Self-directed Robot for Car Driving Using Genetic Algorithm

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Abstract The big issue with a human driving car is traffic, with the current continuous growth in the world population. The second big issue with the growing population is creating huge chaos, which leads to accidents. Every year nearly 1.35 million people lose their lives due to traffic crashes, and 20 to 50 million face serious injuries with some untreatable disability as of their road injury. Over 80% of accidents happen due to driver error. Other issues are the efficiency of the car as we are slowly transforming into the electric car. This paper introduced car with the self-driving feature using genetic algorithm to reduce the traffic with route optimization, and by reducing traffic, so that many problems related to driving can be solved. It minimizes the rate of an accident and also maximizes the efficiency of the car.

Keywords Genetic algorithm · Path planning · Car driving · Robot · Artificial intelligence

1 Introduction

Genetic algorithm is the process of selecting the fittest from the given population or set of data based on its immunity from previous test results—the result narrows down the selection chosen from the population/set of data for survival in the future. In the genetic algorithm, four stages are viewed. First, at the population, second at selecting dataset from the available considered solution, third at selecting fittest by evaluating the considered population or the dataset using the fitness function, fourth, at the modification in solution according to the situation.

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Further, fitness function takes the dataset as its source and as its product is the possible solution concerning the problem we want to solve. The fitness value is measured periodically in a genetic algorithm, and thus, it should be sufficiently fast. The inefficient fitness measurement process will have an adverse impact on the genetic algorithm (GA) and makes it too sluggish. Modification of dataset is done by changing some of the characteristics of an individual entity in the dataset to yield efficient results. Generally, the modification is used to optimize the dataset to produce the different optimal solutions and create a variance in the dataset. The termination of the algorithm happens when the dataset starts producing the same output as the last generations, which leads to random modification or mutation in data to produce the noticeably different output from the last generations.

By using a GA, we create a situation for AI as human faces to learn. It will increase the accuracy of AI to handle the traffic jams and to avoid the accidental scenario. The system with the route optimization technology and genetic algorithm to train the model creates the nearly perfect self-driving car. The autonomous car's efficiency increases by modification in route optimization dataset by training scenarios like traffic jams, red light, and parking. Training model with accidental scenario by genetic algorithm maximizes the tackling accuracy of accidents compared to drivers. It reduces the rate of accidents globally. The path planning issue of a car driving robot can be expressed as given (beginning area, objective area, 2-D guide of work environment including static deterrents), plan an impact freeway between two indicated points in fulfilling shortest path achieved with obstacles.

Probably the most concerning issue confronted when attempting to upgrade a car direction in a circuit by methods for GAs is the manner by which to pick the principal design utilized. As it is exceptionally hard to acquire programmed driving development from people that have been created by some coincidence, we chose to build up an algorithm to acquire a base direction which can finish a lap. The component of this calculation is basic, it attempts for each portion, all potential combinations of steering and acceleration, looking for the pair of qualities which keeps up the vehicle closer to the focal point of the track. When all segments have been assessed we have acquired the individual taken as a basis for the GA, at that point the driving learning process can begin. Genetic algorithm does not ensure the accuracy is sought, but the outcome is typically approximate to the equilibrium globally. Although the solution is seen as probability-based, specific optima are not included.

This paper concludes that we can maximize the selection process's speed by creating the optimal fitness function. Then we change the speed of evolution of artificial intelligence by sufficient time. Then we are close to creating the AI closer to the human functions. Evolution will take real-world datasets to optimize the process of learning and adapting to the world. The genetic algorithm is currently widely used in the car industry for autopilot driving, which works on a fuzzy control system. In today's world, the live example is autonomous driving which is used in the car. Big companies like Tesla and GM are focusing on the revolution of AI technology in system. Tesla is dominantly using artificial intelligence in their tesla model. Tesla AI is a mix of GA and unsupervised learning. Companies like Tesla, Argo Ai, Ford

Motor Company, and General Motors Company are these big giants which are using AI in their car for autonomous driving. Robotics companies like Boston Dynamics, Neural, and OpenAI all these companies are creating robots.

