

Automated steering design using Neural Network

A project report submitted in partial fulfillment for the degree of

Bachelor of Technology

By

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and

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Under the supervision of

Prof. Dayal Ramakrushna Parhi

Department of Mechanical Engineering



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CERTIFICATE

This is to certify that the progress report of the thesis work entitled “Automated steering design using Neural Network” submitted by Rohan kumar Sabat and Anshu J Behera, has been carried out under my supervision in partial fulfillment of the requirements for the degree of Bachelor of Technology in Mechanical Engineering during session 2011 – 2012 in the Department of Mechanical Engineering, National Institute of Technology, Rourkela.

To the best of my knowledge, the matter embodied in the report has not been submitted to any other University/Institute for the award of any Degree or Diploma.

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ACKNOWLEDGEMENT

We place on record and warmly acknowledge the continuous encouragement, invaluable supervision, timely suggestions and inspired guidance offered by our guide Prof. Dayal R. Parhi, Department of Mechanical Engineering, National Institute of Technology, Rourkela, in bringing this report to a successful completion. We consider ourselves extremely fortunate to have had the opportunity to work under the guidance of such a knowledgeable, dynamic and generous personality.

We are also thankful to Prof. K. P. Maity, Head of Department, Department of Mechanical Engineering; National Institute of Technology Rourkela; for his constant support and encouragement.

Finally, we extend our sincere thanks to all other faculty members and friends at the Department of Mechanical Engineering, National Institute of Technology Rourkela, for their help and valuable advice in every stage for successful completion of this project.

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Abstract:-

If you don't move forward-you begin to move backward.

Technological advancement today has brought us to a frontier where the human has become the basic constraint in our ascent towards safer and faster transportation. Human error is mostly responsible for many road traffic accidents which every year take the lives of lots of people and injure many more. Driving protection is thus a major concern leading to research in autonomous driving systems.

Automatic motion planning and navigation is the primary task of an automated guided vehicle or mobile robots. All such navigation systems consist of a data collection system, a decision making system and a hardware control system. In this research our artificial intelligence system is based on neural network model for navigation of an AGV in unpredictable and imprecise environment. A five layered with gradient descent momentum back-propagation system which uses heading angle and obstacle distances as input.

The networks are trained by real data obtained from vehicle tracking live test runs. Considering the high amount of risk of testing the vehicle in real space-time conditions, it would initially be tested in simulated environment with the use of MATLAB®. The hardware control for an AGV should be robust and precise. An Aerial and a Grounded prototype were developed to test our neural network model in real time situation.

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

It is anticipated that the increase in the number of vehicles in the next two decades will place a considerable amount of strain on the capacity and safety of the present highway system in India. One particularly striking solution to improve highway capacity and safety is through vehicle automation. One of the functions of such autonomous vehicles is the ability to steer automatically while following a designated lane or a vehicle ahead. There has been many advances in the area of automated guided vehicle. Still its performance in actual traffic conditions and its reliability have a long way to go before its implementation in commercial vehicle.

Mobile robots have been extensively used in various fields such as space exploration, military missions and hazardous or unreachable environments. Mobile robots are crucial in automated manufacturing systems or flexible manufacturing systems because they transport materials to and from workstation and ware houses. Also in the ever changing shop floor they can easily navigate their way through to the desired location without any changes in model. Hence an AGV would form the backbone of a flexible manufacturing system in the upcoming years.

CHAPTER 2

Literature Review

2.1 Literature Review

Review of Neural Network Technique for Vehicle Navigation:

In the present autonomous vehicles, a path planning module is utilized to translate observed heading angles at specified ranges into appropriate steering commands. In contrast to path planning, a human driver decides the path trajectory and turns the steering wheel in direct reaction to an observed heading angle and range. Kehtarnavaz and Sohndeals[1] worked with neural network scheme to emulate human driving in order to eliminate the difficulties associated with path planning. The heading angle and range information is computed from the data captured by passive or active sensors. These data were the boundaries of a road or a feature at the back of a lead vehicle.

Though a lot of blood and sweat has been drained into the area of AGV (Automated guided Vehicle) the tests which feed the decision modeling system with data have largely remained costly and inconvenient.[2] A paper proposed by, Todd et al. The Robotics Institute, Carnegie Mellon University, Pittsburgh, USA, describes a simple but a powerful platform, designed to work on any passenger vehicle, developed at Camegie Mellon University. The platform, called PANS (Portable Advanced Navigation Support) is a robust but a very simple system which could provide better on-road performance than the current Navlab 2 at a substantially lesser cost. A rehabilitated US Army HMMWV called “The Navlab 2” is a good platform for off-road steering, where additional ruggedness is necessary and short missions are the norm. It is not well built for on-road driving research because of its size, complexity, and temperamental operational nature.

A substitute of using image processing was presented in a paper by BirsalAyrulu, BillurBarshan[3]. The study investigates the processing of sonar signals using neural networks

which are commonly encountered features in indoor robot environments. Differentiation of such features is of interest for intelligent systems in different applications. Different representations of amplitude and time-of-flight measurement patterns acquired from a real sonar system are processed. In most cases, best results are obtained with low-frequency component of the discrete wavelet transform of these patterns. Modular and non-modular neural network structures mostly trained with the back-propagation and generating shrinking algorithms are used to incorporate learning in the identification of parameter relations for target primitives.

A back-propagation neural network was proposed by Cheni et al. [4] , as a controller for an AGV system (driverless "automated guided vehicle"). At the present stage of development, the input layer consists of two neurons and receives the state signals of the tracking errors the camera image processor, and the sole neuron in the output layer provides the command signal of a reference yaw rate signal for the vehicle. Simulations and preliminary experimentation on a prototype vehicle showed that one hidden layer is adequate to provide good driving for such a time-varying nonlinear dynamic system.

Kurd S. and Oguchi K. ,[5] presented the idea of using Discrete reference markers The conventional control of Automatic Guided Vehicles (AGV) which use discrete reference markers includes a three-term PID controller to control the operation and the motors of the vehicle. The parameters of the PID controller were altered whenever the vehicle was to be operated. The best performance with respect to chosen PID parameters was a matter of trial and error. In this paper, a neural network controller is proposed as an indirect-controller to obtain the best control parameters for the main controller in use with respect to the location of the AGV.

Steering of an autonomous vehicle requires the permanent adaptation of behavior in relationship to the various situations the vehicle is in. A paper described by Kuhnert et al. University of

Siegen, Institute for Real-Time-Systems / Germany[6], which implements such adaptation and optimization based on Reinforcement Learning (RL) which in detail purely learns from evaluative feedback in contrast to instructive feedback. In this way it self-explores and self-optimizes actions for situations in a defined environment. The target of this research is to determine to what extent RL-based Systems serve as an enhancement or even an alternative to classical concepts of autonomous intelligent vehicles such as modeling or neural nets.

The research reported in this paper, by Alain et al. Kornhauser Princeton University [7] highlights on the automated steering aspects of intelligent highway vehicles. Proposed is a machine vision system for capturing driver views of the on-coming highway environment. In this paper acceptable steering commands for the vehicle is generated to investigate various designs of artificial neural networks for processing the resulting images. A computer graphical simulation system, called the Road Machine has been developed, which is used as the experimental environment for analyzing, through simulation, alternative neural network approaches for controlling autonomous highway vehicles in various environments.

Another paper by Chan et al. [8] state that, Human blunder is the main cause of the numerous road traffic accidents which every year take the lives of lots of people. Driving protection is thus a major concern foremost to investigation in autonomous driving systems. A project at the Centre for Computational Intelligence (C2i), NTU, aims at using fuzzy neural constructions such as GenSoFNN-Yager to recognize intelligent driving i.e., to learn to autonomously park, make U-turns, drive, and even choose when to change lane, leave behind, etc. The recent work on Intelligent Speed Adaptation and Steering Control (ISASC), a novel feature of which is the ability to anticipate the road outline and negotiate through curves safely, is presented here in this project. The planned system was developed and tested on a driving simulator. Experimental

results from the simulator show the robustness of the system in learning from example the desired human driving skill and applying this knowledge to negotiate new unseen roads.

Proportional-Integral-Derivative (PID) is another concept for automated navigation by Ahmad saifizul Abdullah et al. [9]. It describes how Proportional-Integral-Derivative (PID) controller and vision based concept to an automatic steering control system is used to cause the vehicle to track the reference under various path planning. Simulation results show that the proposed control system achieved its objective even though it is less robust in maintaining its performance under various environments.

Visual control of locomotion is essential for most mammals and requires coordination between perceptual processes and action systems according to, Wilkie RM, WannJP[10]. Previous research on the neural systems engaged by self-motion has focused on heading perception. This is only one perceptual subcomponent. For effective steering, it is necessary to perceive an appropriate future path and then bring about the required change to heading. By means of function magnetic resonance imaging (fMRI) in humans, we reveal a role for the parietal eye fields (PEFs) in directing spatially selective processes relating to future path information. A parietal area close to PEFs appears to be specialized for processing the future path information. When steering adjustments are imprecise a separate parietal area responds to visual position error signals. A network of three areas, the cerebellum, the supplementary eye fields, and dorsal pre motor cortex, was found to be involved in generating appropriate motor responses for steering responses.

