<u>21-0651-US-PRO (X-51977-00-PR) Overview</u>

In an example system, a robotic device may navigate an environment through analyzing sensor data using various obstacle detection heuristics. Obstacle detection heuristics may include one or more thresholds that facilitate obstacle detection from sensor data. For example, the robotic device may collect environmental data from a LIDAR sensor and/or a camera on the robotic device, and the robotic device may use the environmental data to compute the dimensions of an observed obstacle. The dimensions of the observed obstacle may be compared to the obstacle detection heuristics to determine whether the area with the observed obstacle is a driveable area for the robotic device. For instance, the obstacle detection heuristics may indicate that an object with a height of six inches or more is not driveable. If the observed obstacle has a height of five feet, then the area with the observed obstacle may be indicated as not driveable. In contrast, if the observed obstacle has a height of five inches, then the area with the observed obstacle may be indicated as driveable.

Each heuristic may be tuned based on the environment in which the robotic device is operating. For example, a robotic device initially may be tasked with moving objects in an area with many narrow openings and small objects, before the robotic device is subsequently reassigned to a different area with large openings and large objects. In the area with small objects, the heuristic describing the minimum distance between objects needed for the robotic device to successfully pass through may be the width of the robotic device to accommodate the narrow openings in the environment. However, when the robotic device changes areas, this heuristic describing the minimum distance between objects may be adjusted to a larger threshold to accommodate the large objects being moved in the large open areas, since the large objects may have a width greater than the robotic device.

In practice, obstacle detection heuristics may include a large set of heuristics, including minimum/maximum distance between objects, angles at which the object meets the floor, the amount of time that has passed since the last LIDAR scan, and so on. A combination of these heuristics may be used to determine the driveability of an area, and as mentioned above, each heuristic may be tuned based on the situation. Because a robotic device may operate in a variety of environments and navigation may be tuned on a very large set of obstacle detection heuristics, manually tuning these heuristics may be difficult and tedious.

Further, tuning obstacle detection heuristics based solely on a new environment may cause regressions in robotic device behavior if the robotic device happens to return to an old environment. For example, a robotic device that moves objects may be relocated from an environment with large openings and large objects to an environment with narrow openings and small objects. The obstacle detection heuristics may be tuned to operate in the more open space (e.g., a heuristic describing the minimum distance between objects may increase in value to accommodate the larger objects). However, if the robotic device moves back into the less open space, then the robotic device may have difficulty detecting any driveable paths because the object detection heuristics were tuned to a more open environment.

Provided herein are methods to systematically determine driveability and prevent regressions in robotic device navigation through quantifying the effect of algorithmic changes including updated obstacle detection heuristics. Namely, past environmental sensor data that were collected by the robotic device for determining driveability and the respective trajectories through which the robotic device successfully navigated may be used as a basis to evaluate the updated obstacle detection heuristics. Because the trajectories through which the robotic device drove through successfully are assumed to be driveable trajectories, updated obstacle detection heuristics may be evaluated based on the environmental sensor data that was collected in determining these trajectories to quantify the amount of degradation to the results obtained by the updated obstacle detection heuristics.

In some examples, the robotic device may collect LIDAR data in the form of 3-dimensional (3D) point clouds to determine driveability. The 3D point cloud may be segmented and an occupancy grid may be generated based on the segmented 3D point cloud. Segmentation of the 3D point cloud as well as generation of the occupancy grid may depend heavily on heuristics, which are collectively referred to as obstacle detection heuristics herein. The occupancy grid may include cells that represent areas in the environment with each cell indicating whether the respective area is driveable or not. The obstacle detection heuristics may be adjusted to generate a more accurate occupancy grid and/or to better segment the 3D point cloud, which may also ultimately be used to generate a more accurate occupancy grid.

The obstacle detection heuristics may be tuned in a variety of ways. For example, the obstacle detection heuristics may be manually tuned by an operator periodically when the robotic device changes environments. Alternatively, the obstacle detection heuristics may be automatically tuned using an optimization framework, such as Google Vizier. Based on the environmental sensor data and drivable trajectories on the respective areas that were indicated to be driveable, the optimization framework may optimize the obstacle detection heuristics to thresholds that optimize driveability determinations. For example, the optimization framework may be an algebraic equation, mathematical formula, and/or algorithm that is a function of the obstacle detection heuristics and the collected environmental sensor data.

In some examples, tuning of the obstacle detection heuristics may only be based on more recent environmental sensor data. Updating the obstacle detection heuristics using a smaller set of data may be easier for an operator when done manually and may result in lower computation times when done using an optimization framework. However, the obstacle detection heuristics may then not reflect conditions in past environments.

The updated obstacle detection heuristics may thus be evaluated based on past trajectories successfully navigated by the robotic device. The past trajectories of the robotic device and the respective collected environmental sensor data may have been stored in a database on a server or in the robotic device and the updated obstacle detection heuristics may be evaluated on at least a subset of these past trajectories. For example, if the past trajectories of the robotic device and the respective collected environmental sensor data is stored in a database on a server, the robotic device may retrieve a set of randomly selected samples from the database to evaluate the updated obstacle detection heuristics. Similarly, if the past trajectories of the robotic device and the respective environmental sensor data are stored in a database on the robotic device, the stored past trajectories and the respective environmental sensor data may only be a subset of the past trajectories and the respective environmental sensor data.

