Proceedings of NILES2021:
3rd Novel Intelligent and Leading Emerging Sciences Conference

Obstacle Avoidance of a Point-Mass Robot using Feedforward Neural Network

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2021 3rd Novel Intelligent and Leading Emerging Sciences Conference (NILES) | 978-1-6654-2157-7/21/$31.00 ©2021 IEEE | DOI: 10.1109/NILES53778.2021.9600550

***Abstract*—Machine learning is presently acknowledged as a significant ingredient of research in many fields, including robotics. The use of robots to perform assorted tasks is evident in difficult, uncompromising, and hazardous spaces and sectors such as manufacturing, transportation, healthcare, landmines, mining, patrolling, disaster relief etc. For a robot to carry out its assigned task, it normally has to navigate safely without collisions to different locations, which also means understanding its working environment, collectively known as the robot navigation problem. This paper considers finding a solution using neural networks to the robot navigation problem, particularly the path planning problem that includes fixed obstacles. The objective of the path planning problem is to find a route to the final destination that is optimal and also collision-free. Different training algorithms and network structures are used to construct models that can predict a turning angle for the point-mass robot which will be used to avoid obstacles in the robot's path to the destination. This paper will present a comparative analysis of the performance of different feedforward neural network models. The results suggest that the feedforward neural network model with 10 neurons and Bayesian regularization performed the best. The model has been used to avoid obstacles in two different environments. The trajectories show that the robot has safely avoided obstacles in its path and reached the destination.**

Keywords— machine learning, neural network, navigation, robot, performance

I. Introduction

A robot is a machine that replicates human actions and is able to carry out complex and different tasks in industries such as manufacturing, logistics, home, travel, health, mining, civil, military, and transportation [1, 19, 20, 21, 22, 23, 24, 36]. Since robots are mostly mobile, navigation in its environment is of utmost importance. While navigating in its environment, a robot must avoid collision and unsafe conditions to reach a specific location. There are four categories of robot navigation problems: localization, path planning, motion control, and cognitive mapping [5]. This paper looks at the path planning problem.

Robot path planning is an active area of research for the last four decades due to its application in real-world applications. The basic objective of robot path planning is to find an optimal and safe path from source to destination. The literature consists of many research work associated with path planning [9, 33, 34, 37, 38, 39, 40, 41]. Solving path planning problems can be divided into classical, heuristic, and machine and deep learning methods, although there are different clusters and categories stipulated in the literature. Classical methods include artificial potential field [13], cell decomposition [11], road map [14] and virtual force field [4]. Heuristic methods include optimization algorithms such as fifrefly, ant-colony, paticle swarm and many more [6, 15, 42, 43]. Machine and deep learning approaches include algorithms such as neural networks, decision trees, Naïve Bayes, and many more. This paper focuses on the machine and deep learning techniques.

Machine learning utilizes data to learn and subsequently carries out a task based on experiences without being programmed. Machine learning has been applied to industries and sectors such as finance, healthcare, social media, transport, to name a few [2]. Over the years, there has been a significant increase in the use of machine learning techniques in robotics, especially in the area of motion planning and control. In recent times, areas where robotics has utilized machine learning and became popular include modeling vehicle dynamics [16], legged locomotion [16], off-road rough-terrain mobile Robot navigating [24], Robot vision [12], Field Robotics [16], humanoid Robotics [29] and medical and surgery Robotics [29].

This paper aims to use feedforward neural network to solve the path planning problem for a point-mass robot. In particular, models will be constructed using three different network structures and training algorithms selected from literature to predict a turning angle. The point-mass will use the turning angle to avoid fixed obstacles of different sizes in its path to the final destination.

The main contribution of the paper are:

(1) Feedforward neural network models: different neural network models are used to train the data and predict the turning angle of a point-mass to avoid obstacles.
(2) Comparison of the models: mean squared error is used to measure the different neural network models used

in this paper. According to the literature, the model with a lower mean squared error is considered the best model.

(3) Training data: new training data of different scenarios have been obtained using computer simulations. That is, the data is not obtained from real-life experiments or downloaded from any websites.

Organization of the paper: Section II presents the literature review. The objectives of the paper are presented in section III. The modeling of the point-mass robot is described in Section IV. Section V discusses the dataset, the training algorithms, and the performance measure of the models used in this paper. Section VI discusses the proposed model architecture. In Section VII, the comparison of the neural network models in terms of mean squared error is presented with discussions. Section VII also presents the trajectory of the point-mass robot in two different scenarios using the best feedforward neural network. Finally, the paper concludes in Section VII, discussing its contributions and recommendations for future work.