2 Literature Survey

Mobile robot is used in various types of situations, and it is essential for them to move in places with objects and deterrents. So as to explore the robot in an impact freeway, path planning calculations have been introduced. The principal objective of path planning is to decide the ideal conceivable way among the underlying point and the characterized objective situation in the least possible time. To obtain the goal, a new technique is proposed by using genetic algorithm [1]. However, it may be difficult to collect data from far-off destinations or from exceptionally unfriendly conditions. An algorithm is proposed that allows mobile robots to find the ways free of human intervention [2]. The mobile robot encloses the estimation devices and records the information at that point either sends it or takes it back to the administrator. Sensors are needed to identify obstructions in the path, and machine intelligent is needed for the robot to design a way nearby these deterrents. Further, an approach based on genetic algorithm is used to construct a path planner that considers both accurateness and speed as parameters [3, 4]. Moreover, a distributed model was proposed for autonomous robot navigation [5]. An algorithm was proposed based on fuzzy inference system (FIS) which finds a response to the route issues of a self-ruling automated vehicle [6, 7]. This self-ruling automated vehicle is viewed to be navigating in unpredictable conditions involving various stationary items. In realistic environment, there are certain planning problems related to motion like indoor application comprise of number of rooms, lobbies, different entryways with numerous static and dynamic impediment in between. To solve this navigation issue, an algorithm was proposed that uses adaptive path planning [8]. A comparison model based on parallel elite genetic algorithm (PEGA) was developed to compare the working of robots in different environments [9]. This model was further enhanced to work in dynamic environments also [10]. An algorithm based on hybrid metaheuristic genetic algorithm was suggested to discover ideal distance among beginning and final point [11]. Researchers focus on the fact that in certain situations, and they have to take in account conditions like temperature and pressure for gathering data from remote sites. Considering this fact, certain models for robots are developed to explore a situation in which no human is there [2, 12]. Further, a model was proposed to develop reconfigurable robot based on genetic algorithm to achieve path planning [13, 14]. However, sometimes performance varies with different parameters and environments, and to overcome this problem, more robust algorithm considering dynamic paths is proposed for navigation task [15, 16]. Table 1 shows the contribution of different authors.

Table 1 Contribution of different authors

Authors	Connected System	Localization	Assessment	Planning and Control	Datasets and Software	Implementation
Manikas et al. [2]		✓				
Shamsinejad et al. [3]		✓		✓		
Di Gesu et al. [5]		✓	✓	✓		
Patial et al. [6]	✓				✓	✓
Pol and Murugan [8]		✓		✓	✓	
Tsai et al. [9]	✓	✓	✓	✓		
Huang and Tsai [11]	✓				✓	✓
Cheng et al. [12]	✓	✓			✓	
Tanev et al. [14]			✓	✓		✓
Proposed work	✓	✓	✓	✓	✓	✓

3 Proposed Work

Car simulator used the fuzzy control system, GA, and particle swarm optimization to simulate the movement of the autonomous car on the map. Input contains the car's three distance sensors (front, 45° left and right), which can be achieved from the defined equation of motion, the car's position and the angle between the car and the horizontal axis taken as $\emptyset(t)$. Output is steering wheel rotation angle. The goal is to hit the end line without hitting the wall and output the trajectory of motion (including the position of each point in time, the value of the sensor, and the angle of rotation of the steering wheel) as a text file, then display on the graphical interface. The equation of motion is given from Eqs. (1) to Eq. (4).

$$x(t+1) = x(t) + \cos[\emptyset(t) + \theta(t)] + \sin[\theta(t)]\sin[\emptyset(t)] \tag{1}$$

$$y(t+1) = y(t) + \sin[\emptyset(t) + \theta(t)] - \sin[\theta(t)]\cos[\emptyset(t)] \tag{2}$$

$$\emptyset(t+1) = \emptyset(t) - \arcsin\left[\frac{2\sin[\theta(t)]}{b}\right] \tag{3}$$

