21-0619-US-PRO (X-51836-00-PRO) Overview

A robotic device may include a perception system to facilitate navigation and task fulfillment. The perception system may include cameras, LIDAR sensors, and/or other sensors that facilitate a better understanding of the environment. The perception system may be independently controlled by the robotic device to view the environment from different perspectives. For example, a robotic device may have a perception system that includes a LIDAR sensor with a 360 degree horizontal field of view and a pan-tilt camera that may have a more limited field of view than the LIDAR sensor but may provide additional information about the environment that the LIDAR sensor may be unable to provide. The pan-tilt camera may thus be controlled to pan and/or tilt in order to collect data outside the limited current field of view. For example, the pan-tilt camera may only be able to see objects in the direction that it is facing, and it may not be able to see objects in the opposite direction that it is facing or to the side of the direction that it is facing. To view objects in a direction the robotic device is not facing, the robotic device may control the pan-tilt camera to turn and observe objects in those directions. For example, the robotic device may intend on moving backwards, and the robotic device may control the pan-tilt camera to rotate 180 degrees to observe behind the robotic device. In some examples, the LIDAR sensor may also be controlled to collect data outside its current field of view. Another variation may be that the perception system may be controlled as a whole to collect data outside the LIDAR sensor's and/or the pan-tilt camera's field of view.

One challenge that may arise in these examples is determining how the robotic device should control the perception system and/or sensors in the perception system. For example, the robotic device may be navigating in a crowded environment with many obstacles. The robotic device may intend to navigate forward, but the robotic device may detect an object in front of it.

Because the perception system may not be able to observe every area of the environment at the same time, the robotic device may need to control the perception system to observe obstacles in other potential paths, including to the right and the left of the robotic device. In some situations, an inefficient control method may cause the robotic device to awkwardly jerk its perception system from side to side to determine which direction to move. However, this may provide a less than optimal response time and user experience.

Further, the perception system may be involved in multiple processes and it may be difficult to determine which process to prioritize. For example, the perception system may be used to determine details about objects, determine the state of a changing environment, find specific objects in the environment, and so on. It may thus be difficult to determine which of these processes to do before another, and inefficient prioritization may result in a robotic device that takes more time to execute tasks, among other issues.

Provided herein are methods to determine how to control a perception system of a robotic device through a data-driven approach based on perception system trajectories controlled by one or more operators. In some examples, an operator (e.g., a remote human operator) may be tasked with manually controlling the perception system based on data received from the robotic device. The trajectory of the perception system as controlled by the remote operator and various sensor data from the robotic device may be stored and used to train a machine learning model that can output perception system trajectories. The machine learning model may then be used to determine perception system trajectories whenever the robotic device is operating. This approach may be a more streamlined approach to determining perception system trajectories and may facilitate more intuitive movements of the perception system, which may give rise to better user experiences.

An operator may be able to operate the perception system of a robotic device in a variety of ways. In some examples, the operator may be walking with the robotic device as the robotic device is navigating in the environment. The operator may guide the perception system using a control system that is communicating with the robotic device (e.g., a joystick controller). However, this approach may result in less than accurate training data, because the operator is not presented with the data that the robotic device collects and instead relies on the operator's perception and memory. Alternatively, the system may include a computing device with a screen (perhaps attached to the robotic device). The robotic device may present sensor data to the operator, and based on the presented sensor data, the operator may guide the perception system using a control system that is communicating with the robotic device. Such an approach may result in more accurate training data, since the operator is being presented with sensor data that the robotic device collects.

In further examples, the operator may be presented with sensor data and operate the robotic device remotely. For example, the remote operator may be located in a base station that receives sensor data from the robotic device, perhaps including LIDAR data, camera data, and so on. The sensor data may be processed into an operator-friendly format before being presented to the operator. Further, the remote operator may be presented with data indicating where the robotic device intends to navigate to next, and the remote operator may make a decision on how to control the perception system based on where the robotic device intends to navigate to next and the sensor data representing the environment. The remote operator's control instructions may be communicated back to the robotic device, and the perception system may be controlled based on those control instructions. This process may be continued in the same environment or in a variety of environments until sufficient training data is collected.

Additionally or alternatively, determining how to control the perception system may be an immersive experience for the remote operator. For example, the remote operator may use a virtual reality headset that displays a representation of the environment in which the robotic device is operating. The representation of the environment in which the robotic device is operating may be created using sensor data communicated from the robotic device. Because the operator is being presented with environmental data as collected by the robotic device, the perception system trajectories may be more accurate, and additional sensor data collected after the perception system has moved may better capture environmental information.