II. Related Work

In literature, there are many instances where machine learning algorithms have been used for robot path planning. Duan and Hang used the imperialist competitive algorithm (ICA) to train a novel hybrid method for the globally optimal path planning of Unmanned combat aerial vehicles (UCAV), which was based on the artificial neural network (ANN) [8]. This hybrid method was compared with the artificial bee colony (ABC) algorithm. This study aimed to reduce the uncertainty of the evolutionary computation caused by the probability model. This is achieved by minimizing the objective function, which reflects the accuracy criterion, root-mean-square error (RMSE).

In [27], the authors used the neural network-based mean-field game (MFG) theoretic approach to control collation amongst unmanned aerial vehicles (UAVs) for mission-critical applications. The MFG learning control algorithm is used to control and optimize the real-time acceleration of each UAV to avoid inter-UAV collisions. The model was trained using two partial differential equations, namely Fokker-Plank-Kolmogorov (FPK) and Hamilton-Jacobi-Bellman (HJB) equations. The mobile surveillance system is another area where path planning optimization is utilized. Wai and Prasetia designed an online adaptive neural network (ANN) controller to control surveillance UAV [29]. This controller was able to predict energy consumption while anticipating disturbances. The proposed ANN control claims to improve average root-mean-square error (RMSE) of horizontal and vertical tracking performance by 49.083% and 37.50% in comparison with a proportional-integral-differential (PID) control and a fuzzy control under the occurrence of external disturbances.

Wang et al. proposed a new algorithm, namely fuzzy neural network (FNN), which was used to optimize path distance while moving the robot from the start to the target [31]. The FNN can be processed in parallel and is self-learning like a neural network. However, it can also process fuzzy information like fuzzy theory and complete the fuzzy inference function. The algorithm claims to have a faster convergence speed and improves the mobile robot's intelligence level.

Rapidly random-exploring tree (RRT) and its variants are quite popular for their ability to quickly and efficiently explore the state space, but they suffer sensitivity to the initial solution and slow convergence to the optimal solution. This leads to a huge consumption of memory and time to find the optimal path. To overcome this problem Wang et al. proposed a solution that would quickly find a short path in many applications, such as the autonomous vehicle with limited power/fuel [32]. The new algorithm proposed, neural RRT* (NRRT*), which is based on a convolutional neural network (CNN), is used to predict the probability distribution of the optimal path on the map. The NRRT* utilizes a non-uniform sampling distribution generated from the CNN model. Just like mobile robots and UAV's, the autonomous underwater vehicle (AUV) system has a great number of applications. Zhu et al proposed an integrated biologically inspired self-organizing map (BISOM) algorithm for task assignment and path planning of an AUV system in three-dimensional underwater environments with obstacle avoidance [35]. This algorithm embeds the biologically inspired neural network (BINN) into the self-organizing map (SOM) neural networks. The SOM neuron network assigns a team of AUVs to achieve multiple target locations in underwater environments while BINN updates the weights of the winner of SOM. The performance of the BISOM algorithm was compared with the potential field-based particle swarm optimization (PPSO) algorithm in terms of path length, time complexity, and energy consumption.

A major application of neural networks in path planning is the online adaptation and re-computation of the path of automated vehicles when faced with newly detected and closely located objects in uncertain operational environments. Sung et al. trained two neural networks using the offline path planning algorithms [28]. Then the two resultant neural networks' performance is analyzed in a simulation environment where unknown objects are suddenly detected by an automated vehicle. This study investigates the important properties of the training data that make the neural network more reliable as an online path planner. Human-like path planning can be a challenge for automated vehicles.

Rehder et al. used the convolutional neural network (CNN) as a basis to train the planning networks to imitate human demonstrations in complex traffic situations [23]. A Value Iteration Network (VIN) was trained to imitate human motion planning behavior and the simulated trajectories demonstrated that human actions can be reproduced. The design aspects of VIN were the map size, the choice of the transition filters and the transition costs, and the fully convolutional residual network with dilated kernels were used to predict the transition cost.

Prasad et al. proposed to solve the findpath problem of a mobile point-mass robot using ANN [17]. In this study, two neural networks were trained via multilayer perceptron to predict the direction and angle of turn of the robots to move in the free space of the workspace while avoiding obstacles. The first neural network indicates whether the robot should turn or not, while the second determines the precise angle of turning.