Another paper by Tung et al. [11] says that existing neural fuzzy (neuro-fuzzy) networks can be broadly classified into two groups. The first group is basically fuzzy systems with self-tuning abilities and requires an initial rule base for its training. The second group of neural fuzzy

networks, alternatively, is capable of formulating the fuzzy rules from the numerical training data. No preliminary rule base needs to be specified prior to training. However, most existing neural fuzzy systems encountered one or more of the following major difficulties. Those are (1) Inconsistent rule-base; (2) Heuristically defined node operations; (3) Susceptibility to noisy training data and the stability-plasticity dilemma and (4) Requirements for preceding knowledge such as the number of bunches to be computed. Here, a novel neural fuzzy system that is immune to the above-mentioned insufficiencies is proposed. Driving a vehicle is a very hard task that humans can perform relatively well. It is very appealing to capture the human driving expertise in the form of an intuitive set of IF-THEN fuzzy rules. The driving simulator records and stores the steering and speed control actions of a human driver under different road scenarios. Subsequently, the GenSoFNN network is used to formulate a set of fuzzy rules that fits the recorded driving behavior from the simulator of the human driver. This set of fuzzy rules generally forms the knowledge base of the auto pilot system and is subsequently validated in auto-pilot mode.

The paper [12] proposes an innovative approach for solving the problem of obstacle evading during management tasks performed by redundant manipulators. Q-learning reinforcement technique has been used in the developed solution, which is based on a double neural network. Q-learning has been generally applied in the field of robotics for attaining obstacle avoidance navigation or computing path planning problems. Classical Jacobean matrix approach or minimization of redundancy resolution of manipulators operating in known environments is used in most studies to solve inverse kinematics and obstacle avoidance problems. Researchers who tried to use neural networks for solving inverse kinematics often dealt with a single obstacle present in the working field. This paper focuses on calculating inverse kinematics and obstacle

avoidance for complex and unknown environments, having multiple obstacles in the working field.

In this thesis Ian Lane Davis, present both a novel neural network example and a method for solving sensing and control tasks for mobile robots using this neural network paradigm. Real world responsibilities have driven the advancement of this methodology and its components, and we apply our methodology successfully to two robotics applications. We conclude that for some tasks, our novel modular neural network method can attain comparable or better performance than an old-fashioned monolithic network in a much reduced training time.

In this paper, an intelligent transportation control system (ITCS) using wavelet neural network (WNN) and proportional-integral-derivative-type (PID-type) learning algorithms [14] is proposed to increase the protection and effectiveness in transportation process. The proposed control system is composed of two controllers and those are neural controller and an auxiliary compensation controller. The neural controller acts as the chief tracking controller, which is designed via a WNN to mimic the merits of an ideal total sliding-mode control (TSMC) law. To regulate the parameters of WNN on-line for further promising system stability and obtaining a fast convergence the PID-type learning algorithms are used which are derived from the Lyapunov stability theorem. Moreover, based on H1 control technique, the auxiliary compensation controller is developed to attenuate the effect of the approximation error between WNN and ideal TSMC law, so that the attenuation level can be achieved within limit. Finally, it is applied to control a marine transportation system and a land transportation system to investigate the effectiveness of the proposed control strategy. The simulation results demonstrate that the proposed WNN-based ITCS with PID-type learning algorithms can be used to achieve favorable control performance than other control methods.

Autonomous Land Vehicle in a Neural Network (ALVINN) [15] is an ANN based navigation system that calculated a steer angle to keep an autonomous vehicle inside the road limits. In this work, the gray-scale levels of a 30 x 32 image were used as the input of neural networks. In order to improve training, the original road image and steering were generated, allowing ALVINN to quickly learn how to navigate in new roads. A disadvantage of this work is the high computational time. The architecture has 960 input units fully connected to the hidden layer to 4 units, also fully connected to 30 units in output layer. This ANN topology requires larger computational use as compared to other methods. Regarding that issue, this problem requires real time decisions therefore these topology are not efficient.

Later, the EUREKA project Prometheus [16] for road following was successfully performed, which provided trucks with an automatic driving system to reproduce drivers in repetitious long driving situations. In this project, the developed system also included a function to warn the driver in dangerous situations. A limitation of this project was an excessive number of heuristics created by the authors to limit the false alarms caused by shadows or discontinuities in the color of the road surface.

Another interesting work developing an autonomous vehicle e-control system, by Shihavuddin et al. [17], approaches the path map generation of an unknown environment using a proposed Trapezoidal Approximation (TA) of road periphery. At first, a blind map of the unknown environment is generated in computer, and then the image of the unknown environment is captured by the vehicle and a radio frequency transmitter module to send the signal to computer using. After that, the image is preprocessed and the road boundaries are detected using the TA. So, the vehicle operates independently avoiding all obstacles, and the issue with this approach is

the dependency of the camera tilt angle, because the vehicle moves through the trapezium and reaches the next approximated trapezium having a previously tilt angle.

Chronis and Skubic [18] have in their research worked on the difficulties in programming robots. A programming by demonstration or PbD paradigm has been discussed. This paradigm extracts robot behavior from the control actions demonstrated and its environment. The work is in an attempt to develop robot programming methods that allow the task use by domain experts for robots as semi-autonomous tools. Due to this, there was an intention of injecting human behavior into the acquired behavior. For these reasons, the programming by demonstration paradigm was chosen as opposed to preferring an autonomous learning method. The study tests the feasibility of training a neural network from demonstrated navigation actions which are generally collected from a simulator. The network was trained with three different training data collection and the results were compared. The three methods were a mouse driven software joystick, a novel PDA interface and a programmed control. For the purpose of corridor following behavior a neural network configuration was developed that can be used in training a mobile robot. A mapping between inputs and outputs of the network from the training data set is required for good level of convergence of the feed forward MLP. For robust control and better path planning the network should be provided with a range of conditions the training data must contain the complete range of possible sensor variations. From experimental results it can be found out that the most robust behaviors are produced by the PDA generated training sets.

CHAPTER 3

Analysis of Neural Technique for Automated Navigation

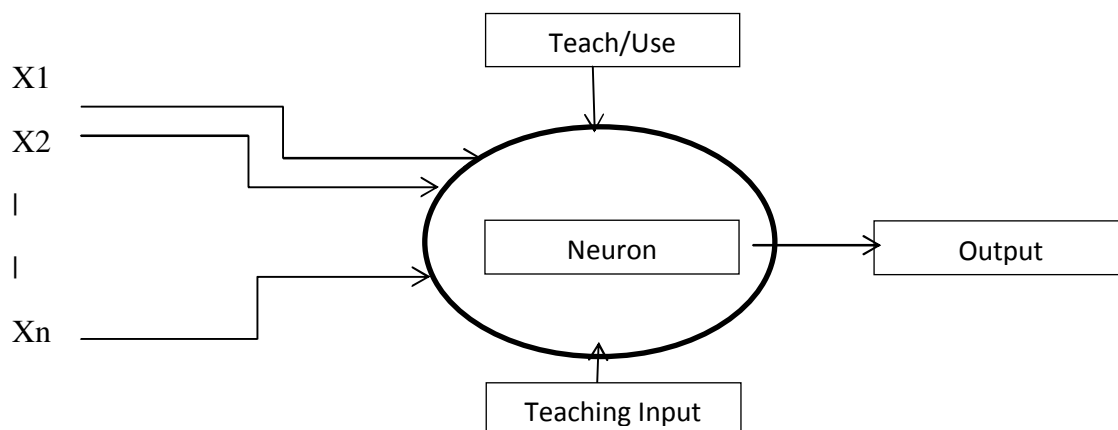
3.1 Analysis of Neural Technique for Automated Navigation

3.1.1 Introduction to neural networks:

An Artificial Neural Network (ANN) is a paradigm for information processing that is inspired by the way biological neural network, such as the brain, processes information. The central block of this paradigm is the unique structure of the information processing system. It consists of a large number of highly interconnected and organized processing elements (neurons) working together to process and solve. ANNs are like people and they learn by example. An ANN is usually implemented for a specific task, such as pattern appreciation or data classification, through a learning process.

3.1.2 A simple neuron: -

A synthetic neuron is an element which takes many inputs and gives one output. There are basically two modes of operation; the training mode and the using mode. In the training mode, for particular input patterns the neuron can be trained to fire or not fire. In the using mode, if the input pattern is taught, the taught output becomes the current output. If the input pattern is not, the firing rule is used to determine whether to fire or not.



(Figure: 1: A Simple Neuron)

3.1.3 Network layers: -

The artificial neural networks consist of three layers: input layer, hidden layer and output layer.

