# A Study on the Improvement of Navigation Accuracy with ArUco Markers

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Abstract. In this paper, we propose an error decreasing technique using ArUco Marker, in a robot navigation system using SLAM (Simultaneous Localization and Mapping) in which errors occur due to packet loss and time delay. This technique enables more accurate estimation of the position and orientation between the robot and ArUco Marker. Through camera calibration, we convert 3D input values of a real object into undistorted 2D data and establish corresponding relationships between dimensions. Additionally, we use homogeneous transformation matrices to estimate the current direction and degree of rotation of a robot using the marker. Most of robots can reach their destination area through navigation with trial and errors with some time consumption. Therefore, we introduce ArUco Marker to reduce such errors and designed navigation algorithm to enable relatively precise driving with enough fast time. Finally, we compare the navigation accuracy using SLAM of the conventional scheme with the proposed method of twice modifications of the marker information which can reduce the navigation error around actual destination and resulting in accuracy improvement through the position correction process using ArUco Marker recognition.

Keywords: Computer Vision, ArUco Marker, SLAM.

# 1 Introduction

As the increasing interests in the area of artificial intelligence the market with autonomous driving and camera technology in robots has grown in a recent decade. Additionally, robots use SLAM (Simultaneous Localization and Mapping) technology to simultaneously estimate their location and create a map to facilitate navigation. However, errors in location estimation and movement occur due to the robot's operating state, environment, and communication errors. Various attempts have been made to address these issues including GPS technology. However, there are limitations to accurate movement in poor communication environments [1]. Moreover, robots have become commonly used in everyday life, such as robot vacuum cleaners, however, there are some problems of decreased efficiency due to repeated position correction and communication, leading to a significant computational burden in the docking process at charging terminals [2].

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Thus, we propose an algorithm that simplifies the previous complex processes related to robot docking and charging, enabling the robot to move more quickly and accurately to its destination. Before the algorithm is operated, camera calibration is performed in which the internal parameters, external parameters, and distortion coefficients of the camera are estimated, establishing a correspondence relationship between 2D images and 3D dimensions [3].

The experimental results are presented in the last section. When only conventional navigation technology is used, the error distance to the destination is within 50cm~70cm. However, the error was decreased to less than 1cm using the ArUco marker-based navigation error correction technique proposed in this paper, effectively improving the accuracy of robot movement.

# 2 Experimental process

#### 2.1 Movement to destination position using SLAM

To conduct the experiment, the SLAM algorithm was utilized to estimate the current indoor location of the robot and generate a map using data collected from a LIDAR sensor and depth camera [4]. Subsequently, navigation was performed based on the generated map. The configuration of the navigation system is presented in Figure 1.



Fig. 1. Navigation system configuration

In order for a robot to move towards a designated destination, it repeats the process of Fig. 1. to estimate its location and identify obstacles to set an optimal path.

#### 2.2 Camera calibration

To utilize ArUco markers or specific objects for marker recognition, camera calibration is necessary to address measurement errors caused by camera distortion such as position, distance, and direction. In this paper, a camera calibration method is adopted using a 7x10 checkerboard pattern [3]. We capture images of the board at various angles using the camera and detect the corners of the board. The coordinate values of these corners are recorded for subsequent camera calibration procedures. By utilizing the size data of the defined board and the detected coordinate values, distortion coefficients of the camera's intrinsic and extrinsic parameters can be estimated.

#### 2.3 ArUko Marker Tracking and Position calibration

By utilizing camera calibration to estimate the distortion coefficients of external parameters, the real distance between the camera and marker can be more accurately estimated. This process involves converting the captured image into a binary representation and extracting the marker coordinates using a marker dictionary and its corresponding parameters [5]. Once the marker is detected, information such as the boundary region, data inside the dictionary and the position and orientation vectors between the ArUco marker and the camera can be obtained. In this paper, we propose an algorithm for pathfinding by utilizing the position and orientation vectors. Firstly, a homogeneous transformation matrix is constructed to calculate the distance and rotation direction between the marker and the camera to determine the direction and position (distance) of the robot (camera). The obtained position using the homogeneous transformation matrix [6] can be expressed as follows.

$$\begin{bmatrix} X' \\ Y' \\ Z' \\ 1 \end{bmatrix} = \begin{bmatrix} R \mid t \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = \begin{bmatrix} R11 R12 R13 t_x \\ R21 R22 R23 t_y \\ R31 R32 R33 t_z \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$
(1)

Using the obtained position, it is possible to predict the optimal path. The basic process involves recognizing the marker, stopping, fixing the position of camera to the center of the marker, and then calculating the distance and rotation angle. The path can be approached in various ways thereafter. One method involves moving straight to the destination along the shortest path and then adjusting the direction of the robot based on the pre-calculated rotation angle. Another method uses a Manhattan distance-based path. In this process, using trigonometry, the X value (distance moved forward after exploration) and Y value (distance moved backward after 90-degree rotation from X movement) are calculated based on a triangle with the distance between the camera and marker as the hypotenuse. This allows for more accurate movement in the desired direction. Compared to the conventional method of modifying the position after movement, this method of calculating the path and approaching the destination in reverse direction has the effective advantage of less position modification and errors. Another method involves using rotation vectors. The degree of rotation is monitored in real time to determine the direction in which the robot needs to move. Figure 2 illustrates the process of robot movement using the calculated angle and distance based on straight distance, Manhattan distance, and marker tracking algorithms to set the moving path.



Fig. 2. Marker tracking and moving process.

# **3** Results and conclusions

The purpose of this study is to determine the average error distance in destination navigation using only markers and experimentally validate markers with high recognition rates at that distance. Each experiment was performed 10 times, taking into account the environment. Error was measured based on the distance between the center point of the arrival point and the center point of the robot after arrival. Performance evaluation was conducted by comparing with the conventional method using only navigation. Experiment 1 used straight distance, Experiment 2 used trigonometric functions and Manhattan distance, and Experiment 3 used curvature calculation based on the position and direction of the markers. The average results of error distance measurement for each group and the performance improvement rate evaluated by comparing with the control method are shown in Table 1.

Table 1. Performance evaluation results (10 runs).

Test	control method	method 1	method 2	method 3
AVG Error [m]	0.674	0.0625	0.022	0.014
Improvement [%]	0	978.4	2963.636	4714.286

As shown in Table 1, the proposed method demonstrates a performance improvement of over 900% compared to that of conventional method. Particularly, method 2 shows a performance enhancement of 2963%, and method 3 shows a significant improvement of 4714%, highlighting the advantages of the proposed approaches.

### Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2022H1D8A3038040).

#### References

- D. Schleicher.: Real-Time Hierarchical Outdoor SLAM Based on Stereovision and GPS Fusion. IEEE Transactions on Intelligent Transportation Systems 10(3), 440-452 (2009).
- M. C. Silverman.: Staying alive: a docking station for autonomous robot recharging, Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No.02CH37292), 1050-1055 (2002)
- Zhang, Z.: A Flexible New Technique for Camera Calibration. IEEE Transactions on Pattern Analysis and Machine Intelligence 22(11), 1330–1334 (2000).
- B. L. E. A. Balasuriya.: Outdoor robot navigation using Gmapping based SLAM algorithm, MERCon, 403-408 (2016).
- S. Garrido-Jurado.: Automatic Generation and Detection of Highly Reliable Fiducial Markers Under Occlusion, Pattern Recognition 47(6), 2280-2292 (2014).
- Luca Carlone.: A Tutorial on SE (3) Transformation Parameterizations and on-manifold Optimization, Journal of Mathematical Imaging and Vision 53(2), 167-190 (2015).

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