Where b is the length of the simulated car, x and y are the coordinates of the car, and the $\theta(t)$ is the angle of the steering wheel such that:

$$\left\{ \begin{array}{c} \emptyset(t) \in [-90°, 270°] \\ \theta(t) \in [-40°, 40°] \end{array} \right\} \tag{4}$$

Fuzzy control system uses the custom seven fuzzy rules and discrete center of gravity defuzzifier. It uses the following functions, i.e., fuzzy start, fuzzy control, discrete center of mass, fuzzy rules center, fuzzy rules right, fuzzy rules left. Car simulator uses the real-evaluated genetic algorithm (GA) to train the radial base function network (RBFN), and RBFN controls the vehicle. The gene is defined as three parameters of mixed-dimensional vector RBFN (w, m, σ). The fitness function in the input case is the mean variance of the predicted output of the dataset and the RBFN value. The lowest fitness value is the best RBFN parameter. Car simulator can also use particle swarm optimization (PSO) for RBFN preparation as shown in Eq. 5.

$$\begin{aligned} F(x) &= \sum_{j=1}^{J} w_j \varphi_j(x) + \theta \\ &= \sum_{j=0}^{J} w_j \varphi_j(x) \end{aligned} \tag{5}$$

The arrangement of the radial base function network is shown in Fig. 1. Figure 2 shows the working of the proposed model.

In Fig. 1, x is the dataset input and uses the Gaussian base function given by Eq. 6.

