IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE)
e-ISSN: 2278-1684, p-ISSN: 2320-334X
PP 27-31
www.iosrjournals.org

Using an AI Technique Navigation and Path Planning for Mobile Robot on Webots Platform

Krishna Kant Pandey[1], Mahesh S Pol[2], (Prof.) D R Parhi[3]
[1,2,3] Department of Mechanical Engineering, National Institute of Technology, Rourkela, India

ABSTRACT: *The mechanics of robotics science consistently dealing with one most successful creation of this discipline i.e. mobile robotics. To control navigation strategies for mobile robot is the very common area of research in robotics. Aim of this investigation is to observe the range of requirements as well as recognize with major areas within the scale and to discuss proper systems for achieving these requirements. In recent, mobile robotics is one of the most favorable areas for research, in which how to control the motion inside environment; study well. To create collision free navigational path for mobile robot on working platform without physical interaction between human; recurrent neural network (RNN) techniques is implemented with sensors, which mobilize the environment data at the stage of path formation. AI (RNN) technique covers a continuum degree of technologies based on application. In this article, various prehistoric methodologies and several progressive space sciences with engineering techniques, as well as development and control of navigation system well defined. For theoretical and experimental analysis Webots simulation software is used. Finally, RNN simulation result shows the effectiveness of the control algorithms.*

Keywords: *Mobile Robot, Navigation, Path Planning, Sensor Integration, Webots*

I. INTRODUCTION

Form last decade, requirements related to control unit of mobile robot is the essential concern and which is the reason; navigation and path planning studied extensively. To generate online map for path planning sensors network has been used widely. Hence, robot move from one pose to another and avoid obstacles on run time in effective manner. In addition, to conduct autonomous navigation on ambiguous environment, where stationary and moving obstacles (human, robots) co-exist, a mobile robot must be able to detect uncertainty at real time [11], [12]. The robot system employed with wheel encoders, sensor network, odometers and camera to detect nearby obstacles. This paper deliver recurrent neural network (RNN) based learning methodology.

RNN approach [8], [9], [10] has been extensively used in recent year, if integrated map learning (integration of sensory) required. During the navigation, current position of the robot can be known continuously from sensor fusion, odometry and camera readings. During navigation, the mobile robot is continuing with significant navigation errors, which can be made due to equipment readings; accordingly, estimated location is far from the actual one. Therefore, switching between local and global frames is employed for a calibration purpose after odometry errors are accumulated. This methodology offers two advantages compare to other method. Primarily, the gathered odometry errors can be balance and precious navigation may be achieved. Secondly, if sensor fusion is not achieved, at that time robot navigation remain without a disturbance under the calibrated local coordinate frame for a short distance.

II. ANALYSIS OF RELATED WORK

In the area of robotics science researchers contributes essential interest in the part related to autonomy of robot as well as its flexibility in different environment and constraints. To solve related problem different methods has been used. The success of any projecting system depends on its efficiency and effectiveness of the solution, after implementation in real world. Day by day researchers conducted various investigations to improve robot autonomy; accordingly, today control projects have been developed widely.

In particular, recurrent neural network RNN is a dynamic part of neural network, which involves both methodology feed forward and feedback connections [2], [13]. RNN mainly used for optimize the control problem. Recently many robotics projects cover RNN to develop suitable control systems and optimize the navigation map [4], [5]. Further, localization problem related to mobile robot is the estimation of robot's location and orientation comparative to its environment. In addition, it is the major problem related to mobile robotics science as well as it plays principle role for much successful navigation. Moreover, to develop the control algorithms, which has ability to create collision free path (to follow obstacle avoidance behavior) [14], [1], [3]; is the module of advanced robotics control systems.

III. PATH PLANNING ALGORITHMS

In this work, we suggested an algorithm for mobile robot navigation as well as design system with the combined effect of sensor network as well as learning algorithms (RNN), to solve the problems with path planning and obstacle avoidance for smooth environment. Further, the kinematics structure of robot defined as follow: it has two axes i.e. front axis-composed of two steer standard wheels and operated by a servo motor through rack and pinion, which follow the control architecture of rear axle. On the other hand, drives wheels are fixed in the rear axle of the robot and controlled by two servo motors. In addition, infrared sensors and camera are mounted on the body for obstacles detection (front, left, right). Odometery mounted for distance measurement, travel by mobile robot.

