Optimization of robot path and IoT communication path based on artificial intelligence.

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Abstract

The Internet of Things (IoT) and robotics are very popular research topics, and they have begun to enter people's daily life, and both robots and the IoT have the problem of path optimization. For robots, Although the map can be established in advance and the robot can avoid obstacles, the robot's travel map is likely to change at any time, and a new path needs to be generated at this time. The IoT will provide users or monitoring system information with the best transmission speed path. The traditional optimal path is usually the shortest distance or shortest time. But because it ignores some variables, such as the probability of accidents. Or with the shortest time or distance, the results are planned in this way, but the best plan becomes the worst. Based on the above requirements, this paper uses artificial intelligence to optimize the path between robots and the IoT. question. The method expected in this paper is to parameterize the length of each path, the number of obstacles, whether there will be collisions, etc., and then use the artificial intelligence algorithm of multi-tree and Long short-term memory (LSTM) to find the best path.

Keywords: Path Optimization, Internet of Things (IOT), Robot, Recurrent Neural Network (RNN), Long short-term memory (LSTM).

1. Introduction

Path planning is one of the important topics in robotics and Internet of Things (IOT) applications. In the case of a robot, in order to allow the robot to complete the task quickly, it is hoped that the robot will complete the task with the shortest path. In the application of the Internet of Things, it is also hoped to provide services with the best transmission quality and the fastest transmission speed. But is the so-called shortest path really the best path? For example, on the robot path, there is a shortest path, so all robot path planning uses this path. Communication in the Internet of Things is also similar, all communications are concentrated in one communication node. The result of this is the "congestion" of robot or Internet of Things communication. At this time, the so-called shortest and best path is likely to become the "worst" path. Therefore, how to avoid such a result and make path planning achieve the best result is what this paper tries to discuss and solve. For example, Inkyung Sung [1] et al. proposed a neural network-like algorithm to use offline path data for real-time path planning. Its main purpose is to avoid collisions with obstacles in the environment when the robot is operating. Fatin Hassan Ajeil [2] and others proposed (Aging-Based Ant Colony Optimization, ABACO) algorithm for grid-based mobile robot path planning. In addition, in the research of Radmanesh [3] et al., it is proposed that although the A* path algorithm is very simple, if it is a very complex map, or if there are many variables in the entire map, it will consume a lot of computing resources. However, in the above research, after the path planning, the condition of the actual robot during operation has not been taken into consideration. For example, the originally planned path is no longer available, or all path planning calculates the same result, which will make the original optimal path planning result worse. In addition, in the robot part, although the current SLAM [4] (Simultaneous Localization and Mapping, SLAM) has been quite mature, but there are still several problems. For example, sensors such as lidar or image, if they are not detected, or because of sensor errors, the environment is constructed incorrectly, these will cause problems in the follow-up robot path planning, and there are similar problems in wireless communication. For example, it is necessary to optimize the communication quality or speed through other communication nodes, but it is impossible to know the status of the bandwidth and number of connections of the surrounding communication nodes. In this way, if only the signal strength is used to process the communication data, there may also be a problem that the best efficiency cannot be obtained. Therefore, this thesis tries to use artificial intelligence. On the issue of path planning, in addition to finding the results of the shortest path or the shortest time, it will also include possible states, such as whether all planning results are The same, or the probability of possible path conditions, as well as issues such as path quality and update rate are taken into account. Through this method, the level of the entire path planning can be made more complete, and when new variables appear, they can also be added to the planning conditions in real time. Through this method, it is hoped that the path planning can optimize the result and be able to Taking into account many possible situations and probabilities, instead of just pursuing the shortest path to obtain the shortest time, so that the entire path planning can actually be closer to the real situation in the communication between the robot and the Internet of Things, and truly achieve the goal of optimization.

