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Research Article

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Principle Operation of a Line Follower Robot

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Abstract

A rudimentary autonomously guided robot called a "Line Follower Robot" (LFR) follows a line written on the ground to either find a white line on a dark surface or a dark line on a white surface. Working on the LFR is quite interesting. We will discover how to construct a black line follower robot in this study utilizing an Arduino Uno and a few readily available parts.

Keywords: Arduino Uno, Path Following, Avoiding Obstacle, Mobile Robot.

1. Introduction

Mobile robots have drawn the attention of many academics in recent years because to their agility, adaptability, and capacity to be used in a variety of challenging missions, particularly in regards to autonomous navigation in the warehouse or restricted region [1–10]. There is a rising demand for complicated applications nowadays, when the working environment includes humans moving robots, or unexpected impediments [11-13]. At this point, robots and people are regarded as mobile impediments that make up the dynamic environment. Since then, the camera application-based "Navigation" approach has generated a lot of interest since it overcomes the drawbacks of the conventional line-detection method while also enabling path optimization [14–19]. Furthermore, because the working space is typically a warehouse or small space, the robot's capacity to operate must be adaptable and able to follow a predefined trajectory while avoiding moving impediments that may occur without deviating from a safe planning trajectory [20–23]. Since the environment is static and mapped, and obstacle locations are assumed to be known in advance, there are currently many traditional researches and approaches, such as RRT*, A* Visibility Graph, and Fast Marching Tree, that are primarily focused on autonomous path planning for mobile robots [24-27]. In addition used complex algorithms to prevent collisions, including Adaptive Genetic, Bacterial Evolutionary Algorithm, Predictive Behavior, and Partial Swarm [28-37]. The dynamic environment map must be built and updated manually using those approaches, which results in low forecast accuracy. The obstacle avoidance approach based on fuzzy logic control develops specific rules in accordance with the prior information. Recently, intelligent control algorithms have also been applied to obstacle avoidance. The method to fuzzy logic control has strong robustness, real-time performance, and less reliance on the environment. However, there is a symmetry phenomenon that cannot be explained. The neural network-based obstacle avoidance technique creates controllers based on the location of obstacles. However, gathering data and teaching the network to discover a path take a lot of effort. When an obstacle's knowledge is lacking or unknowable, conventional obstacle avoidance algorithms are useless. Designing an intelligent control requires knowledge or experience [38–39]. Contrary to other artificial intelligence algorithms, reinforcement learning (RL) is a learning technique that doesn't need any rules [40-43]. RL is a machine learning technique that modifies the environment by using the environment's feedback as an input. One of the most widely used RL algorithms is Q-learning. With the help of the Q-value function, the environment is examined by the algorithm, which focuses on value-based reinforcement learning that is updated over time [44-47]. Recently, it has also been used to combine intelligent control and Q-learning [48-52]. These research, however, are limited to simulations and trials using straightforward static objects. Additionally, there isn't a clear discussion of how to construct the controller for a robot to follow a processed path (virtual).

As is well known, Q-learning relies on a trial-and-error learning process where the agent experiences several failures before finally succeeding. Both money and time are very much in short supply. This indicates that the training is challenging to carry out in a real environment and is frequently done in simulation. From it is clear that robot applications using Q-learning can be trained in virtual environments before being applied in the actual world [48,52]. The training environment for the RL agent in a virtual environment is established in this research to overcome these issues. The user can gather numerous responses in diverse locations while the virtual environment simulates the actual scenario. The contribution of this study is that:
• Unlike other traditional, artificial and intelligence algorithms, the obstacle avoidance methodology for moving obstacle in this paper does not use any prior dataset for training or experience for design the controller.
• The training data are transferred to robot and work real time in the real application.
• From the experiment the RL proved to have better performance than intelligent control algorithm in terms of total time and errors [53].

2. How a Line Follower Robot Works

Line follower robots (LFRs), as previously mentioned, follow lines, and in order to do so, they must first be detected by the robot. The LFR's line detecting technique must now be implemented, which is the question at hand. We all understand that a black surface absorbs the most light, resulting in a maximum reflection on a white surface and a minimum reflection on a black surface. So, in order to find the line, we will exploit this quality of light. An IR sensor or an LDR (light-dependent resistor) can be used to detect light. We chose the IR sensor for our project because of its superior precision. Two IR sensors are placed on the left and right sides of the robot, respectively, in order to detect the line. The robot is then positioned on the line so that it is directly between the two sensors. A transmitter and a receiver are the two components that make up infrared sensors. The IR receiver is a photodiode, which detects the signal produced by the transmitter. The transmitter is just an IR LED that produces the signal. When an object is exposed to infrared light from an IR sensor, the light reaching the black part of the object absorbs it, producing a low output, while the light striking the white part of the object reflects back to the transmitter, being picked up by the infrared receiver, producing an analog signal. Using the aforementioned technique, we move the robot by operating the wheels that are connected to the motors, which are managed by a microprocessor. Let's call the left motor and right motor the two sets of motors that are typically seen in line-following robots. Based on the signals from the left and right sensors, respectively, both motors rotate. The robot must execute four sets of motions, including forward motion, left turn, right turn, and stopping.

Moving forward: In this scenario, the robot should advance, i.e., both motors should rotate so that the robot goes forward, when both sensors are on a white surface and the line is between the two sensors. Actually, due to the arrangement of the motors in our configuration, each should rotate in the opposite direction. But for ease of use, we'll refer to the motors as rotating forward.

Turning left: The left sensor in this instance detects the black line and sends a signal to the microcontroller since it is on top of the dark line whereas the right sensor is on the white portion. The robot should turn to the left because the left sensor is sending a signal. As a result, the right motor rotates forward while the left motor rotates backward. The robot then pivots to the left.

Turning right: Although this circumstance is identical to the left case in that just the right sensor is present, the robot should nevertheless turn to the right in this instance. The left motor rotates forward to move the robot in the correct direction, while the right motor rotates backward to turn the robot in the opposite direction.

Stopping: In this instance, the black line may be simultaneously detected by both sensors because they are on top of the line. The microcontroller is programmed to think of this as a reason to stop. As a result, both motors are turned off, which stops the robot from moving [54-69].

3. Conclusion

I've evaluated a lot of articles on line-moving robots and obstacle detection in this paper. Its basic operation and execution strategy are also addressed.

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