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Identification of Contact Avoidance Zones of Robotic Devices in Human-Robot Collaborative Workspaces

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Abstract: The objective of this study was to establish a framework for producing indoor maps and locating robotic devices in a manufacturing environment. The framework employs computer vision techniques to construct the map and identify the presence of human workers. It defines the contact avoidance zones around human workers and existing obstacles. Once the location of the robot is identified, the map is used to plan paths to ensure safe human-robot collaboration for mobile and collaborative robots in shared workspaces with humans. The incorporation of avoidance zones into the map allows the robotic devices to anticipate the movements of workers and prevent collisions, this decreases the risk of injuries in collaborative environments. This paper illustrates the implementation of robots evading unforeseen contact with pre-defined contact avoidance zones, employing two distinct examples as demonstration.

Keywords: Collision avoidance, worker safety, human-robot interaction, collaborative workspace.

1. INTRODUCTION

With the increasing demand for automation in various industries, the use of robotic devices in human-robot collaborative workspaces has become more prevalent. However, ensuring the safety of humans working in close proximity to robots remains a major concern. To avoid injuries caused by unexpected contacts, contact avoidance zones (CAZ) are crucial in such collaborative environments. The zones define the regions around a human worker, or the surrounding obstacles, where a robot should not enter or should not operate, to prevent any potential physical injury. To identify the CAZ of robotic devices, indoor localization techniques such as WiFi-based positioning, visual odometry, inertial navigation, and laser-based scanning can be used. Other methods include kinematic analysis (Ballen-Moreno et al, 2022), force-torque sensing (Vasic & Billard, 2013), vision-based detection (Fan, Zheng, & Li, 2022), and adherence to safety standards.

In collaborative workplaces, where humans and robots work together to complete tasks, CAZ are critical to prevent injuries caused by unexpected contacts. Indoor localization technique is important in creating accurate and effective CAZ around humans or obstacles in collaborative workspaces. By accurately determining the location of the robot and the obstacles around it, indoor localization allows the robot to navigate its environment safely and avoid collisions. It helps the robot determine its position, trigger alerts or safety mechanisms, and improve the precision and reliability of the CAZ to ensure human safety. The size and shape of these zones can vary depending on the type of robot and the task being performed. Contact avoidance zones are typically defined using sensors, such as cameras or distance sensors, that detect the presence of humans in the robot's vicinity. When a human worker is detected within the CAZ, the robot must slow down or stop to prevent any potential collisions or injuries. Updating the map of the workspace as soon as the robot moves to a new location is necessary to ensure the CAZ can be promptly updated. A method was proposed to identify contact avoidance zones based on kinematic analysis to define the workspace boundaries of a robot (Truong et al., 2014). This method involves analyzing the robot's joint limits and reachability to determine the maximum workspace in which the robot can operate. Similarly, force-torque sensing has been used to detect contact between humans and robots in collaborative workspaces. Han (Han et al., 2019) developed a method that uses force-torque sensors to detect any unexpected contact between a human and a robot. This method involves setting a threshold for the force-torque sensors and triggering an emergency stop when the threshold is exceeded. Vision-based systems have also been used to detect the presence of humans in the workspace and provide feedback to the robot's control system (Cheng and Haney, 2022). Collaborative robot standards, such as ISO/TS 15066 and RIA/ANSI 15.06, provide guidelines for the design and operation of collaborative robotic systems (Rosenstrauch, Pannen, & Krüger, 2018). These standards define the maximum allowed forces and pressures that a robot can exert on a human and provide guidance on the use of sensors and control systems to ensure safe collaboration. To date, there has not been a comprehensive approach that takes into account the presence and movement of the robot, indoor localization, and the detection of both stationary and moving obstacles in the planning of the robot's trajectory. The purpose of this study is to fill this gap and propose a viable solution for safe operation of robotic devices in collaborative environments.