GEOMETRIC MODEL

To develop the robot motion, we illustrate the kinematics configuration of mobile robot presented by "Fig.1". Where, ICR is the instantaneous center of rotation, 'R' is the radius of gyration, "x_m',x_m" is the direction of the robot, given by the main axis that is perpendicular to axis of front wheels and 'θ' is the angle of direction i.e. the angle between (x_m',x_m) and (x',x). We assume that the robot movement is either a pure translation or a pure rotation with a constant velocity:

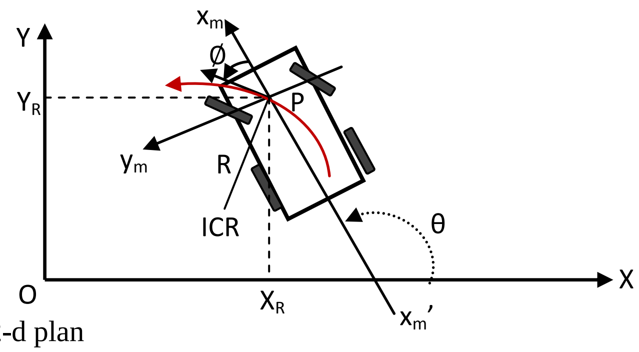

Fig.1 robot model in 2-d plan

At that time, our device possesses two types of motion first one is rectilinear and second is circular. These models mathematical presented by equations:

For rectilinear motion:

$$X_i = X_{i-1} + t_{i-N} * \omega_m * m_w * \cos(\theta_i) \quad (1)$$

$$Y_i = Y_{i-1} + t_{i-N} * \omega_m * m_w * \sin(\theta_i) \quad (2)$$

$$\theta_i = \theta_{i-1} \quad (3)$$

For circular motion:

$$X_i = X_0 + m_w * (\sin(\theta_i) - \sin(-\omega_g * t_{i-N} + \theta_i)) \quad (4)$$

$$Y_i = Y_0 + m_w * (-\cos(\theta_i) + \cos(-\omega_g * t_{i-N} + \theta_i)) \quad (5)$$

$$\theta_i = \theta_{i-1} + pas \quad (6)$$

Where 'θ' indicates the directional angle of robot axis, 'r_w' is the radius of wheel and 'N' denotes the periodic motion of wheel. Similarly, 'ω_g' denotes the angular gyration velocity, 'ω_r' represent the angular velocity of wheels and 'pas' indicates the step of rotation during test period. This approach involves navigational path planning algorithm for wheeled robot in known as well as partially unknown (due to presence of human and robot) environment. Further, robot measures mobile distance with reference to its actual position. With reference to path planning; to find a sequence of movement inside environment is the most problematic area. Indeed, we know that between two states (i.e. robots pose to goal pose) eternity mode of paths configuration is possible. Accordingly, we have finding out perfect and shortest path related to two states of configuration. In fact, the evaluated path do not poses complete straight line between two configuration, and maximum time it follow straight line. Accordingly, radius of gyration is fixed (up to 110 degree with rack and pinion) due to partially use of steered slandered wheel for front side or follower side. The robot receive signal from teleoperator or follow the sensory information after fusion as well as compare actual data to reference data to find perfect navigational path.

Obstacle Avoidance Algorithm

At each interval, infrared sensors S1, S2, S3, S4 and S5 provides the obstacle distances as well as environmental information and based on these information (after sensor fusion and integration) robot construct its navigational path. We consider values only; which are less than or equal to 10 cm for analysis of shortest and perfect path. In order to find the possibility of path the value greater than 10 cm stated as '0' and '1' if less than. On the other hand, if robot navigates towards the goal, at the same time classification of obstacle situation that may disturb the movement of robot has been made "Fig. 2 and 3(a)". The output trajectory towards target 'S = [T1 T2 T3 T4 T5 T6 T7]' for different states, which signifies the seven possible states and avoid the obstacles as shown in "Fig. 2 and 3(a)". If the robot does not receive any signals from its sensory part during his movement; then, we say that rout is clean; free navigation possible. Now, addition of eighths output T8 activate the free path and robot decides itself to move forward. Target achieving provides eight outputs for different environmental conditions; therefore all are presented as single function:

F = 0: free path T8 activated, F = 1: Output T1 activated, F = 2: Output T2 activated, F = 3: Output T3 activated, F = 4: Output T4 activated, F = 5: Output T5 activated, F = 6: Output T6 activated, F = 7: Output T7 activated

Description of an Algorithm

To describe in detail, firstly the robot receives its target coordinates inside environment and clarify its actual position in these directional frame i.e. O, x, and y. After that localizes the environment conditions such as neighbors' obstacles, wall and other uncertainty with the help of sensors and camera.