2. System Architecture

In the traditional path planning method, the length of the calculated path and the length of time are usually used to plan, but there are usually several problems in this way, (1) there will be a problem of path concentration, that is, all the shortest paths are used in planning Or plan in the shortest time, but this will cause all planning results to be concentrated on one path, which will cause congestion. (2) It is impossible to consider the temporary state, such as a car accident or road damage, which will also cause a detour even though the optimal path is planned. (3) The path data has not been updated for a long time, so the original shortest path is no longer available. (4) Although it is the shortest path or the path with the shortest time, but because the road condition is unstable or the quality of the road condition is not good, it cannot be driven at the fastest speed, which will also deteriorate the result of the shortest path. Based on the above problems, we are thinking about using artificial intelligence to deal with these problems. On the basis of path planning, we still use A*[5] as the basis of path planning, because this algorithm is simple to calculate, although it can only be used to find the shortest path, but we use this basis, coupled with artificial intelligence processing, try to find a path that considers various variables, and then let the user or use specific options to find the most suitable path. In the part of artificial intelligence algorithm, we choose LSTM [7] based on recurrent neural network RNN [6]. The conditions and the establishment of the model can achieve different results such as one-to-one, one-to-many, many-to-one, and many-to-many, and such characteristics are just suitable for the application of path planning, that is, according to different needs and settings, find out a variety of options, and then find out the best feasible solution according to the actual situation and user needs, instead of only a single shortest path or shortest time. Figure 1 is the basic structure diagram of RNN, x represents the input data, h is the output, the result of yesterday's prediction can be used as the data of today's prediction, forming a long chain. But in practice, RNNs do not perform as expected in long-term memory. For example, in the known RNN model, if there are situations that appear in a long period of time, these long-term situations will be "forgotten" during the long-term learning process, that is, they will not appear in the end. Now in the final result, these "forgotten" factors will appear.

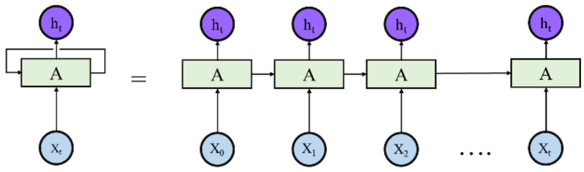

Fig. 1. The RNN basic structure diagram.

Therefore, LSTMs are designed to improve the short-term memory of RNN. Although the RNN constitutes a huge neural network, if we enlarge the internal units of the standard RNN, it is a rather simple architecture. Its architecture is shown in Figure 2, usually only one layer, including an equation called the activation function, there are several choices for this equation, which is represented here by the hyperbolic function tanh.

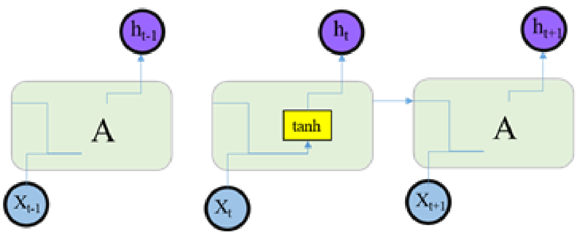

Fig. 2. The LSTMs basic structure diagram.

In LSTMs, it is more complicated and is mainly divided into several parts. Its architecture is shown in Figure 3. In this Figure 3, the first area is the core concept of LSTMs: adjustment through gates. The horizontal line from left to right in area 1 is used to represent the cell state. It can be imagined as a road that runs through all cells, that is, to bring information from one cell to the next. For example, yesterday used A condition, the "memory" of planning

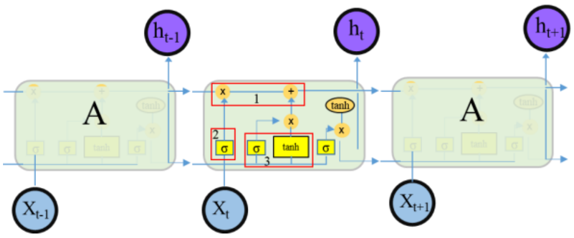

Fig. 3. The LSTMs structure diagram.

the path using condition B the day before yesterday.

But this memory can be adjusted through the orange gate. In this paper, the control of this gate will be handled by using conditions such as accuracy rate and demand degree. The range is 1%~99%. It is mainly used as the ratio of different states or requirements, or the length of the path, The choice of the length of time, etc., and since we will not turn all the ratios into 0, the conditions used in the past will be retained, and can still be used as the result of planning at an appropriate time. The part in area 2 is used to determine how much the judgment results of the previous layer should be retained. Similarly, we also use the range of 1% to 99%. The area 3 is used to determine how much information is used for judgment. Since LSTMs are based on the RNN algorithm, the current-end neurons have accumulated a lot of calculated data, which will cause a lot of calculations for operations and decision-making. Time, so there must be a trade-off, and this area is for this purpose. In this article, we use the conditional structure of the multi-element tree. The biggest difference between this and the traditional binary tree is that the binary tree only has "0" and "1" ", "true" and "wrong" judgments, while the multiple tree will provide more options, and these options are also derived from the user or the past planning results, here we are for each condition The setting range of is 0%~100%.