The study proposes a framework combining computer vision and indoor localization techniques (Zafari, Gkelias, & Leung, 2019) to enable robotic devices to detect obstacles and human workers in their surrounding environment while determining

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their position in the workspace. The framework consists of three steps: 1) collecting a point cloud of the indoor workspace and converting it into a spatial map marked with unavailable cells; 2) using a Bluetooth indoor localization technique to determine the robot's position; and 3) synthesizing a local map that incorporates contact avoidance zones. The robots employed in this study is equipped with a depth camera to detect obstacles and human workers. The collected data is integrated into a temporary map used for trajectory planning of mobile and collaborative robots. Depending on the type of robot used in the application, the trajectory can be the motion of the end-effector in space or the movement of the entire robot on the floor. The study aims to fill the gap in the lack of an integrated approach that considers contact avoidance, indoor localization, and detection of obstacles and human workers to safely operate robotic devices.

The manuscript is structured as follows. Section two provides an overview of the experimental setup and the framework of the proposed approach. Section three details the procedures for constructing the spatial indoor map and the localization methods used. Section four explains the synthesis of contact avoidance zones for both mobile and collaborative robots. Section five discusses two navigation examples presented in the 2D plane and int the 3D space for validation of the effectiveness of the proposed framework. Section six is the discussion of the conclusion of this study.

2. EXPERIMENTAL SETUP AND INDOOR MAP

In this study, a Zebra Freight 100 mobile robot was used to navigate the simulated workspace. A Kinect 360 RGB-D camera was used to acquire the RGB images of the surrounding environment, the point cloud of surrounding objects, and the movements of existing human workers. The detection range of the camera is 0.7 m to 6 m. The adequate range is suggested to be within 1.2 m to 3.5 m. Maps of the fixed structures and obstacles were taken across the workspace and stitched together before the collaborative task began.

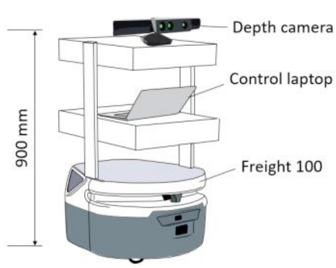

Figure 1. Configuration of the mobile robot and the depth camera.

The setup of the robotic platform is illustrated in Figure 1. The depth camera (Kinect 360), which takes RGB images, was positioned at a height of 900 mm above the ground. The depth camera is responsible for scanning the indoor environment for updating the map. To assist the robot in self-localization, nine Bluetooth beacons were strategically installed in the experimental area at designated locations, ensuring that each beacon was within a recommended distance of 4 m. To determine the robot's position in the experimental area, a laptop computer was used to pick up the Bluetooth signals transmitted by the beacons and determine the position of the robot. The computer also captured the depth images to generate a point cloud of the workspace and track the movements of any human workers presented. The collected data, including the movement and localization information, was integrated to generate a moving trajectory for the robotic device. Figure 2 demonstrates the localization and path planning procedures employed by the robotic device. The sensor inputs required are crucial, as they enable the robot to detect its surroundings before the path planning and control strategy can be implemented.

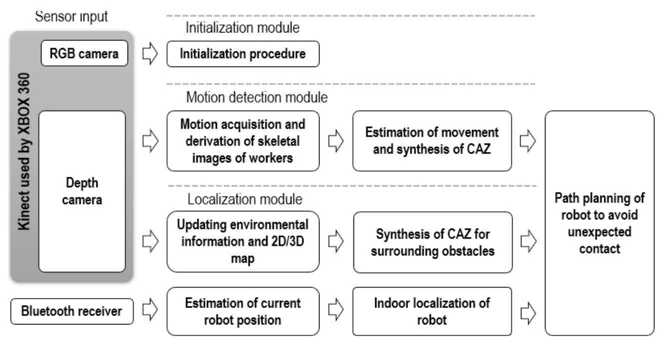

Figure 2. Proposed framework of robot localization, identification of contact avoidance zones, and path planning.

In this study, a Universal Robot UR-3e was employed as the collaborative robot platform. This robot has six degrees of freedom and an arm span of 500mm. It is capable of automating tasks with a payload of up to 3 kg and features a force-torque sensor that can measure forces up to 30 N and torques up to 10 Nm. The UR-3e, as illustrated in Figure 3, was used to validate the synthesis of the contact avoidance zones. To avoid any interference with the robot's movement, a Kinect 360 was positioned beneath the platform's table.

Figure 3. UR-3e robot used as the experimental platform.