In summary, different types of neural networks has been used to solve the path planning problems. Of course, the literature shows that there exists different problems in path planning and the methods depends on the problems. This research is similar to [17], where the authors used multi layer perceptron to solve the path planning problem, however, the details such as mean squared error or any other measure for performance is not discussed.

III. Objectives

Let P be the point-mass, W be the workspace and $O_1, O_2 \ldots, O_n$ be fixed circular obstacles. $O_1, O_2 \ldots, O_n$ are randomly placed in W. Assume that the location of P and $O_1, O_2 \ldots, O_n$ is a priori known. The goal is to move P in W from the initial position to target using a velocity function and avoid $O_1, O_2 \ldots, O_n$ using a machine learning model. The machine learning model will predict an angle that will be used to avoid obstacles. We will consider different neural network models in the paper. The objectives are:

1. Compare different neural network models suitable to predict the angle for obstacle avoidance.
2. Simulate the trajectory of P in W with $O_1, O_2 \ldots, O_n$ using the best neural network model.

IV. Modelling the Point-Mass Robot

Definitions of the bounded workspace, W, and a point-mass, P, are adopted from [17, 18]. Figure 1 shows a schematic representation of P in W, with start point and target. P moves towards the target from a location with a velocity, v. The workspace is a rectangular region with four boundaries, namely, left, right, upper and lower boundaries.

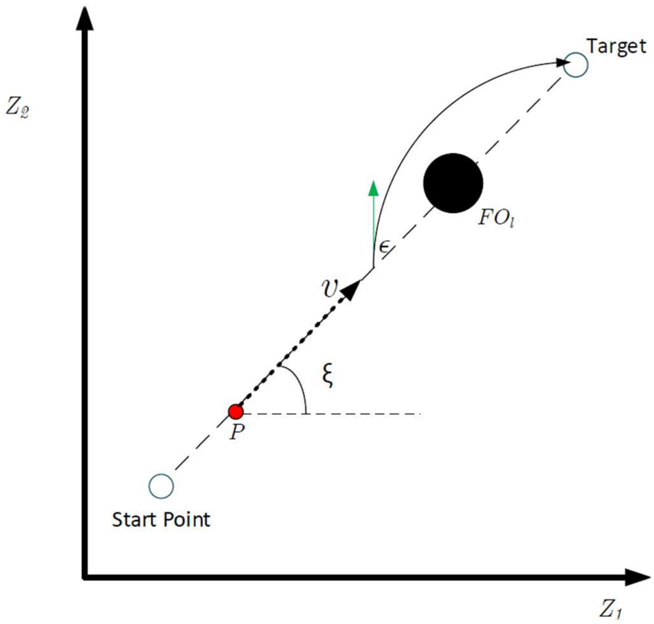

Fig. 1. Schematic representation of a point-mass P in a workspace W.

As shown in Figure 1, the point-mass P moves towards the target from a start point at a velocity, v, and on its course, it will avoid any stationary obstacle (FO is a fixed obstacle) in its path. The direction of the point-mass movement towards the target is determined by ξ. To avoid an obstacle, ϵ (turning angle) is used. If $\epsilon = 0$, then the point-mass will move straight towards the target. If $\epsilon > 0$, then the point-mass will turn left, otherwise it will turn right.

V. Methodology

A. Dataset

The training and testing data for the machine learning algorithms were constructed using MATLAB software. As shown in Figure 2, the training environment consists of a point-mass, starting position (initial), obstacles of different sizes, a target, three buttons (start, stop, next), and a slider. A point-mass will move with a velocity towards the target. Any obstacle that comes in its path will be avoided manually using the slider. The slider represents ϵ as discussed in section 4. When the slider is kept at the center, the value for ϵ is zero; the point-mass will move straight towards the target. If the slider is shifted towards the right, the value for ϵ increases and the point-mass turns right; otherwise, the point-mass will turn left.

