value and the K-Means++ method was applied. The result is shown in Figure 7, and the

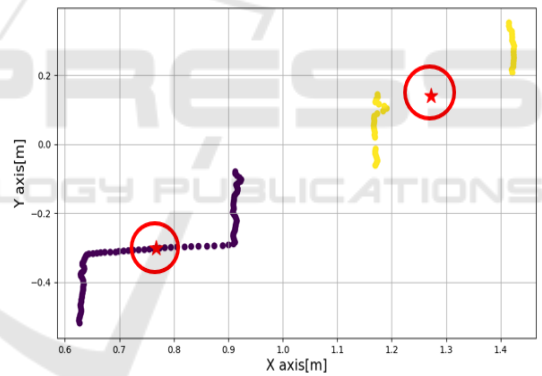


Figure 7: Results of the stairs data clustering using the K-means and its centroid.

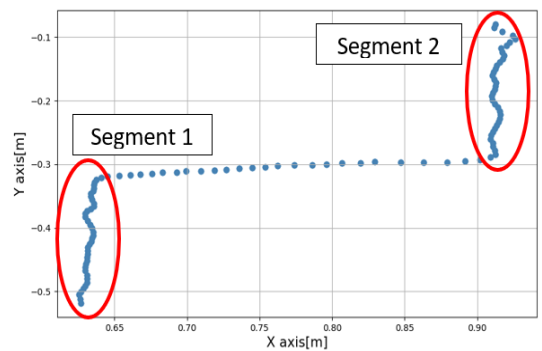


Figure 8: Measurement target stairs selected as a result of comparison between each cluster.

centroid is a star shape in the graph. For the cluster clipping for an actual stair information measurement in two clusters, the clipping was performed through comparing the area size of the cluster, and the results are shown in Figure 8.

Algorithm 1 shows the pseudo code implemented to segment the continuous Y-axis data for detecting risers in this clipped Shape-1 data, and the set by user value in the case of the set distance during this experiment is 0.007 and the minimum segment length is 10.

```

Input: set distance = set by user, index number = 0, minimum segment length = set by user
Result: segmented lines
for i from start to end of LiDAR data do
    if calculate distance(x[i], y[i], x[i+1], y[i+1]) > set distance then
        index number = i + 1
        if i - index number > minimum segment length
            coordinates of x = from index number to i in LiDAR data of x coordinate
            coordinates of y = from index number to i in LiDAR data of y coordinate
        else
            pass
    else
        pass
    
```

Algorithm 1: Segment separation algorithm for detecting risers.

Figure 9 shows the results of applying the RANSAC algorithm to the detected segments based on the applied algorithm, and based on these two riser coordinate values, the riser height and tread depth were measured using Equation (3), (4) and (5) and the angle of pitch value was calculated.

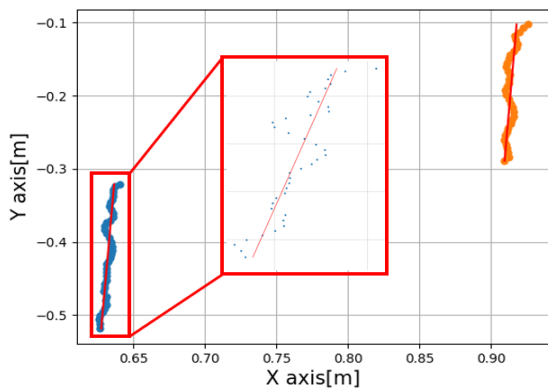


Figure 9: Results of applying RANSAC for the riser height.

The angle of pitch value is shown in Table 3. These values are the results of 10 repeated measurements while maintaining a certain distance in the environment presented in Figure 5. The measurement results showed that the riser height and tread depth values were around $\pm 13\text{mm}$ on average and the angle of pitch value was $\pm 1^\circ$ accuracy compared to the actual stairs information.

Table 3: Segment separation algorithm for detecting risers.

Trials	Riser height[m]	Tread depth[m]	Angle of pitch[°]
1	0.272	0.186	34.3
2	0.269	0.198	36.3
3	0.271	0.186	34.4
4	0.27	0.198	36.2
5	0.268	0.186	34.7
6	0.269	0.199	36.4
7	0.269	0.187	34.8
8	0.271	0.198	36.1
9	0.271	0.198	36.1
10	0.269	0.198	36.3
Avg.	0.269	0.193	35.6

4 CONCLUSIONS

This study presented a method for calculating the angle of pitch value based on shapes of stairs in order to actively drive on stairs when entering or exit the stairs using a wheelchair or wheelchair-combined auxiliary device using an orbital wheel platform. The proposed method used the K-Means and RANSAC algorithms as preprocessing algorithms to vertically scan the stairs using a 2D LiDAR sensor and to measure the riser height and tread depth of the stairs based on the distance and angle values between the sensor and the stairs. The riser height value and tread depth value were measured based on the two riser coordinate values finally derived through the RANSAC algorithm. Finally, the angle of pitch value of the stairs was calculated using a trigonometric function based on the measured riser height value and tread depth value. The calculation results showed an average of 36° in 10 trials, which showed an average error of about 1° compared to the actual step information, verifying the appropriateness of the proposed algorithm.