1. The input units convert the raw information that is fed into the network.
2. The output from each hidden unit is determined by input units and the weights on the connections between them.
3. The behavior of the output units depends on the output of the hidden units and the weights between them.

The hidden units are free to build their own representations of the input. The weights determine when each hidden unit is active, and so with modification of weights, a hidden unit can choose what it represents.

3.1.4 The Learning Process

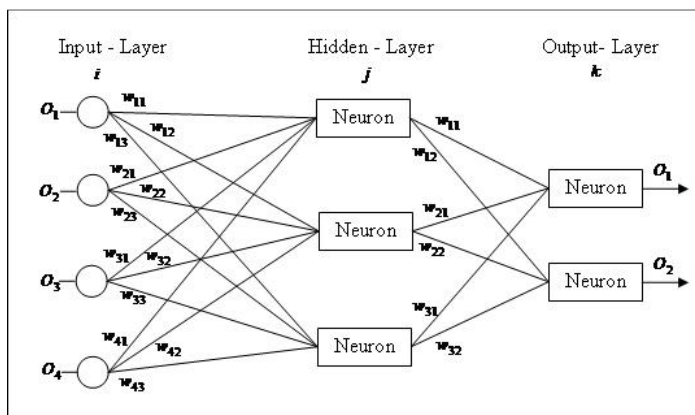
The memorization of patterns and the succeeding response of the network can be classified into two general paradigms. In Associative mapping the network learns to produce an output on the set of input units whenever another output is applied on the set of input units. The associative mapping is of two types.

Auto-association: An input pattern is associated with itself and the pattern output units match the trained one. This is used to offer pattern completion, i.e. to produce a pattern when some portion of it or a partial pattern is presented. In the second case, the network essentially stores pairs of patterns associating two sets of patterns.

Hetero-association: is associated with two recall mechanisms:

Nearest-neighbor recall, where the output produced corresponds to the input pattern stored, which is closest to the pattern presented Interpolative recall, where the output pattern leads to interpolation which is similarity dependent of the patterns stored compared to the pattern presented. Another model, which is a variant associative mapping, is classification, i.e. when input patterns are to be classified into a fixed set of classifications.

Every neural network owns knowledge which is contained in the weights. A learning rule for altering the values of the weights must lead to modification of the knowledge stored in the network as a function of practice.



(Figure 2: Sample ANN model)

Data is stored in the weight matrix W of a neural network. The determination of the weights is called the learning process. Following the way learning is performed, we can discriminate two major categories of neural networks:

Fixed networks: The weights are fixed, i.e. $dW/dt=0$. In such networks, the weights are determined according to the problem to solve.

Adaptive networks: The weights can be changed, i.e. $dW/dt \neq 0$.

Entirely, the learning methods used for adaptive neural networks can be classified into two chief categories:

Supervised learning which includes an external teacher, so that each output unit is told what its anticipated response to input signals ought to be. In the learning process global information may be a necessity. Models of supervised learning comprise error-correction learning, reinforcement learning and stochastic learning. A vital issue about supervised learning is the problem of error convergence, i.e. the minimization of difference between the desired and computed values. The goal is to find out a set of weights which reduces the error. One well-known method, which is common to many learning methods, is the least mean square (LMS) convergence.

Unsupervised learning uses no external teacher and is centered upon local information. It is also stated to as self-organization, in the way that it self-organizes data presented to the network and detects their emergent group properties. Examples of unsupervised learning are Hibbing learning and competitive learning.

3.1.5 Transfer Function: -

The characteristics of an ANN (Artificial Neural Network) depend on both the weights and the input-output function (transfer function) that is quantified for the units. These functions are of three types:

1. linear (or ramp)
2. Threshold
3. Sigmoid

For linear units, the output is proportional to the total weights and input. For threshold units, the output are binary, liable on whether the entire input is larger than or less than some threshold value. The output varies continuously but not linearly as the input changes in case of sigmoid units. Sigmoid units bear a greater similarity to real neurons than do linear or threshold units, but all three must be rough approximations.

3.1.6 Types of Neural Network

1. Feed-forward neural network: It was the first and possibly most simple type of artificial neural network invented. In this network the information moves in single direction. From the input nodes information goes to the hidden nodes (if any) and finally to the output nodes. There is absence of any cycles or loops in the network. Feed-forward networks can be constructed from various types of units, e.g. binary McCulloch-Pitts neurons, one example being the perceptron.
2. Learning Vector Quantization: Learning Vector Quantization (LVQ) may be understood as neural network architecture. It was proposed by Teuvo Kohonen, firstly. In LVQ, representatives of the classes parameterize, together with an appropriate distance measure, a distance-based classification scheme.
3. Recurrent neural network: Opposing to feed-forward networks recurrent neural networks (RNNs) are models with bi-directional data flow. While a feed-forward network transmits data linearly from input to output, RNNs also propagate data from later units to earlier units. RNNs can be used as general sequence processors.
4. Fully recurrent network: This is the basic architecture established in the 1980s: a network of neuron-like units, each with a directed link to every other unit. All units have a time-varying

real-valued initiation. Each assembly has a modifiable real-valued weight. Some of the nodes are called input nodes; some are called output nodes, the rest hidden nodes. Most architecture below is special cases.

5. Hopfield network: The Hopfield network is of historic interest although it is not all-purpose RNN, as it is not designed to process systems of patterns. Instead it requires static inputs. It is an RNN in which all contacts are symmetric. Designed by John Hopfield in 1982, assures that its dynamics will converge. If the links are trained using Hebbian learning then the Hopfield network will perform as robust content-addressable memory, resistant to connection alteration.
6. Simple recurrent networks: This special case of the Hopfield network was employed by Jeff Elman and Michael I. Jordan. A three-layer network is used, along a set of "context units" in the input layer. There are links from the hidden layer or from the output layer to the context units fixed with a weight of one. At each time step, the input is transmitted in a standard feed-forward fashion, and then a simple backprop-like learning rule is applied. The fixed back connections result in the context units always preserving a copy of the previous values of the hidden units (since they propagate over the connections before the learning rule is applied).
7. Echo state network: The echo state network (ESN) is a recurrent neural network with a sporadically linked random hidden layer. Only the weights of output neurons can be changed and be trained. ESN are good at replicating certain time series

3.1.7 The Back-Propagation Algorithm: -

To train a neural network to perform some task, we must change the weights of each unit in such a manner that the difference between the desired output and the actual output is reduced. It requires that the neural network computes the error offshoot of the weights (EW). In other words, it must calculate how the error fluctuates as each weight is increased or decreased slightly. The back propagation algorithm is a commonly used method for finding the EW.

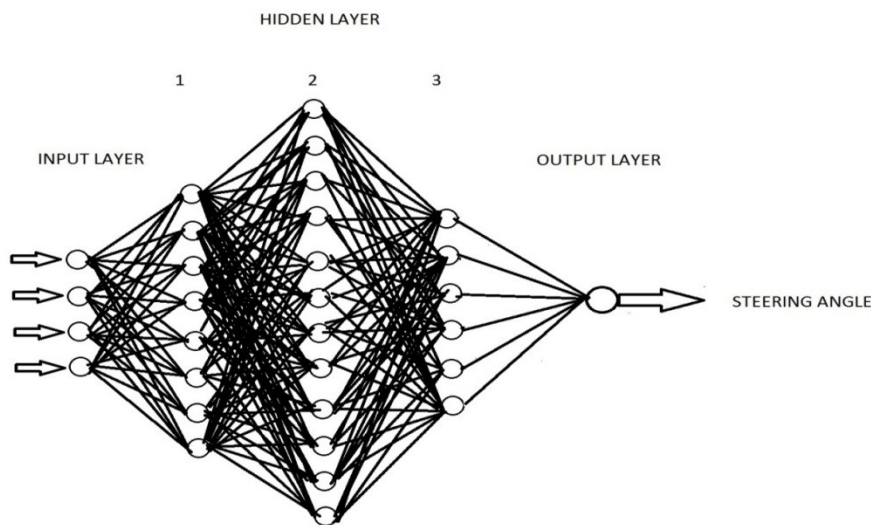
The back-propagation algorithm is easiest to realize if all the units in the network are linear. The algorithm computes each EW by first determining the EA, the rate at which the error variations as the movement level of a unit is altered. For output units, the EA is just the difference between the real and the wanted output. To compute the EA for a hidden unit in the layer just before the output layer, we first recognize all the weights amongst that hidden unit and the output units to which it is linked. Product of weights the EAs of those output units and add the products. These sum equivalent the EA for the chosen hidden unit. After computing all the EAs in the hidden layer penultimate to output layer, we can similarly compute the EAs for other layers, affecting from layer to layer in the opposite direction of the way activities propagate through the network. This is what gives back propagation its name. Once the EA has been computed for a unit, it is simple to calculate the EW for each incoming link of the unit. The EW is the creation of the EA and the activity through the incoming link.