3. OBSTACLE DETECTION AND ROBOT LOCALIZATION

To synthesize a spatial map of the workspace where the robots collaborate with human workers, the CAZ in the space need to be defined. In this study, the CAZ is defined as regions where robots should not enter or operate to ensure the accidental collisions do not occur. The spatial map used by a robot needs to include three main pieces of information: 1) the locations and sizes of fixed structures in the workspace; 2) the location of the robot itself; and 3) the projection of the movement trajectories of collaborative human workers. To build such a map before a robot implements contact avoidance zones, the information needs to be obtained by appropriate tools.

3.1 Testing environment and the initial position of robots

This study was conducted in the Robotic Research Lab at the facility of the National Institute for Occupational Safety and

Health (NIOSH) in Morgantown, West Virginia. The experimental area used in this room is a 7.5 m × 7 m × 2.5 m area. To ensure that mobile robots can operate optimally, they need to be aware of their current position and be able to self-locate during initialization. In this study, the collaborative robot was stationed in a fixed location, thus maintaining a constant position. Physical landmarks and Bluetooth beacons were strategically placed at specific points in the lab to aid indoor navigation. To initiate the experiment, the mobile robot was first returned to its initial position, which was achieved by using two QR codes (Lee et. al, 2015) as the landmarks of initial position, each measuring 150 mm × 150 mm. The robot used its depth camera to capture RGB images of these landmarks and calculate the distance between itself and the landmarks. This enabled the robot to determine its initial position accurately at a designated location. The initialization process was implemented using OpenCV and Python, and Figure 4 illustrates the point cloud map of the experimental area and one measured distance between the landmark and the robot while the robot returned to the initial position. The landmark shown in Figure 4 is located at the (7, 5) m at height 1 m in the experimental area, which was used as the initial position for the mobile robot. The collaborative robots, UR3e, UR10e, and AAB, were located at (2.5, 3.5) m, (2.3, 7) m, and (5, 3.5) m stationary. Apart from the UR3e, both UR10e and ABB robots followed preprogrammed motions without any interaction with surrounding workers.

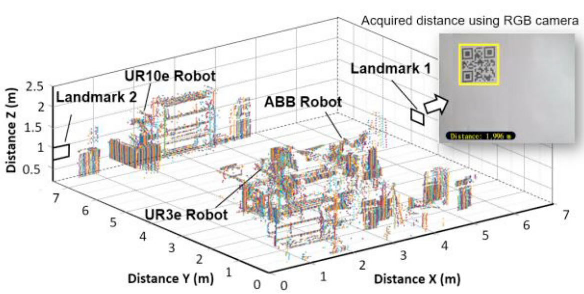

Figure 4. Acquired point cloud of the experimental area using depth camera and measured distance using QR code as localization landmarks.

3.2 Indoor mapping using depth camera

Prior to navigating the workspace and performing assigned tasks, the robots must possess an indoor map for path planning purposes. Additionally, the robots must possess the ability to update the map for future reference while operating. The map processed by the robots should show the presence of obstacles in 3D and information that the robots cannot access or need to avoid. To build such a map for robot manipulation, it is necessary to determine how a robot moves within the workspace. The mobile robot only navigates within the 2D plane of the workspace. The collaborative robot's control unit needs to take the regions occupied by obstacles and their surrounding regions in 3D coordinates. This study utilized an RGB-D camera to capture information in both 2D and 3D space simultaneously. The depth information collected by the RGB-D camera was then transformed into point cloud data of the experimental area and stitched together.

Once the point cloud data is acquired, it be processed and analyzed to extract useful information about the environment, such as the location and size of objects, the geometric shape of the surrounding environment, and the potential obstacles. Based on the type of applications, the map generated by the point cloud needs to be adjusted. The operation of the collaborative robots needs to avoid the contact with surrounding obstacles, which needs to convert the point cloud into a spatial map. This conversion starts from mapping the workspace into gridded cells. Figure 4 illustrates the acquired point cloud of the experimental area.