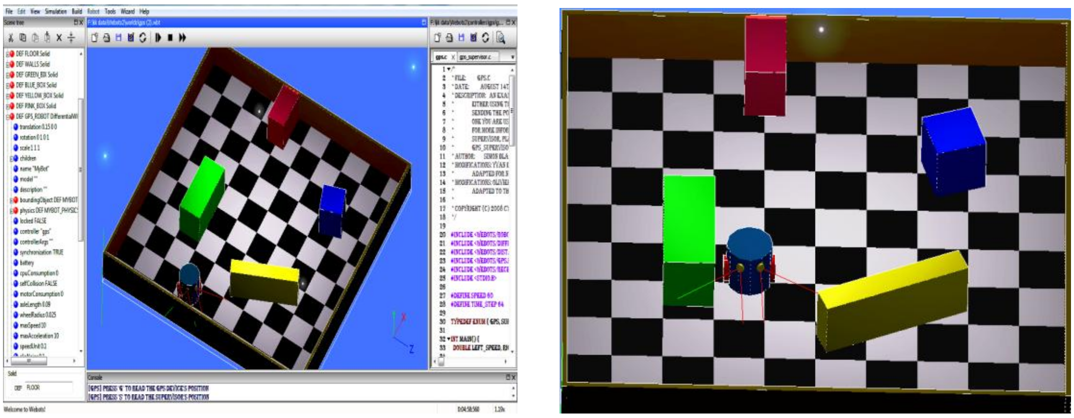

Fig. 2(a) represent the overall configuration of the model (b) show the obstacle detection by mobile robot

To predict the next movement stage, sensor fusion delivers the perfect data after integration. Similarly, the robot drafts its path confidence according to integrated data; two feasible cases calculated. First one, if the sensors data indicates obstacles are present in the path, at the same time obstacle avoidance algorithm is activated to create collision free path; otherwise the robot continues its motion unless the target is not reached. After each period of certain time, the robot updates its position (coordinate) using the localization algorithm. Finally stop condition is arising for mobile robot. Condition is, if the distance between robot and target is less than or equal to 2 cm; implies that robot follow the stop condition. This approach is well developed on webots simulation platform including different obstacle conditions "Fig. 2".

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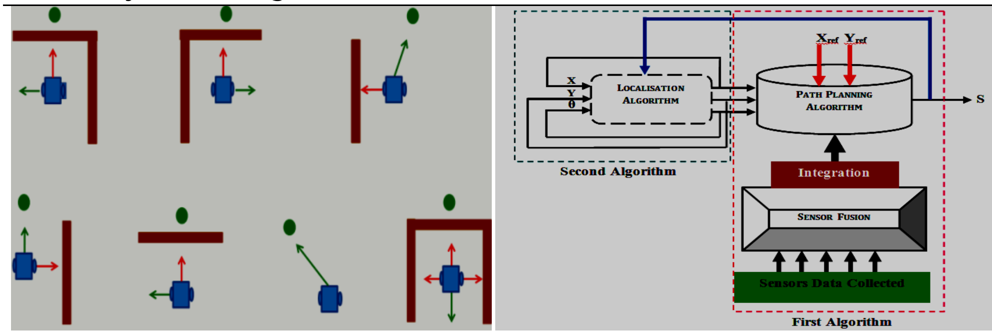
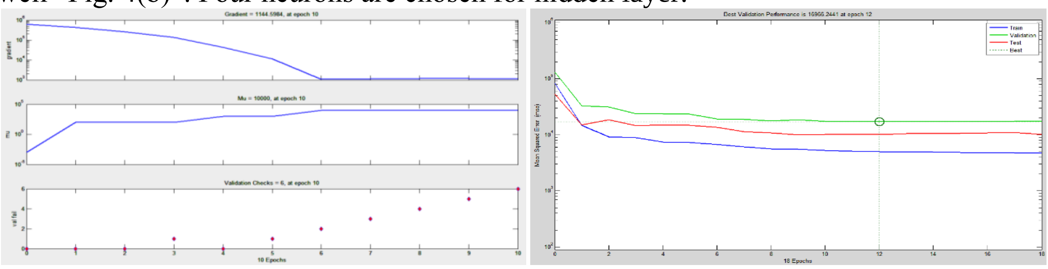