CHAPTER 4

System Modeling using Neural Technique

4.1 System modeling using Neural Technique:

A neural network based model was designed to control the steering angle of the vehicle. A four layered model with 2 hidden layers was used. A sigmoid function was used as transfer function. The input neurons are that of left obstacle side distance, right obstacle side distance, front obstacle distance, and target angle. The output neuron was that of steering angle. The model was trained with simulated data and the weights were updated through back propagation. Then with the help of MATLAB and its neural network tool box, simulation was carried out. The model was simulated with various type of obstacles, target range.



(Figure 3: Neural model developed for the project)

Steps involved in setting up the neural network in MATLAB:-

1. The network manager was opened with the command `nnTool` in command window.
2. The input 4×10 matrix and the target matrix 10×1 were defined.
3. A new network was created with the input and output matrix and to other data were as follows
 - i. Network type: feed forward backprop

- ii. Training function: TRAINGD
 - iii. Adaptation learning function: LEARNGDM
 - iv. Performance function: MSE
4. The numbers of hidden layers were varied to get the best possible result by hit and trail.
 5. The termination criteria were 1000 epochs or $E < 1.1e^{-10}$, which reaches first the training stops.
 6. Then new input matrix was imported and the output steering angle was found out by using the function “simulate network” in NNTOOL.

This neural network will be used to intelligently navigate a grounded vehicle and an aerial automotive.

4.2 STEPS INVOLVED MODELING OF NEURAL NETWORK IN MATLAB INTERFACE: -

1. Create feed-forward back-propagation network. `net = newff([S1 S2...S(N-1)],{TF1 TF2...TFN1});` where, S_i size of i th layer, for $N-1$ layers, TF_i Transfer function of i th layer. (Default = 'tansig' for hidden layers and 'purelin' for output layer. Various transfer functions are as follows

Compet: Competitive transfer function

Hardlim: Hard limit transfer function

Hardlims: Symmetric hard limit transfer function

Logsig: Log-sigmoid transfer function

Netinv: Inverse transfer function

Poslin: Positive linear transfer function

Purelin: Linear transfer function

Radbas: Radial basis transfer function

Satlin: Saturating linear transfer function

Satlins: Symmetric saturating linear transfer function

Softmax: Softmax transfer function

Tansig: Hyperbolic tangent sigmoid transfer function

Tribas: Triangular basis transfer function

2. Create an input matrix containing input values.
3. Create a target matrix whose values are fixed by manual calculations.
4. Set the train function. There are many train functions such as
 - a. trainb: Batch training with weight and bias learning rules
 - b. trainbfg: BFGS quasi-Newton backpropagation
 - c. trainbfgc: BFGS quasi-Newton backpropagation for use with NN model reference adaptive controller
 - d. trainbr: Bayesian regularization
 - e. trainbuwb: Batch unsupervised weight/bias training
 - f. trainc: Cyclical order incremental update
 - g. traincgb: Powell-Beale conjugate gradient backpropagation
 - h. traincgf: Fletcher-Powell conjugate gradient backpropagation
 - i. traincgp: Polak-Ribière conjugate gradient backpropagation
 - j. traingd: Gradient descent backpropagation
 - k. traingda: Gradient descent with adaptive learning rule backpropagation
 - l. traingdm: Gradient descent with momentum backpropagation
 - m. traingdx: Gradient descent with momentum and adaptive learning rule backpropagation

- n. `trainlm`: Levenberg-Marquardt backpropagation
 - o. `trainoss`: One step secant backpropagation
 - p. `trainr`: Random order incremental training with learning functions
 - q. `trainrp`: Resilient backpropagation (Rprop)
 - r. `trains`: Sequential order incremental training with learning functions
 - s. `trainscg`: Scaled conjugate gradient backpropagation
5. Set the train parameters such as

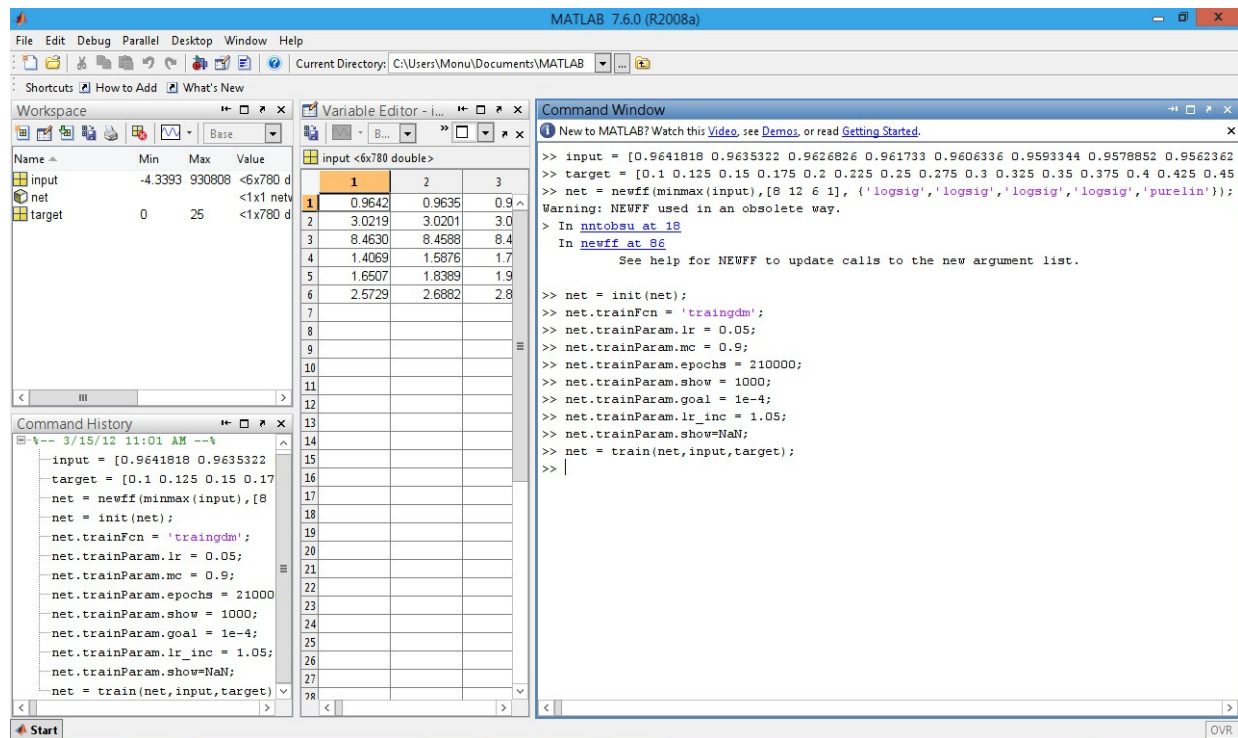
SYNTAX	MEANING
<code>net.trainParam.epochs</code>	Maximum number of epochs to train
<code>net.trainParam.goal</code>	Learning rate
<code>net.trainParam.max_fail</code>	Maximum validation failures
<code>net.trainParam.mc</code>	Momentum constant
<code>net.trainParam.min_grad</code>	Minimum performance gradient
<code>net.trainParam.show</code>	Epochs between showing progress
<code>net.trainParam.showCommandLine</code>	Generate command-line output
<code>net.trainParam.showWindow</code>	Show training GUI
<code>net.trainParam.time</code>	Maximum time to train in seconds

(Table 1: Syntax Definition)

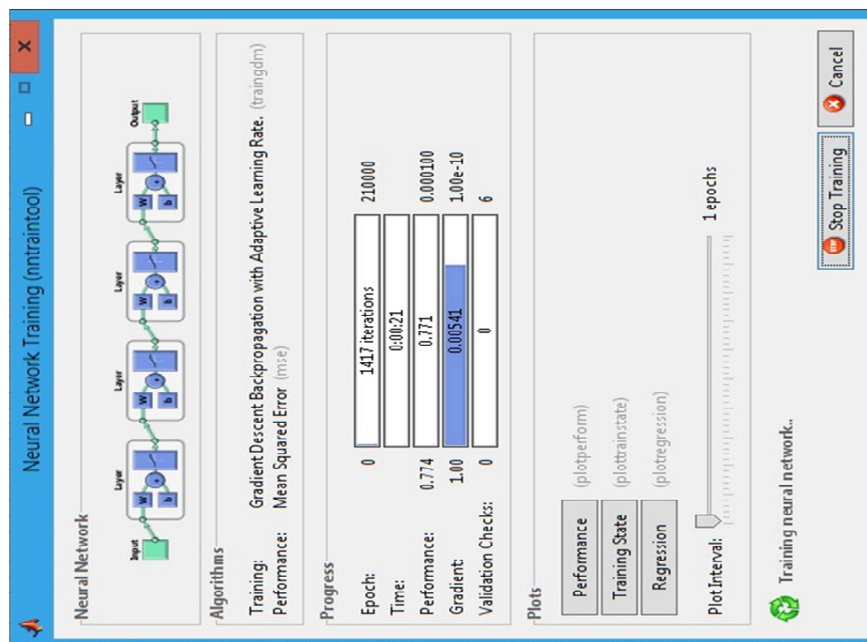
- 6. Train the network. `net = train(net,input,target);`
- 7. Then analyze the output by giving the same input.