To enable effective path planning for both navigation of the entire mobile robot and movement of end-effector of the robot, each corresponding 3D space of the individual operational areas was partitioned into a grid of cells. Each cell has dimensions of 100 mm × 100 mm × 100 mm, resulting in a total of 75 × 70 × 25 cells for the entire experimental space. Figure 5 depicts the cells in the 3D map that are converted from the point cloud with the occupied cells. Any cell that contains detected obstacles is marked as occupied, indicating that the robot or its end-effector must avoid entering or operating in these cells to prevent collision or accidental contact. Similarly, the two-dimensional plane was partitioned into 75 × 70 grids to facilitate the robot's planner trajectory from one location to another. The cells that are already occupied, as shown in Figure 6, are marked as unavailable on the planner map to prevent potential collision. The grey scale of the map is corresponding to the height of the obstacles. Both maps need to be updated every time the depth image is recaptured to ensure that the map is the most current one.

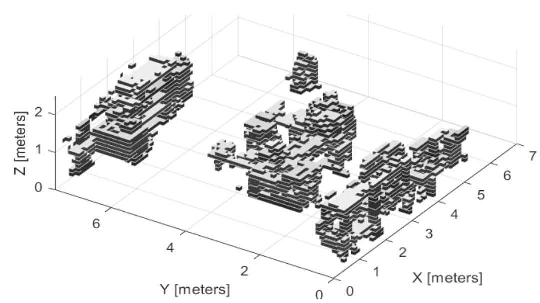

Figure 5. Occupied cells converted from point cloud in the gridded spatial workspace.

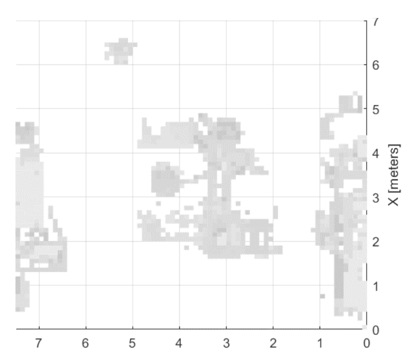

Figure 6. Occupied cells in the gridded planner map.

3.3 Bluetooth indoor positioning

The indoor positioning technique used in this study was using the transmission of Bluetooth signals between beacons and robots, which determines the locations of deployed mobile robots. The basic principle of this method is to use the attenuation characteristics of Bluetooth signals in space for positioning. The specific implementation includes:

1) Deploying Bluetooth beacons: Multiple Bluetooth beacons need to be deployed in the target area. The locations and ranges of the beacons can be pre-arranged or determined through calibration. When the robot is within the target area, the beacons continue to send Bluetooth signals. In this study, the locations of installed beacons were predetermined.

2) Receiving Bluetooth signal: Each robot receives the signals sent by the beacons through the equipped Bluetooth receiver.

3) Determining the distance: The distance between the robot and each beacon can be calculated based on the received Bluetooth signal strength.

4) Robot localization: Once the distances between the individual beacons are calculated, the robot's position can be determined by triangulation or other algorithms.

To determine the distance between the robot and the beacon using Bluetooth signals, two values, RSSI and TxPower were used. RSSI stands for Received Signal Strength Indicator, which depends on distance and broadcast power and can be used to estimate the distance between transmitter and receiver. TxPower represents the RSSI measured at 1 m from the beacon, which is the beacon signal strength seen on the robot. These values were used to estimate the location of the robot in the target workspace. The equation (Chen et. al, 2022) used to estimate the distance between each beacon and the robot is

$$d = 0.89976 \times \left(\frac{RSSI}{TxPower}\right)^{7.7095} + 0.111.$$

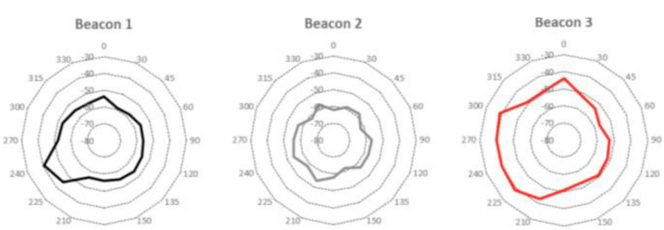

Figure 7. Polar plots of the TxPower strengths of individual beacons measured by the robot.