Based on the algorithm presented in this study, it is expected that it will be more flexible and safe drive on stairs when entering or exit the stairs if applied as a control parameter for autonomous stairs driving of a wheelchair or wheelchair-combined assistive

device using an orbital wheel platform. However, the algorithm presented in this study is a method verified at 45cm from the front of the stairs and 55cm in height, and the sensor attachment location should be selected in consideration of this.

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REFERENCES

- United Nations. (2023). World Social Report 2023: Leaving No One Behind In An Ageing World.
- Miodrag Počuč, Valentina Mirović, Jelena Mitrović Simić, Caglar Karamasa. (2021). Mobility analysis of persons with disabilities. *Discrete Dynamics in Nature and Society*.
- AH Taylor, NT Cable, G Faulkner, M Hillsdon, M Narici, AK Van Der Bij. (2004). Physical activity and older adults: a review of health benefits and the effectiveness of interventions. *Journal of Sports Sciences*. vol. 22, no. 8, pp. 703-725.
- United Nations. (2022). Disability-Inclusive Communications Guidelines.
- Jesse Leaman, Hung Manh La. (2017). A Comprehensive Review of Smart Wheelchairs: Past, Present, and Future. *IEEE Transactions on Human-Machine Systems*, vol. 47, no. 4, pp. 486-499.
- Amiel Hartman, Vidya K. Nandikolla. (2019). Human-Machine Interface for a Smart Wheelchair. *Journal of Robotics*.
- André R. Baltazar, Marcelo R. Petry, Manuel F. Silva, António Paulo Moreira. (2021). Autonomous wheelchair for patient's transportation on healthcare institutions. *SN Applied Sciences*. vol. 3, no. 3.
- Korean Consumer Agency. (2011). A Survey on Safety Accidents in Wheelchairs.
- Weijun Tao, Junyi Xu, Tao Liu. (2017). Electric-powered wheelchair with stair-climbing ability. *International Journal of Advanced Robotic Systems*. vol. 14, no. 4.
- Bibhu Sharma, Branesh M. Pillai, Korn Borvorntanajanya, Jackrit Suthakorn. (2022). Modeling and Design of a Stair Climbing Wheelchair with Pose Estimation and Adjustment. *Journal of Intelligent & Robotic Systems*. vol. 106.
- M Basavanna, M Shivakumar, K.R Prakash, Pratham Bhomkar. (2021). ROS Based 3D Mapping of an Indoor Environment Using Fusion of Orbbec Astra Camera and Lidar on Turtlebot Mobile Robot. *2021 5th International Conference on Electrical, Electronics, Communication, Computer Technologies and Optimization Techniques (ICEECCOT)*. pp. 323-327.
- Chen Wang, Zhongcai Pei, Shuang Qiu, Zhiyong Tang. (2023). RGB-D-Based Stair Detection and Estimation Using Deep Learning. *Sensors*. vol. 23, no. 4.
- Daisuke Endo, Atsushi Watanabe, Keiji Nagatani. (2017). Stair Climbing Control for 4-DOF Tracked Vehicle Based on Internal Sensors. *Journal of Robotics*.
- Su-Hong Eom, Sun-Jong Na, Jung-Hwun You, Hyun-Chang Hwang, Eung-Hyuk Lee. (2020). A Study on Estimation of a Stair Entry Angle and Operation for The Stair Climbing Aid Platform of Wheelchair. *2020 International Conference on Electronics, Information, and Communication (ICEIC)*. pp. 867-869.
- Hyun-Chang Hwang, Won-Young Lee, Jong-Hee Ha, Eung-Hyuck Lee. (2021). A Study on Autonomous Stair-climbing System Using Landing Gear for Stair-climbing Robot. *Journal of IKEEE*. vol. 25, pp. 362-370.
- Jia sheng Liu, Jian po Guo, Zhen kai Xiong, Hua Li. (2020). Design of intelligent recognition and positioning algorithm for stairs based on depth camera. *2020 2nd International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI)*. pp. 339-343.
- Haruka Matsumura, Chinthaka Premachandra. (2022). Deep-Learning-Based Stair Detection Using 3D Point Cloud Data for Preventing Walking Accidents of the Visually Impaired. *IEEE Access*. vol. 10, pp. 56249-56255.
- HM Government. (2013). Protection from falling, collision and impact.
- Shweta Mittal, Om Prakash Sangwan. (2019). Big Data Analytics using Machine Learning Techniques. *2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*. pp. 203-207.
- Abiodun M. Ikotun, Absalom E. Ezugwu, Laith Abualigah, Belal Abuhajja h, Jia Heming. (2022). K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. *Information Sciences*. vol. 622, pp. 178-210.
- Sunglok Choi, Taemin Kim, Wonpil Yu. (2009). Robust Video Stabilization to Outlier Motion using Adaptive RANSAC. *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*. pp. 1897-1902.