4.3 MATLAB PROGRAMME:

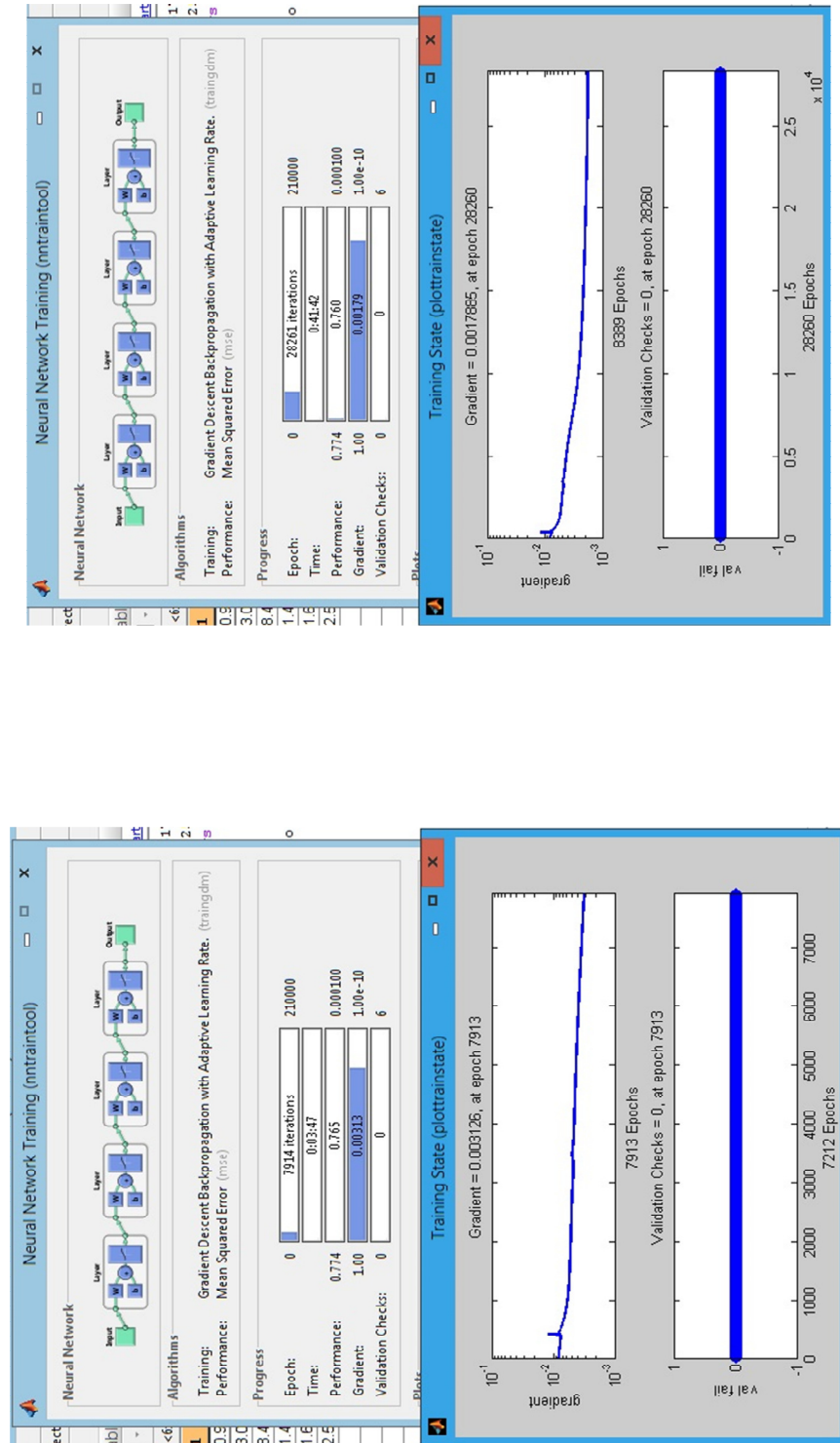
```
net = newff(minmax(input),[8 12 6 1], {'logsig','logsig','logsig','logsig','purelin'});  
net = init(net);  
  
net.trainFcn = 'traingdm';  
  
net.trainParam.lr = 0.05;  
  
net.trainParam.mc = 0.9;  
  
net.trainParam.epochs = 210000;  
  
net.trainParam.show = 1000;  
  
net.trainParam.goal = 1e-4;  
  
net.trainParam.lr_inc = 1.05;  
  
net.trainParam.show=NaN;  
  
net = train(net,input,target);  
  
output = sim(net,input)  
  
net.IW{1,1};  
  
net.LW{2,1};  
  
net.LW{3,2};
```

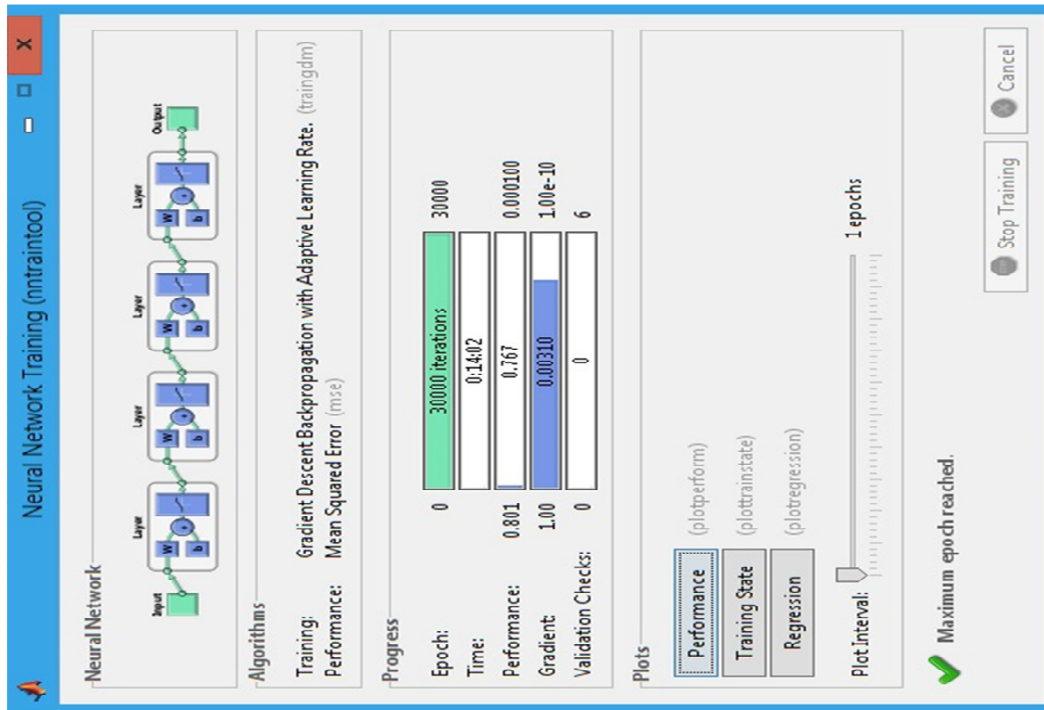
(Figure 4: GUI of MATLAB showing the Neural Network Programme)



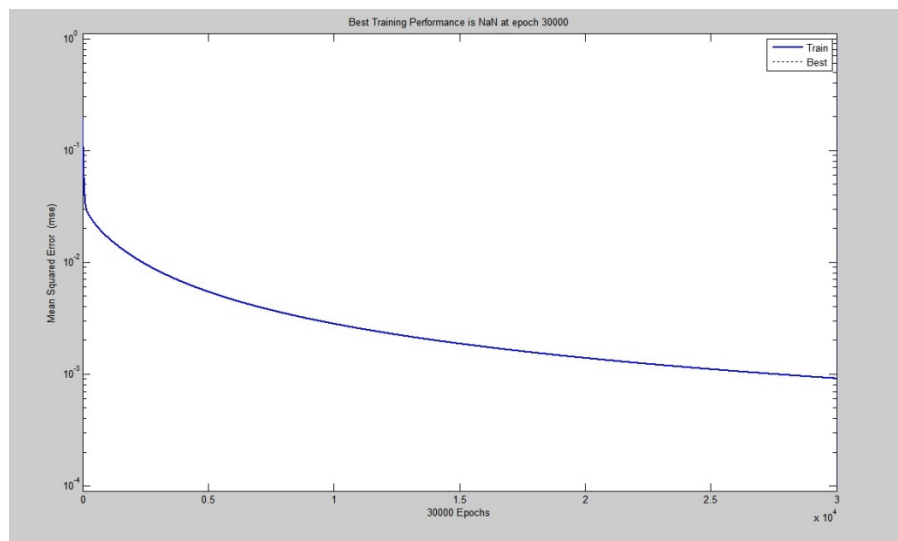
(Figure 5 training of Neural Network)