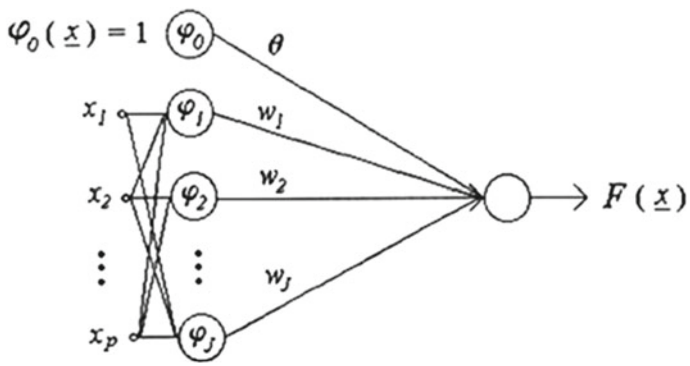

Fig. 1 Arrangement of the radial base function network

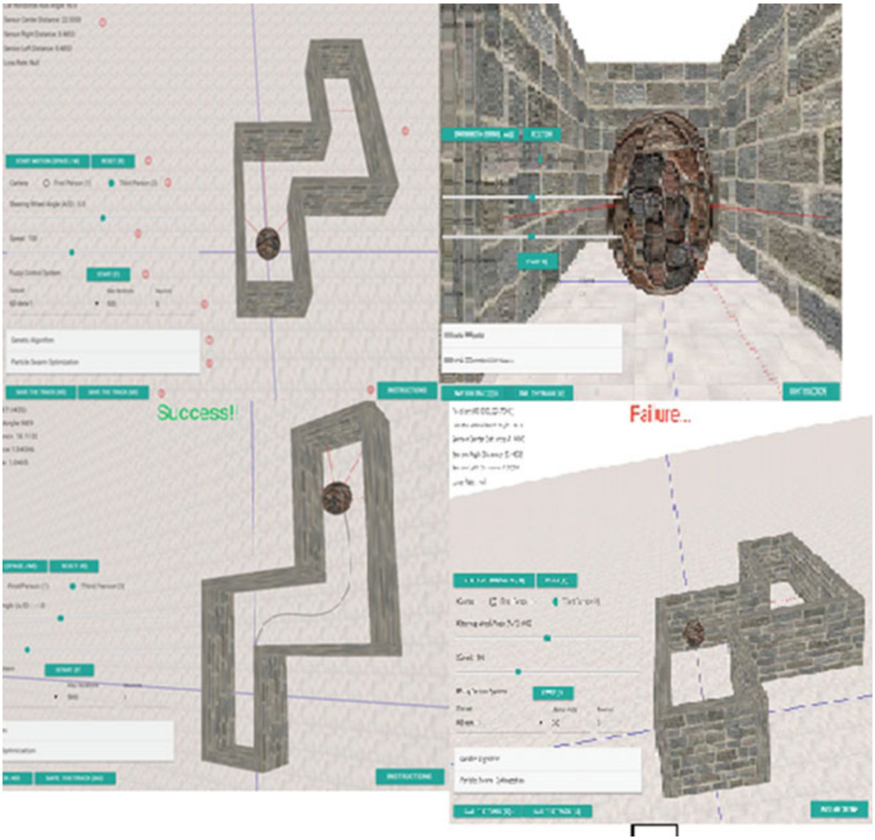

Fig. 2 Model for car simulator

$$\varphi_j(x) = \exp\left\{-\frac{x - m_j}{2\sigma_j^2}\right\} \tag{6}$$

Where w, m, σ are parameters of optimization algorithm. The fitness function is given by Eq. 7.

$$E(n) = \frac{1}{2}\sum_{1}^{N}(y_n - F(x_n))^2 \tag{7}$$

where y is the expected output and $F(x)$ is the RBFN output.

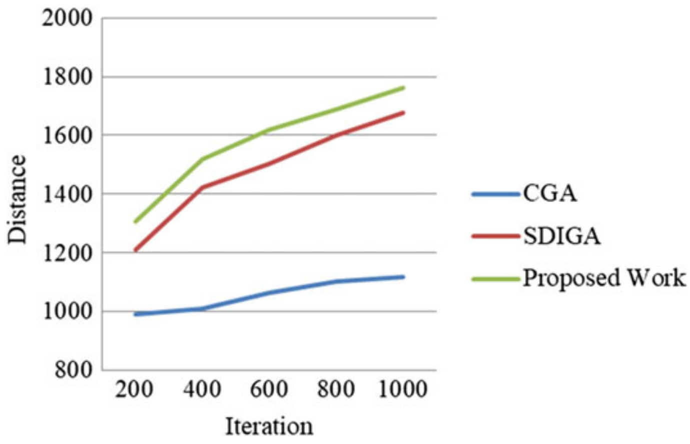

Fig. 3 Comparative results

4 Result and Discussion

In this paper, car simulator used particle swarm optimization (PSO) for RBFN preparation. The PSO coordinate is defined as the three mixed dimension vector parameters of RBFN (w, m, σ). For the input case, the fitness function is the mean variance of the predicted value of the data collection and the RBFN value. The lowest fitness rating is a good parameter for RBFN. The proposed model has the following features: status button, control button, camera first person/third person switch, rotation angle of steering wheel and moving speed, start the fuzzy control system, RBFN parameters setting, GA parameters setting, PSO parameters setting, save the trajectory and data, operating instructions, and graphic interface. Figure 3 shows the comparison of distance and the iteration used by different algorithms. The results show that our algorithm reduces the optimal path distance.

5 Conclusion and Future Scope

This simulator this fully automated could be a part of human interaction with steering of car and to reduce the time. This simulator will eliminate the human driver. The novelty of this paper is to save time and money. In terms of time, algorithm will require more practical world dataset to fully automate. There are many future challenges that we can implement to make our model better. Some of the factors that can be considered to make our model more effective are sprung mass bounce, wheel bounce, resistance levels, and engine braking system. Moreover, resistance levels can be increased to maintain the speeds of the simulated vehicles. The problems like for a vehicle, if surface and initial speed are given, various combinations of steer and braking will be provided in solution that will lead to rollover.

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