Fig. 3 (a) various situation of obstacle avoidance (b) architecture of the control algorithm for erection of navigation strategies

With reference to environment, the safe and perfect path searching by robot towards target depends upon execution of precious motion at different location with different moment. Consequently, robot performs different tasks with reference to position of the obstacle such as front obstacle-turn left or right according to target, back obstacle-free movement, turn right and left-if obstacle (robot & human) in motion. The proposed algorithm performs our tasks with different stages or simply says, algorithms divided into two sub-algorithms to perform tasks and presented by "Fig. 3(b)": First is path planning algorithm that uses the target coordinates 'X_{ref}' and the current coordinates of the robot (X, Y, θ) and second is the localization algorithm. Both algorithms solve using intelligent technique and first learning algorithm results depend upon second one.

Intelligent Algorithm **(RNN Localization)**

The proposed work is based on part of neural network [6], [7] (NN) learning technique i.e. (RNN) and solved by combined effect of localization with recurrent neural network (RNN). This project explores; how to planned mobile robot predict its position periodically using odometry system as well as how to updates its coordinates systems. The RNN is implemented for path planning and navigation after sensor fusion as well as updates its navigation map according to sensor data. In addition, 'Se' stands and includes the sampling data for further reference and express robot configuration in the Cartesian coordinates system (O, x, y) based on rotational principle. In fact, the robot calculates its future or current configuration with reference to previously maintain position and navigation action. Indeed, RNN stands for position parameters (X,Y,θ) and work already executed by the robot as the output 'S'. Accordingly, the network provides the new configuration to the robot (X, Y, θ), depends upon previous network. After that, combined all network to evaluate the final output as presented in Fig. 3(b) and 4. The backpropagation algorithm based on Levenberg Marquardt network function training pattern has been used for learning purpose. In addition, hyperbolic tangent sigmoid transfer function is used for the hidden layer and linear transfer function used for the output layer. According to the means squared errors, measurement of the network's performance has been done well "Fig. 4(b)". Four neurons are chosen for hidden layer.



(a) *(b)*

Fig. 4 (a) show the value in test phase, (b) curves represent the errors of train (blue line), validation (green line), test (red line) and best (dotted line) data

At the time of training phase navigation, significant improvement has been considered with robot movement and it is all about due to communication with RNN over simply neural network. Finally, we have check the fixed architecture with different data of RNN and the outputs of test phase are represented by "Fig. 4". In this figure straight line represents the desire position at each interval. Including four inputs for path planning (i.e. 'X-Xref','Y-Yref', 'θ' and function of obstacles 'F') and one RNN output (i.e. 'S') the overall RNN processes has been projected. With RNN, after setting the weights and preferences; system tested with different base. "Fig. 4" represents the result of MSE for test phase of RNN with curves.

Notice that, if the distance increases as well as many changes has been made with direction of the mobile robot, at that time inaccuracy of the robot configuration substantially increases the inaccuracy due to cumulative errors, which created during the integration of different elements with displacement of robot. Accordingly, the use of backpropagation methodology reduces these types of errors and learning creation achieve preciously by robot.

IV. CONCLUSION

This investigation is based on RNN for path planning as well as development of autonomous navigation learning algorithm for a mobile robot, functioning in a known and partially unknown environment in presence of obstacles. Firstly, we learnt obstacle avoidance algorithm and secondly developed the localization technique for mobile robot navigation, which is essential stage for development of path planning algorithm. In addition, obstacle avoidance algorithm plays an important role while mobile robot developing the collision free path. To control the robot, two integrated RNNs algorithm are developed and both are connected in series. Environmental map develop by robot depends upon sensor fusion and learning of RNN. The advantage of RNN based methodology is that, it can't require any heavy mathematical model. The robot motion depends upon RNN network which is connected in series and integrated over time to time. In this paper, firstly RNN helps to develop the localization technique after that, embedded for path planning. As a result, the developed intelligent algorithm offers the mobile robot to construct its collision free path as well as robot able to find its target in an environment. In addition, the developed algorithm is easy to implement in realistic world. Finally, it offers abundant capability to the robot, to estimate its position inside environment with precious rate and attain target in efficient manner.

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