For example, if the user only needs the shortest path and the shortest time, and other conditions are not considered, then the relevant conditions can be set to a maximum value or ignored. Through this mechanism, the entire path planning can be made more flexible. It can appropriately reduce the calculation time required due to too much data. Through such a mechanism, LSTMs will eliminate too long data for RNN, and can not provide more conditional screening mechanisms and other shortcomings. This is very helpful for us to use LSTMs algorithm for robot path planning and node path planning for Internet of Things communication. Next, we will explain how to use LSTMs to plan the communication path between robots and the Internet of Things.

2.1. *Experimental methods and results*

In the path planning part, this article uses the Titu database of Yunlin and Chiayi, Taiwan. The reason for choosing this database is that many places in this area are mountainous, so road conditions often have to be closed due to weather or engineering Or slow down, and we use this database to randomly select data in small areas, and then use LSTMs to plan and test the entire route. In the path planning part, this paper not only uses the basic data such as each path in the database and the time required for the driving path as planning parameters, but also adds the following parameters for path planning:

(1) Data update rate: This parameter refers to how often the map database is updated. This is one of the key points that affect the planning results. The higher the update rate, the better the accuracy of the data, and these data can be used through actual paths. And update.

(2) Accident occurrence rate: This refers to the possibility of accidents such as closure and blockage of the path, usually due to weather or unwarranted conditions, and this parameter is also adjusted through the accumulation and update of actual data.

(3) Allocation rate: mainly to avoid that all planning results are the same, which will cause path blockage and reduce the efficiency of planning results.

(4) Expectation indicators: mainly users can choose the shortest path, the shortest time, or choose to take a longer detour and spend a little more time, but it can avoid possible congestion caused by heavy traffic during commuting hours or when everyone uses the shortest path and other issues.

In addition, after the path planning in advance, the test status will be sent back to the database in real time during the actual test. If there is congestion, slow down, or other conditions, the relevant parameters will be updated in real time. Through such a mechanism, the status of the database can be kept up to date at any time. In the part of the experimental platform, it is divided into robots and IoT modules. In the part of the IoT module, we use the test platform designed by the STM32 microprocessor. This platform supports wireless communication functions such as WI-FI, Bluetooth, and LoRa, so it can be used Different wireless communication makes data transmission faster and more reliable. This module is shown in Figure 4. In the mobile robot part, we use the robot shown in Figure 5. This is a robot that can perform tasks outdoors. It also has the functions of laser positioning and 3D laser environment construction. It also uses STM32 microprocessors. The communication module of the machine, so the execution of the entire path planning, as well as the subsequent update of the map database, etc., can be updated accurately and in real time.

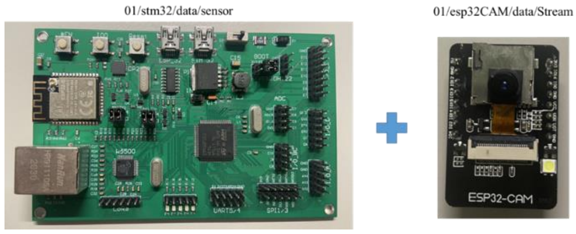

Fig. 4. Base on STM32 chip IoT Module Block Diagram.

Fig. 5. Mobile robot.

This article uses the above-mentioned IoT modules and mobile robots to test the results of path planning using LSTMs. The overall operation is in good condition. During the test process, we also encountered path blocking, unexpected path interruption, and others mentioned at the beginning of this article. Different situations can be resolved and re-planned normally in this system.

3. Conclusions

This paper proposes an artificial intelligence path planning method using LSTMs. This method is based on the RNN algorithm, but through the adjustment of relevant data and parameters, the less frequently occurring data will not be excluded as when using RNN. Moreover, the use of data and parameters can make the overall planning result better through learning and parameter control. Through this method, we actually tested the IoT module of the STM32 microprocessor and the mobile robot, and the preliminary results were normal. However, due to the relationship between time and related equipment, it has not been tested with various platforms and map databases. We will continue to test in the future and hope to be able to develop it in the end. A path planning system that considers the real environment and can be used in practice.

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