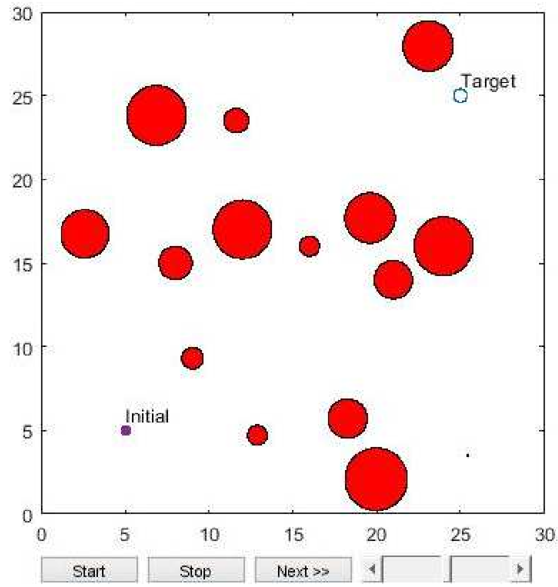

Fig. 2. Training data collection environment.

Table I describes the dataset. There are three attributes (Theta, Thetaobs and 1/MINDIST) and one class (turning angle) in the dataset. The dataset consists of 10511 observations. The dataset does not consist of any missing values or outliers.

TABLE I. DATASET DESCRIPTION.

Attribute	Description	Value Range
Theta	Numeric data. It is the orientation (measured from the positive x-axis) of the line joining robot's current position and the center of its target.	-1.0408 – 1.2866
Thetaobs	Numeric data. It is the orientation (measured from the positive x-axis) of the line joining robot's current position and the center of the closest obstacle.	-1.57 – 4.7119
1/MINDIST	Numeric data. Euclidean distance is used to calculate the minimum distance between the point-mass robot and the obstacles.	1 – 5.2516
Turning angle (class)	Numeric data. It is ϵ in figure 1.	-1 – 1

The proposed feedforward neural network is trained using this dataset. The three attributes (theta, thetaobs, 1/MINDIST) become the network's input, which is known as the input data. The class data is also presented to the network known as target data. The target data defines the output of the network. The input and target data are randomly divided into training, validation, and testing data. The authors have used 70% (7357 samples) of the data to train the network, 15% (1577 samples) of the data to validate, and the remaining 15% (1577 samples) of the data to test the network.

MATLAB R2018a software is used to train, validate and test the network. Also, this software is used to model, simulate the point-mass robot in its environment and collect training data as well.

B. Feedforward Neural Network and Training Algorithms

Table II shows the training algorithms with their description used in this paper. These training algorithms will be used to train the feedforward neural network and construct different models that will be used to predict the turning angle.

TABLE II. TRAINING ALGORITHMS.

Training Algorithms	Description
Levenberg-Marquardt	A network training function that uses Levenberg-Marquardt optimization to update weight and bias.
Bayesian Regularization	A training function that minimizes squared errors and weights and determines the correct combination.
Scaled Conjugate Gradient	The scaled conjugate gradient method is used to update bias and weight.

Altogether, there will be nine models and three network structures. The first network structure will have one hidden neuron. The second network will have five hidden neurons, and the third will have ten hidden neurons. The three network structures will be trained by the three training algorithms shown in Table II.

C. Model Performance Indicators

Mean Squared Error (MSE) is used to measure the performance of the networks of the nine models. It is the average squared difference between the outputs and the targets. A model with lower MSE, when compared with other models, will be considered as a better model. If the MSE is zero, then it means that the model is error-free.

VI. MODEL ARCHITECTURE

The literature shows that neural network has been widely used in solving path planning problems [7, 10]. Figure 3 shows the architecture of the proposed network.

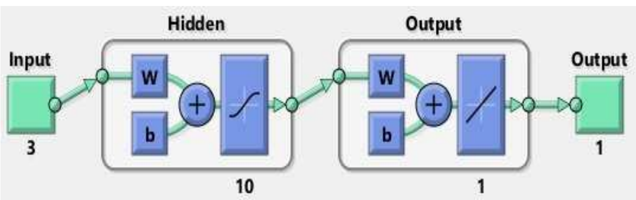

Fig. 3. Proposed network architecture.

The network consists of the input, hidden, and output layers. The input layer consists of predictor values and the output layer predicted values. The hidden layer consists of the activation function, which determines the neurons to be activated based on weight and bias. The output layer shows the predicted value and MSE.

VII. RESULTS & DISCUSSION

A. Model Comparision

The training algorithms shown in Table II have been executed 20 times with 1000 iterations. Table III shows the comparison of the nine models – three network settings with three training algorithms. For 10 neuron settings, the Bayesian regularization performed the best, including the train, validation, and test MSE's while Lavenberg-Marquardt was the closest. In the 5 neuron setting, the model with Lavenberg-Marquardt performed the best while the model with Bayesian regularization was the closest. The model with Scaled conjugate gradient performed the best in 1 neuron setting. However, the model with Bayesian regularization was the closest.