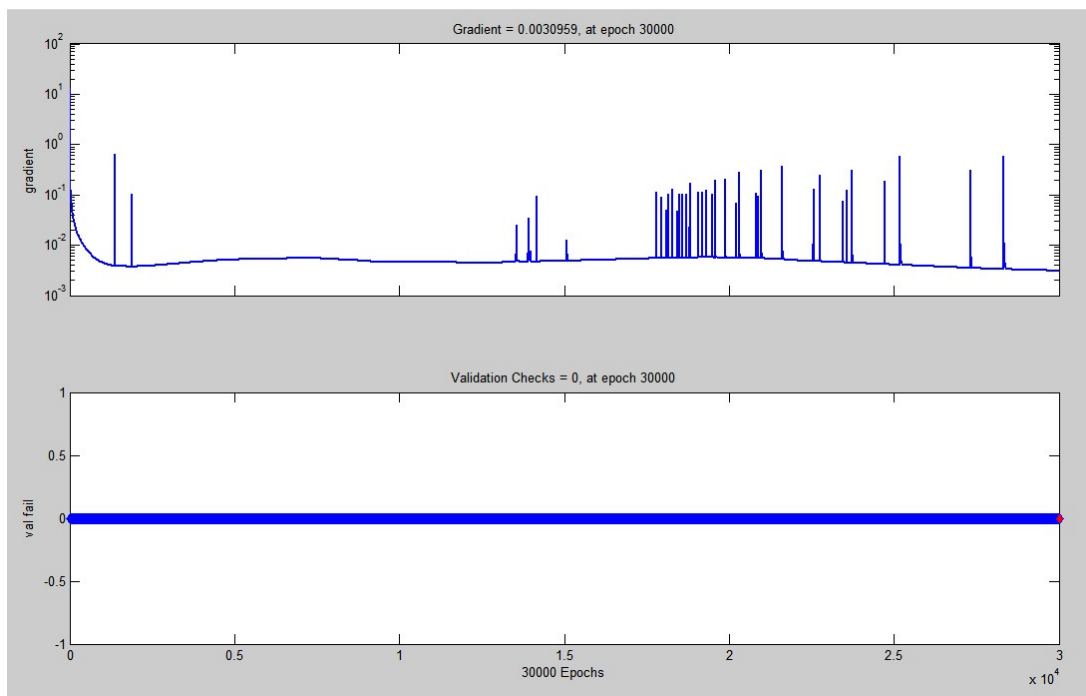
(Figure 6: Training of Neural Network showing Training State)



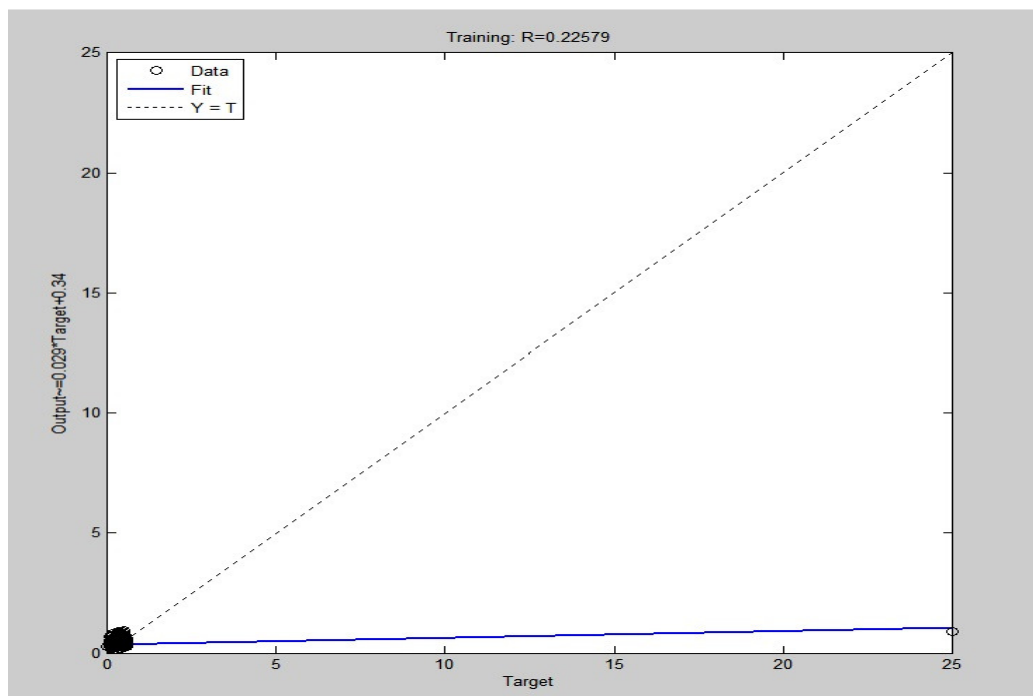
(Figure 7: Completion of training due to Maximum epochs reached)



(Figure 8: Performance plot)



(Figure 9: Training Plot)



(Figure 10: Regression Plot)

CHAPTER 5

Experimental Model

5.1 Experimental Model

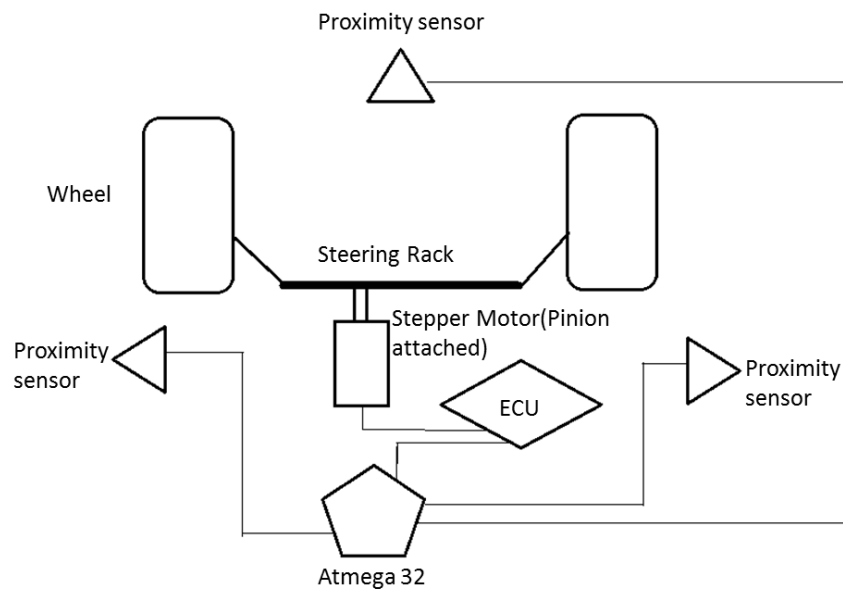
The descriptions of these automotives are as follows: -

5.1.1 Grounded vehicle: -

Our setup utilizes a rack and pinion control steering system as is conventionally used in regular passenger cars. The pinion is mounted over the shaft of the stepper motor.

The stepper motor is controlled by an ECU (Electronic Control Unit) whose output is the angle of rotation of the pinion. The ECU is feed with the digital signal from an Atmega 32 whose basic purpose is to accept the analog signals from the proximity sensors.

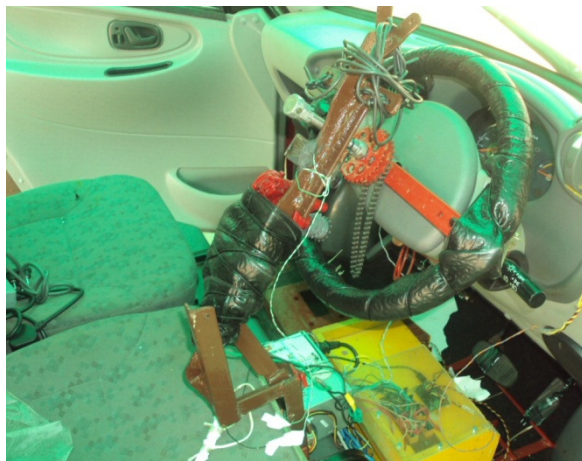
The Atmega 32 uses neural network based code to process the analog signals and sends the output signal, steering angle to ECU.



(Figure 11: Schematic representation of grounded vehicle with INS)

Proximity Sensor: This sensor uses ultrasonic waves to detect objects. Its range is 6"-254". It is programmed to detect objects around the vehicle and to give an analog signal which is fed to the Atmega 32.

Stepper motor: A stepper motor (or step motor) is a brushless, electric motor that can divide a full rotation into a large number of steps. The motor's position can be controlled precisely without any feedback mechanism, as long as the motor is carefully sized to the application. Stepper motors are similar to switched reluctance motor.