To evaluate the accuracy of the proposed Bluetooth localization technique, three iBeacon emitters were installed in a 4 m × 4 m area to determine the position of the mobile robot within the area. Figure 7 illustrates the polar plots of the measured TxPower for each beacon at different angles. It should be noted that the accuracy and reliability of Bluetooth indoor positioning can be greatly affected due to the complex reflection, penetration, and interference of signals in indoor environments. In order to improve the accuracy and reliability of positioning, various techniques can be used to enhance the accuracy of positioning, such as increasing the density of beacons or transmitting multi-channel Bluetooth signals. In this study, nine beacons were used in the experimental area. The initial distance between the mobile robot and individual beacons were calibrated while the robot was started. The distance was also calibrated when the landmarks can be visualized by the cameras to ensure accurate localization.

4. CONTACT AVOIDANCE ZONE AROUND HUMAN WORKERS

Apart from the cells occupied by the obstacles or fixed structures existing in the workspace, the 3D map must also incorporate the regions occupied by present human workers and their movement paths. These cells along the worker's path create the CAZ for avoiding contact. To define these zones, several parameters must be considered, such as the speeds of the human worker, end-effector of the robot, and mobile robots, as well as the space occupied by surrounding objects.

4.1 Human motion acquisition

In this study, the motion acquisition device used was the depth cameras manufactured by Microsoft used for XBOX 360. The camera was oriented in the direction of the mobile robot's movement, and the same camera was installed at the front side of the collaborative robot. The camera captured point cloud data of the surrounding subjects, from which skeletal information of the worker was extracted in 3D coordinates. The recorded data was then processed and analyzed to determine the joint angles, velocities, and accelerations of the body's movements. After extracting skeletal information, the speed of the human worker could be estimated, and the occupied zones during movement could be marked on the 3D map. However, it is important to note that depth cameras can only detect the presence of human workers within a specific distance.

4.2 Static workers and fixed contact avoidance zones

Static workers are human workers who remain stationary while working in the workspace. To identify CAZ around such workers, two different approaches can be taken. When defining the CAZs of a worker, it is not enough to only identify the occupied cells where the worker's location is detected. It is also necessary to predict all the cells that the worker may reach. One approach involves identifying the configuration spaces around all the joints of the worker, but this can be a time-consuming process that requires identifying all configuration spaces and marking occupied space cells on the 3D map. Another approach simplifies the derivation of occupied cells, which involves identifying the size of the worker's body and attaching a larger cell to the entire body of the worker. The distance between each side of this cell and the nearest body part is fixed. This type of cell can be easily identified using skeletal information obtained from the depth camera, providing the advantage of immediate derivation once skeletal information is available. In this study, the distance between each side of the CA. Z to the closest point of the body part was set to be 0.3 m. Figure 8(a) and (b) illustrates the two approaches of CAZ, and Figure 8(c) shows CAZ applied in real time to the acquired human worker skeleton information. In this study, the simplified approach was adopted to obtain a faster derivation rate. If the CAZ is used by a mobile robot, the 3D CAZ can be projected onto the planner map, as shown in Figure 8(c). If the map is used by a collaborative robot, cells occupied by the human worker need to be marked as unavailable.

4.3 Moving workers and dynamic contact avoidance zones

When defining the CAZ of a moving worker, it is not sufficient to only identify the occupied cells where the worker's location is detected. It is also necessary to predict all the cells on the worker's movement path. To determine the accurate CAZ of workers in motion, it is not enough to capture their movement and estimate it after a movement is completed. Instead, it must be estimated while the worker is moving, which involves collecting data on their speed and how often the map of the occupied cells is updated. Figure 9(a) and (b) illustrate the CAZ defined for a worker after completing the movement in both 3D and 2D environments. The average speed of a human worker ranges from 0.89 m/s to 1.79 m/s, with an average of 1.6 m/s according to ISO/TS 15066. To simplify the calculation process, a fixed-size CAZ was applied to the moving worker in this study.