Overall, it can be said that Lavenberg-Marquardt and Bayesian regularization can be used with this type of dataset. The 10 neuron model with Bayesian regularization training algorithm was the best model. This is also confirmed by the Regression R value, which was 0.929, which is closer to 1; that is, there is a correlation between outputs and targets.

The result in this paper partially agrees with [3]. Bharadwaj and Kumar did similar study with 10 algorithms which included Lavenberg-Marquardt and Scaled Conjugate Gradient [3]. Bayesian regularization was not in the list. The model with Lavenberg-Marquadt was able to perform better when compared to others.

TABLE III. COMPARISON OF THE MODELS.

Number of Hidden Neurons	Performance				
	Training Algorithm	Train MSE	Val MSE	Test MSE	Best MSE
1	Levernberg-Marquardt	0.400203	0.398714	0.403201	0.39871
	Bayesian Regularization	**0.273353**	-	**0.264657**	0.27027
	Scaled Conjugate Gradient	0.277166	**0.280017**	0.287419	**0.255762**
5	Levernberg-Marquardt	**0.07706**	**0.085887**	**0.084598**	**0.070365**
	Bayesian Regularization	0.078638	-	0.747274	0.076325
	Scaled Conjugate Gradient	0.11263	0.111159	0.106557	0.094345
10	Levernberg-Marquardt	0.068717	0.064426	0.065201	0.063884
	Bayesian Regularization	**0.063991**	-	**0.064161**	**0.062679**
	Scaled Conjugate Gradient	0.102339	0.106778	0.102642	0.085226

B. Simulation using the Best Model

Figures 4 and 5 show the path of the point-mass robot from a source position to a destination. The figures also show that the point–mass robot is able to avoid obstacles using the feedforward neural network from any initial and target positions with random obstacles.

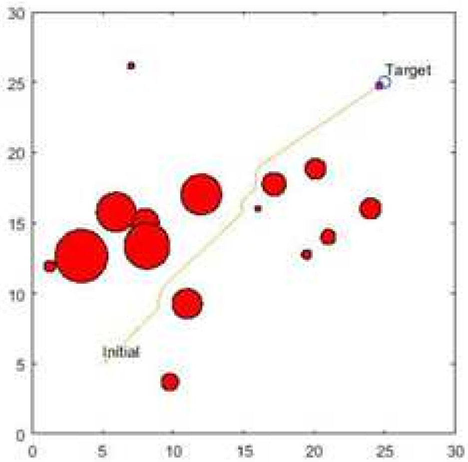

Fig. 4. Point-mass robot's path with the initial position (5,5) and the target position (25, 25).

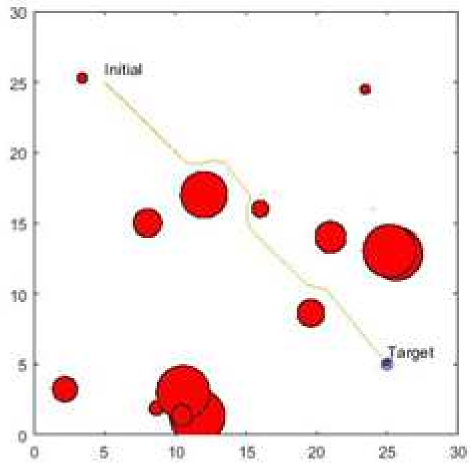

Fig. 5. Point-mass robot's path with the initial position (5, 25) and the target position (25, 5).

VIII. CONCLUSION

This paper provided an overview of models constructed to predict the turning angle of a point-mass robot to avoid obstacles in its path from source to destination. The data utilized in this paper has been collected using MATLAB software. This dataset has not been used before; hence it is the first contribution of the paper.

The dataset is then utilized to construct models of feedforward neural networks. We have used three training algorithms and three different network structures. Out of the three network structures and training algorithms, the model with 10 neurons in the hidden layer and the Bayesian regularization model performed the best. That is, the model had minimum MSE when compared with other models. We have also used the best model to avoid the obstacles on new unseen data through simulations. These were the second and third contributions of the paper.

The literature also confirms that neural network has been previously used in robot path planning problems. This research also shows that feedforward neural network is suitable for path planning problems. The models in this paper can be used for this type of dataset.

In the future work, the authors will investigate deep learning algorithms on path planning problems and also expand the work on other types of problems concerning path planning.

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