(Figure 12 Hardware arrangements on REVAi)



(Figure 13: AB pedal control assembly)

The grounded prototype was developed by modifying a REVAi. REVAi is an electric car, whose compact build and light weight make it an ideal choice for the prototype. Its specifications are as follows:

Integrated Power System Motor: High torque (52 Nm), AC Induction motor, 3 phase 13 kW

peak Controller: 350 Amp microprocessor based with regenerative braking

Charger: 220 V, 2.2 kW, high Frequency switch mode type (optional 100-120V)

EMS: Microprocessor-based battery management system **Power Pack:** 48 V, 200 Amp-hr, EV lead acid batteries.

REVAi Dimensions

Length: 2638 mm

Width: 1324 mm

Height: 1510 mm

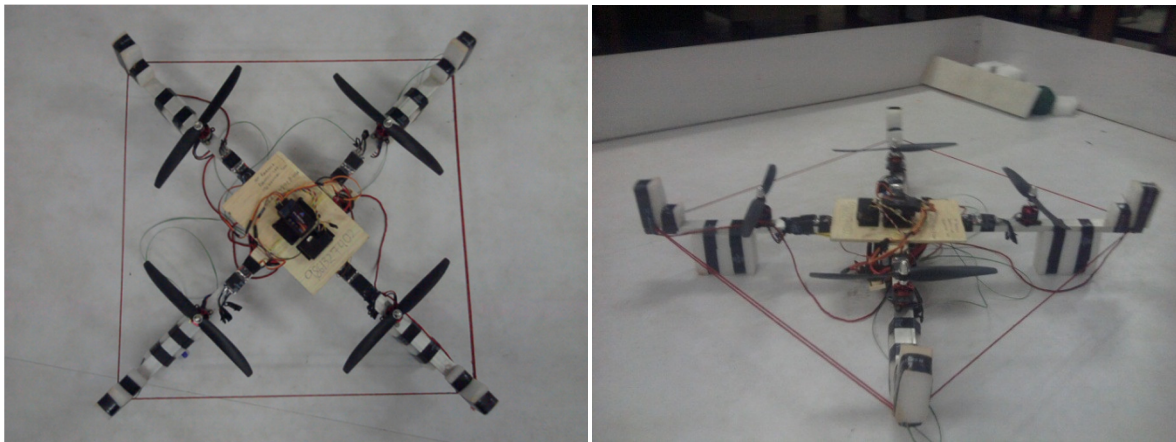
Ground Clearance: 150 mm

Turning Radius: 3503 mm

Curb Weight: 700 kg

The hardware control consisted of a chain drive system driven by a wiper motor to control the steering gear, servo motors to control accelerator and brake actuators. Use of servo motors provides high degree of accuracy in control which is critical in these actuators. A DC gear motor with Max Torque $\geq 120\text{Nm}$ is necessary for steering control.

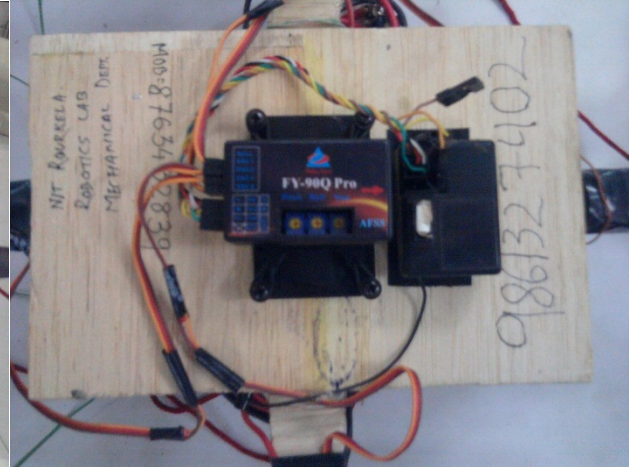
5.1.2 Aerial Automotive (Quadrotor): -



(Figure 14: Developed Aerial Prototype- Quadrotor)



(Figure 15: Brushless out runner DC Motor
with ESC)



(Figure 16: Altitude Flight
Stabilization System with Receiver)

In this aerial automotive we have used 4 stepper motors, 4 ESCs, 1 AFSS, 1 Li-Po 30C 3s 11.1V battery, 1 Pair receiver and transmitter.

AFSS (Altitude Flight Stabilization System): - The FY90Q Pro which is used here is a 3 axis gyro and accelerometer which can detect the deviation of its 4 sides from the horizontal plane and send signals accordingly to minimize the deviation.

ESC (Electronic Speed Controller): - This aerial automotive uses 20A ESCs to control the speed of stepper motor according to throttle position of transmitter.

Li-Po Battery: - The battery used was POWER HD 305C 5000Mah 3S battery.

Stepper Motor: - 4 brushless DC stepper motor was used to provide thrust to the aerial automotive each having a thrust capacity of 700 gms.

Chapter 6

Results and Discussion

6 Results and Discussion:

Following the theoretical analysis of neural network model the navigation mechanism for the areal and grounded vehicle have been developed. The Gradient descent with momentum back-propagation algorithm under the neural network paradigm was developed for decision making. Each of the automated vehicle was controlled by taking four inputs from its environment Left Distance (Distance between the AGV and the nearest obstacle to its left); Right Distance (Distance between the AGV and the nearest obstacle to its right); Front Distance (Distance between the AGV and the nearest obstacle ahead of it) and Heading Angle (position of the AGV in relation with the target destination expressed as an angle). The output was generated after processing the inputs through the above mentioned neural network, which is steering angle (The angle to which the steering wheel of the AGV must be turned).

Experimental data sets were collected by attaching sensors to a commercial vehicle driven by a expert driver in real time space co-ordinate. Experimental data sets include the inputs as well as output (steering angle). This experimental data set is used for training of the neural network model developed in MATLAB.

To evaluate the performance of neural network model, simulations were conducted, maintaining a constant set of input data sets. The input and output training data matrices are as follows.

input	=	0.9522384	0.9642816	0.950939	0.963732	0.94904	0.9631324
0.9641818		0.9498896	0.963632	0.9484404	0.9629824	0.9463416	0.9622328
0.9635322		0.947191	0.9628824	0.945592	0.9621328	0.9431932	0.9612834
0.9626826		0.9441428	0.961983	0.9423938	0.9611334	0.9396952	0.960184
0.961733		0.9407446	0.9609336	0.9387458	0.959984	0.9356474	0.9589346
0.9606336		0.9367968	0.9597342	0.934548	0.9586348	0.931	0.9574854
0.9593344		0.9323492	0.958385	0.9297506	[0.9571856	0.9195562	0.9558864
0.9578852		0.927252	0.9568858	0.9179072	0.9554866	0.9040648	0.9540374
0.9562362		0.914609	0.9551368	0.901966	0.9535876	0.9643816	0.9519884
0.9543872		0.8976184	0.9531878	0.9643316	0.9514888	0.963782	0.9496398

0.9470412	0.9641318	0.9575854	0.938396	0.9625826	0.9556364	0.9646316
0.9440428	0.963582	0.9561862	0.9289012	0.961983	0.9540374	0.9643316
0.9405948	0.9629324	0.954537	0.9648814	0.9612834	0.9521884	0.9640818
0.9366968	0.9621828	0.952688	0.9645816	0.9604338	0.9475908	0.963732
0.9322492	0.9612834	0.9506392	0.9641818	0.9595344	0.9411944	0.9633322
0.9211554	0.9603338	0.9482406	0.963732	0.9584848	0.9650812	0.9628824
0.9061636	0.9591844	0.945492	0.9631822	0.9573356	0.9648814	0.9623828
0.9644316	0.9579352	0.9423438	0.9625826	0.9559862	0.9646316	0.961833
0.9639318	0.956486	0.934448	0.961933	0.9544372	0.9643316	0.9612334
0.9632322	0.9548368	0.923704	0.9611334	0.952688	0.9640318	0.9604838
0.9624826	0.9530378	0.9647314	0.9602838	0.9506392	0.963632	0.9596342
0.9615832	0.950939	0.9643816	0.9592844	0.945492	0.9631822	0.9586848
0.9605838	0.9485404	0.963882	0.958135	0.938346	0.9627326	0.9575854
0.9593844	0.9458418	0.9633322	0.9568858	0.9650312	0.9621328	0.956336
0.958085	0.9427436	0.9627326	0.9554366	0.9647814	0.9614832	0.9531378
0.956586	0.9391456	0.961983	0.9537374	0.9644816	0.9607836	0.9486902
0.9548868	0.9302504	0.9611834	0.9518386	0.9641318	0.959934	0.9652312
0.9529878	0.918157	0.960234	0.9496898	0.963732	0.9590346	0.9650812
0.950839	0.9646814	0.9591346	0.947191	0.9632822	0.9579352	0.9649314
0.9483904	0.9642816	0.9579352	0.9408946	0.9627826	0.9567358	0.9647314
0.945592	0.963732	0.956586	0.9321994	0.9621828	0.9552866	0.9644816
0.9423938	0.9631324	0.9550368	0.9649314	0.9614832	0.9536876	0.9642318
0.9387958	0.9624328	0.9532878	0.9646316	0.9607336	0.9495398	0.9639318
0.934648	0.9616332	0.9512888	0.9642816	0.9598842	0.943843	0.963632
0.9243036	0.9607336	0.94899	0.963882	0.9588846	0.9651312	0.9632322
0.9102614	0.9597342	0.9463916	0.9634322	0.9577852	0.9649314	0.9627826
0.9645316	0.9585348	0.9433432	0.9628824	0.956486	0.9647314	0.9623328
0.9640318	0.9572356	0.9357974	0.9622828	0.9550368	0.9644816	0.961783
0.9634322	0.9557364	0.925453	0.9615832	0.9533378	0.9641818	0.9611334
0.9627326	0.9540374	0.9648314	0.9607836	0.9514388	0.963832	0.9604338
0.961883	0.9521384	0.9644816	0.9598842	0.9465414	0.9634822	0.9595842
0.9609336	0.9499396	0.9640318	0.9588846	0.9397952	0.9630324	0.9586348
0.9598842	0.947441	0.9635322	0.9577352	0.9650312	0.9625326	0.9575354
0.9586348	0.9445926	0.9629824	0.956386	0.9648314	0.961983	0.954737
0.9572856	0.9412944	0.9622828	0.9548868	0.9645316	0.9613334	0.950839
0.9556864	0.9330988	0.9615332	0.9531878	0.9642318	0.9605838	0.9652312
0.9539374	0.921855	0.9606836	0.9512388	0.963832	0.9597842	0.9650812
0.9519384	0.9647314	0.9597342	0.9489402	0.9633822	0.9588346	0.9649314
0.9496898	0.9643316	0.9586348	0.9432432	0.9629324	0.9577352	0.9647814
0.9470912	0.963832	0.9573854	0.9353476	0.9623328	0.956486	0.9645816
0.9441428	0.9632322	0.9559862	0.9649814	0.961733	0.9550368	0.9643316
0.9407946	0.9625826	0.9543872	0.9647314	0.9609836	0.9514388	0.9640818
0.9369468	0.961833	0.9525382	0.9644316	0.960184	0.9463416	0.963732
0.927352	0.9609336	0.9504394	0.9640818	0.9592344	0.9651812	0.9633822
0.9142592	0.959984	0.9480906	0.963632	0.958185	0.9650312	0.9629824
0.9645816	0.9588346	0.9452922	0.9631324	0.9569858	0.9648314	0.9625326