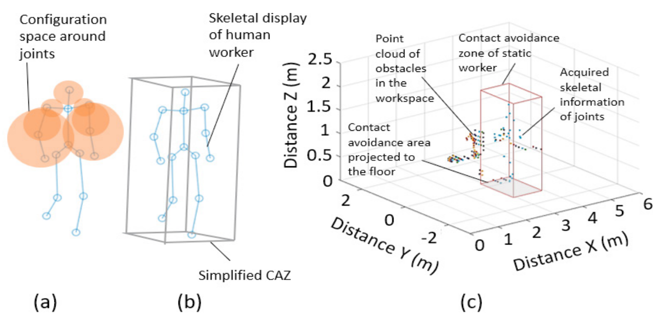

Figure 8. (a) Configuration spaces of individual joints of the worker; (b) the proposed CAZ zone around the worker; and (c) the CAZ attached to the skeleton acquired by depth camera in real time.

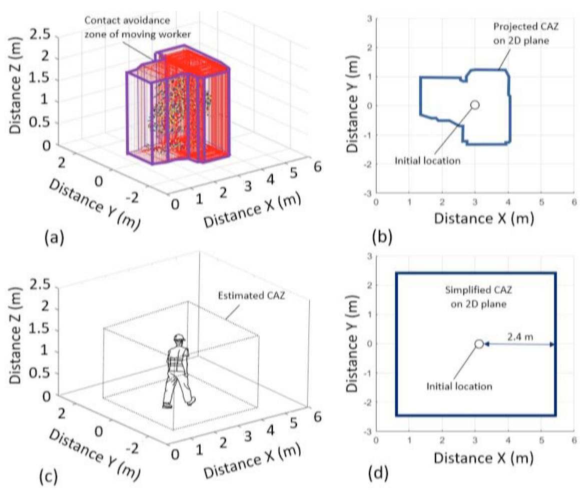

Figure 9. (a) CAZ occupied by a moving worker along the movement path; (b) the projected CAZ on the 2D plane; (c) the simplified CAZ based on moving speed; (d) the proposed CAZ on the 2D plane.

To keep the CAZ up to date on the move, robots must scan the environment and update the map every operating cycle. The update frequency was set to two seconds in this study. It is important to ensure that no unexpected contact occurs during each operating cycle lasting two seconds. To achieve this, the extent of the contact avoidance zones was set to 2.4 m in all four directions of the worker movement. The distance is set to move at 1.6 m/s for 1.5 seconds instead of using a 2 second updating cycle to predict the movement of the worker. The CAZ has a maximum range of 3.39 m. With this assumption, the CAZ can be generated and applied faster to the robot operation. Figure 9(c) and (d) illustrate the CAZ applied to the 3D space and the 2D plane. It is also worth noting that the CAZ in the 2D plane is the projection of the spatial region onto the floor.

4.4 Contact avoidance zone of fixed obstacles

To ensure the safety of human workers and avoid collisions with fixed obstacles within the workspace, it is also necessary to define a space between the robot and these structures. The robot should not enter or operate within this defined space. For collaborative robots, the CAZ around the fixed obstacles can be created by expanding the range of occupied cells shown in Figure 4. The 2D indoor map used by mobile robots is created based on the 3D point cloud data acquired from the workspace. The points in the target area are projected onto a 2D plane to synthesize the 2D map. The synthesized 2D map is then inflated with the specified radius to form CAZs surrounding the fixed obstacles and the structures. In this study, a CAZ radius of 0.3 m was set around fixed structures based on the indoor map. The indoor maps are regularly updated to ensure that the CAZs can be established with the latest information. Figure 10 demonstrates the CAZs surrounding the fixed obstacles based on Figure 6.

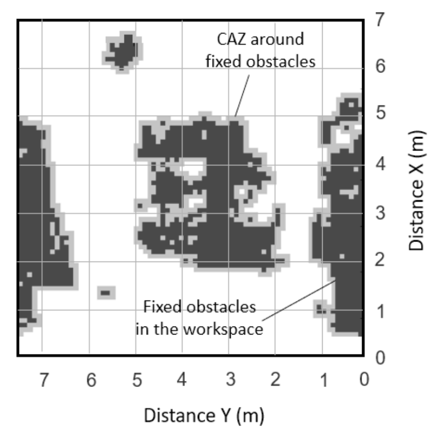

Figure 10. The CAZ around the fixed obstacles in the targeted workspace.