In some examples, the robotic device may determine a path where it intends on navigating to next, and the operator may only control the perception system of the robotic device. The robotic device may send to the remote operator the collected sensor data and the path indicating where the robotic device intends on navigating to next. The remote operator may make a determination on where to move the perception system based on the collected sensor data and the intended trajectory of the robotic device. Alternatively, the robotic device may send only the collected sensor data, and the remote operator may determine where to move the robotic device before sending an indication on where to move the robotic device. In practice, situations where the robotic device determines the intended path may facilitate more streamlined training data collection, because fewer variables may depend on the decisions of the operator.

The sensor data and the operator-directed perception system trajectories may be determined in a variety of environments and using a variety of operators, which may also facilitate better predictions. For example, the sensor data may be collected from crowded environments where the perception system may have to move more to gain an accurate perception of the environment and objects in the environment, from sparse environments where the perception system may not need as many trajectories to obtain an accurate perception of the environment, from environments with many moving objects where the perception system may need to gather more frequent updates, from environments with less moving objects where the perception system may not need to gather as many updates, and so on.

The sensor data collected by the robotic device, the intended future path or paths of the robotic device, and the operator-determined perception trajectory for the robotic device may be stored in a server, on the robotic device, and/or on the computing device of the operator to be used to determine future perception system trajectories.

In some examples, a machine learning model may be used to determine future perception system trajectories after being trained on the stored data. The machine learning model may take, as an input, a planner state, which may include at least one future path for the robotic device in the environment. For example, if the robotic device is at a location and is planning on navigating forward, the planner state may include an indication that the future path may be directly forward from the robotic device. The planner state may include coordinates, perhaps indicating a current position of the robotic device and a future position of the robotic device, directions, and/or other information indicative of the future path. The machine learning model may output perception system trajectories, where each trajectory indicates how to control the perception system to move for a discrete period of time.

The machine learning model may also take, as an additional input, a tracker state, which may include environmental information. For example, the tracker state may include LIDAR sensor data collected from the robotic device and viewed by the human operator. The tracker state may also include representations of movement of objects in the environment. For example, the robotic device may be operating in an environment with a car, and the car may be approaching the robotic device. The tracker state may thus include an indication that an object is approaching and the location of the object as detected through the perception system sensors.

To train the machine learning model, the planner state representing at least one future path for the robotic device, the tracker state representing environmental information, and the operator controlled trajectories may be combined into a training dataset. The planner state and the tracker state may be inputs into the machine learning model and the weights of the machine learning model may be tuned based on the predicted operator controlled trajectories in comparison with the actual operator controlled trajectories. In some examples, the planner state and the tracker state may be vectors including an indication of current location, future location, velocity of the robotic device or object, or a combination thereof.

In some examples, the planner and/or tracker states may be outputs of one or more machine learning models. For example, the planner state indicating future paths of the robotic device may be determined by a machine learning model, and that machine learning model may feed the output into another machine learning model that determines the perception system trajectories. In examples where the input to the machine learning model that determines the perception system trajectories also includes the tracker state, the tracker state may also be determined using a separate machine learning model, and that separate machine learning model may feed the output into the machine learning model that determines the perception system trajectories. Additionally, the planner and tracker states may be determined by a single machine learning model, where the output of the single machine learning model is input into the machine learning model that determines the perception system trajectories. In some examples, a machine learning model that determines the planner and tracker states includes one or more long short-term memory (LSTM) networks.

In some examples, the machine learning model may be trained based on a large dataset including training data from various environments and various operators. After being trained on training data from various environments and various operators, the machine learning model may be fine-tuned based on the specific environment in which the robotic device is operating. For example, the machine learning model may be trained based on a dataset that includes perception system trajectories for a crowded environment, an empty environment, a fast-changing environment, a slow-changing environment, and so on. The robotic device may determine that it is located inside a warehouse and send a message to fine-tune the pre-trained machine learning model on specifically warehouse data and the associated perception system trajectories. In some examples, classifying the environment and fine-tuning the pre-trained machine learning model may be done after the robotic device receives an indication that it has been relocated to a new environment. In further examples, classifying the environment and fine-tuning the pre-trained machine learning model may be done periodically, perhaps when the robotic device is idle at night.

Claims

1. A method comprising:

determining, for a robotic device that comprises a perception system, a robot planner state representing at least one future path for the robotic device in an environment;

determining a perception system trajectory by inputting at least the robot planner state into a machine learning model trained based on training data comprising at least a plurality of robot planner states corresponding to a plurality of operator-directed perception system trajectories; and

controlling, by the robotic device, the perception system to move through the determined perception system trajectory.

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

determining, by the robotic device, a tracker state representing current environmental information, wherein the tracker state is also inputted into the machine learning model, wherein the machine learning model has been trained using also a plurality of tracker states corresponding to the plurality of operator-directed perception system trajectories.

3. The method of claim 1, wherein the planner state is a plurality of coordinates representing the at least one future path for the robotic device in the environment.

4. The method of claim 1, wherein the machine learning model is a first machine learning model, and wherein the robot planner state is an output of a second machine learning model.