In some examples, past trajectories may be paths through which the robotic device has navigated previously, and the respective environmental sensor data may have been used to determine those trajectories. By using environmental sensor data and trajectories for environments previously navigated by the robotic device, the updated obstacle detection heuristics may be evaluated based on environmental sensor data representing areas that have been confirmed to be driveable. The environmental sensor data may be evaluated using the updated obstacle detection heuristics to determine predicted driveable areas. If the predicted driveable areas include the stored driveable trajectories, then the updated obstacle detection heuristics may be indicated as usable, and the updated obstacle detection heuristics may then be used to determine future navigation of the robotic device. In contrast, if the predicted driveable areas do not include all or at least a predetermined number or portion of the stored driveable trajectories, then the updated obstacle detection heuristics may be indicated as unusable, and optionally updated obstacle detection heuristics may be recomputed.

In some examples, a similar method may be performed with non-drivableable areas. For example, a robotic device may be streaming data to a remote operator that is responsible for stopping the robotic device before the robotic device collides with an object or to prevent other potential accidents. The environmental sensor data around these trajectories may also be stored along with the unsuccessful trajectories that describe where the remote operator stopped the robotic device. During further operation, the robotic device may collect additional data which may be used to update the obstacle detection heuristics. The additional data may also be indicative of unsuccessful trajectories. After the obstacle detection heuristics have been updated based on the more recently collected environmental data, the robotic device may evaluate the updated obstacle detection heuristics based on the past unsuccessful trajectories and the respective environmental sensor data. If the predicted non-driveable areas include the stored non-driveable trajectories, then the updated obstacle detection heuristics may be indicated as usable, and the updated obstacle detection heuristics may then be used to determine future navigation of the robotic device. In contrast, if the predicted non-driveable areas do not include all or at least a predetermined number or portion of the stored non-driveable trajectories, then the updated obstacle detection heuristics may be indicated as unusable, and the updated obstacle detection heuristics may be recomputed.

This process of evaluating the updated obstacle detection heuristics based on previously collected environmental sensor data may occur periodically. For example, the updated obstacle detection heuristics may be evaluated based on the previously collected environmental sensor data once a day while the robotic device is idle. Additionally or alternatively, the updated obstacle detection heuristics may be evaluated based on the previously collected environmental sensor data whenever the obstacle detection heuristics are updated.

In some examples, the robotic device may be operating in a first environment before moving to a second environment. The robotic device may collect environmental sensor data and traverse trajectories in the first environment, and the updated object heuristics may also be tuned based on the first environment. When the robotic device moves to the second environment, the obstacle detection heuristics may no longer be optimal for the second environment. Thus, the obstacle detection heuristics may be updated based on the second environment. However, to ensure that the obstacle detection heuristics do not regress in accuracy for the first environment, the updated obstacle detection heuristics may be evaluated based on the data collected in the first environment. If the predicted driveable paths determined using the updated obstacle detection heuristics include the trajectories of the robotic device in the first environment, or at least a subset thereof, the updated obstacle detection heuristics may be used to determine future navigation of the robotic device.

Claims

1. A method comprising:

receiving one or more past trajectories navigated by a robotic device in an environment, wherein the one or more past trajectories are associated with initial environmental sensor data and one or more obstacle detection heuristics;

determining, based at least on subsequent environmental sensor data, one or more updated obstacle detection heuristics;

determining, based on the one or more updated obstacle detection heuristics and the initial environmental sensor data, one or more predicted driveable areas in the environment; and

based on the one or more predicted driveable areas including the one or more past trajectories, using the one or more updated obstacle detection heuristics to determine future navigation of the robotic device.

2. The method of claim 1, wherein the method further comprises:

receiving one or more unsuccessful trajectories partially navigated by the robotic device in the environment, wherein the one or more unsuccessful trajectories are associated with additional initial environment sensor data and one or more additional obstacle detection heuristics;

determining, based at least on additional subsequent environmental sensor data, one or more further updated obstacle detection heuristics;

determining, based on the one or more further updated obstacle detection heuristics and the additional initial environmental sensor data, one or more predicted undriveable areas in the environment; and

based on the one or more predicted undriveable areas in the environment including the one or more unsuccessful trajectories, using the one or more further updated object detection statistics to determine further navigation of the robotic device.

3. The method of claim 2, further comprising identifying the one or more unsuccessful trajectories partially navigated by the robotic device based on one or more operator interrupts of robot navigation.

4. The method of claim 1, wherein the method further comprises:

based on the one or more predicted driveable areas not including the one or more past trajectories, using the one or more obstacle detection heuristics to determine future navigation of the robotic device.

5. The method of claim 1, wherein the environment is a first environment, wherein the subsequent environmental data is based on a second environment.