5. NAVIGATION OF ROBOT WITH THE CONSIDERATION OF CONTACT AVOIDANCE ZONES

Incorporating both the indoor map and the identified CAZ is essential to ensure the secure operation of both the mobile robot and the collaborative robot in the workspace. This involves considering the occupied cells generated from the point cloud, the CAZ associated with the fixed obstacles, and the CAZ of the collaborative human workers. Once all this information has been integrated, the robots can use the resulting map to navigate and operate safely.

5.1 Path planning for collaborative robot

In order to optimize the operation of a collaborative robot, it is only necessary for it to have knowledge of the spatial map within its configuration space, which can be more intuitive. Once the 3D map has been obtained, the robot can apply path planning of the end effector and inverse kinematics to perform tasks more efficiently. The approach of gridding the workspace into 40 × 20 × 20 cells for path planning is exemplified in Figure 11. A collaborative robot performs the task of transferring an object from its starting point to a predetermined waypoint before relocating it to a designated location. With the help of the developed path planning algorithm and the spatial map marked with unavailable cells, the end-effector of the target robot can successfully avoid colliding with surrounding obstacles and transfer the object to the designated location. The optimized planned path was designed to minimize travel distance (Cheng & Haney, 2022) while remaining adaptable to changes in the shape of occupied cells, allowing for path adjustments when needed.

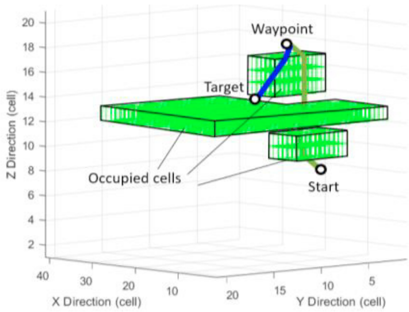

Figure 11. Path planning of an end-effector in using the 3D map with occupied cells.

5.2 Navigation of mobile robot

For a mobile robot, the controller must only update the occupied cells along its path of movement. During each operating cycle, the robot must acquire a depth image to identify any human workers present and determine a 2D map for path planning. Figure 12(a), (b), and (c) provide a visual representation of the path planning process before and after human workers are detected along the robot's moving path, following the updating of the map. The mobile robot started from a specified location. The robot moved to the waypoints using a path planning algorithm. Once the presence of human workers was detected, the map was updated based on the visual feedback of the depth camera. The moving path was adjusted accordingly. Figure 12(b) and (c) demonstrate the human workers presented at different locations when the robot traveled to the specified waypoint. By updating the map in this way, the mobile robot can navigate safely around any human workers present in the workspace, minimizing the risk of accidents or collisions. This approach also enables the robot to perform its tasks more efficiently and effectively, while minimizing any disruptions or safety concerns. Figure 12 demonstrates the efficiency of the path planning method based on recognizing contact avoidance zones within the workspace. This approach ensures smooth adjustments and guarantees no unexpected contact during the mobile robot's travel.

6. CONCLUSIONS

The proposed approach in this study combines computer vision and indoor localization techniques to enable collaborative and mobile robots to update their moving trajectories in order to avoid obstacles and human workers. This method has demonstrated its feasibility in ensuring the safety of robots in the workspace by actively avoiding potential collisions between robot devices, human workers, and surrounding obstacles. It is expected that this active avoidance approach will contribute to reducing the likelihood of potential injuries.

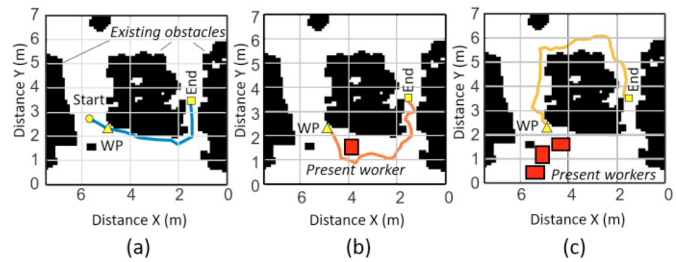

Figure 12. (a) Original path planned in the workspace; (b) adjusted path after a human worker being detected; and (c) adjusted path after the human workers being detected.

7. DISCLAMER

The findings and conclusions in this manuscript are those of the authors and do not necessarily represent the official position of NIOSH/CDC. Mention of any company or product does not constitute endorsement by NIOSH/CDC.

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