0.962033	0.9653312	0.9644816	0.9626326	0.9652312	0.9648814	0.965431
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0.9607836	0.9651312	0.9640818	0.960184	0.9651312	0.9646814	0.965431
0.959984	0.9649814	0.963832	0.965381	0.9650812	0.9645316	0.965381
0.9590846	0.9648814	0.963582	0.965381	0.9649814	0.9641818	0.965381
0.958085	0.9646814	0.9632822	0.9653312	0.9648814	0.963732	0.965381
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0.9652312	0.9640818	0.961983	0.9651312	0.9645816	0.965431	0.9652812
0.9651312	0.963782	0.9607836	0.9650312	0.9644316	0.965381	0.9652812
0.9649814	0.9634822	0.9590346	0.9649314	0.9642318	0.965381	0.9652312
0.9648314	0.9631324	0.965381	0.9648314	0.9640318	0.9653312	0.9651812
0.9646316	0.9627326	0.9653312	0.9646814	0.9635322	0.9653312	0.9651812
0.9644316	0.9622828	0.9652312	0.9645816	0.9628324	0.9652812	0.9651312
0.9641818	0.961783	0.9651812	0.9643816	0.965431	0.9652312	0.9650312
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0.9635322	0.9604838	0.9649814	0.9640318	0.965381	0.9651312	0.9646814
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0.9627326	0.9562362	0.9647314	0.9634822	0.9653312	0.9650312	0.965431
0.9622828	0.9653312	0.9645816	0.9631822	0.9652812	0.9649314	0.965431
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0.9595842	0.9649814	0.963782	0.965381	0.9650812	0.9643816	0.965431
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0.952788	0.9644816	0.9627826	0.9652312	0.9648814	0.965431	0.965381
0.9652812	0.9642816	0.9623328	0.9651812	0.9647814	0.965431	0.965381
0.9651812	0.9640818	0.9611834	0.9651312	0.9646814	0.965431	0.9653312
0.9650812	0.963832	0.9596342	0.9650312	0.9645316	0.965381	0.9653312
0.9649314	0.9635322	0.965381	0.9649814	0.9643816	0.965381	0.9652812
0.9647314	0.9631822	0.9653312	0.9648814	0.9639818	0.965381	0.9652812
0.9645816	0.9628324	0.9652812	0.9647314	0.9634322	0.9653312	0.9652312
0.9643316	0.9623828	0.9651812	0.9646316	0.965431	0.9652812	0.9651812
0.9640818	0.961883	0.9651312	0.9644816	0.965431	0.9652812	0.9650812
0.963832	0.9612834	0.9650312	0.9643316	0.965381	0.9652312	0.9649314
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0.9622828	0.9652812	0.9645316	0.9629824	0.9652812	0.9650312	0.965431
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0.954587	0.9646814	0.9630324	0.9652812	0.9649314	0.965431	0.965431

0.965381	0.9652812	2.990447	3.024005	3.022003	3.023179	3.024805
0.965381	0.965481	2.984816	3.023379	3.021402	3.022503	3.024705
0.965381	0.965481	2.97851	3.022628	3.020726	3.021577	3.024605
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0.9653312	0.965481	2.963345	3.020701	3.0191	3.025156	3.024355
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0.9652812	0.965481	2.93234	3.018199	3.016998	3.025106	3.024055
0.9652312	0.965431	2.903912	3.016697	3.015721	3.025081	3.023854
0.9651312	0.965431	3.023054	3.014996	3.014245	3.025081	3.023629
0.965481	0.965431	3.021953	3.013094	3.010667	3.025031	3.023379
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0.965431	0.965431	3.017173	3.005787	3.024955	3.024955	3.021953
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0.965431	0.965431	3.012719	2.999205	3.02478	3.02488	3.024955
0.965431	0.965431;	3.010041	2.995251	3.024655	3.02483	3.02483
0.965431	3.021877	3.007038	2.990747	3.024505	3.024755	3.02468
0.965431	3.020101	3.00366	2.979711	3.024355	3.024705	3.024505
0.965431	3.017974	2.999856	2.965172	3.02418	3.02463	3.024305
0.965431	3.015496	2.995577	3.02448	3.023979	3.02453	3.02408
0.965381	3.012618	2.990772	3.024105	3.023754	3.024305	3.023829
0.965381	3.00934	2.985367	3.023629	3.023479	3.02403	3.023529
0.965381	3.005637	2.979261	3.023104	3.023204	3.025181	3.023204
0.965381	3.001458	2.972354	3.022478	3.022853	3.025156	3.022828
0.9653312	2.996778	2.964572	3.021777	3.022478	3.025156	3.022403
0.9653312	2.991498	2.945628	3.020952	3.022053	3.025156	3.021902
0.9652812	2.985592	2.921004	3.020051	3.021577	3.025156	3.021352
0.9652312	2.978986	3.023404	3.019025	3.021027	3.025156	3.020726
0.965481	2.971553	3.022478	3.017849	3.019625	3.025156	3.020001
0.965481	2.963245	3.021327	3.016547	3.017748	3.025131	3.019175
0.965481	2.953886	3.020001	3.015071	3.025106	3.025131	3.018224
0.965481	2.943351	3.018474	3.013394	3.025081	3.025131	3.015872
0.965431	2.931514	3.016722	3.011517	3.025031	3.025106	3.012593
0.965431	2.903011	3.01472	3.009365	3.02498	3.025106	3.02473
0.965431	2.866476	3.012493	3.006938	3.02493	3.025081	3.024505
0.965431	3.022703	3.009941	3.00416	3.024855	3.025081	3.024255
0.965431	3.021377	3.007113	2.997328	3.02478	3.025056	3.023904
0.965431	3.0198	3.00391	2.988245	3.024705	3.025031	3.023529
0.965431	3.017924	3.000306	3.024805	3.024605	3.025005	3.023104
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0.965381	3.010541	2.986518	3.024105	3.02423	3.025081	3.021377
0.965381	3.007388	2.980687	3.023779	3.024055	3.025056	3.020676
0.965381	3.00386	2.974081	3.023429	3.023879	3.025005	3.01985
0.965381	2.999906	2.95799	3.023004	3.023679	3.024955	3.018925
0.9653312	2.995452	2.936945	3.022528	3.023429	3.02488	3.017874

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3.015296	3.022403	3.003635	3.023279	3.006087	2.957765	3.015471
3.013719	3.021552	3.000006	3.022178	3.002433	2.934868	3.013194
3.011893	3.020601	2.995877	3.020977	2.998329	2.903612	3.010566
3.007363	3.0195	2.991172	3.019475	2.993675	3.023079	3.007614
3.001107	3.018274	2.985792	3.017773	2.98837	3.021852	3.004235
3.02463	3.016848	2.979586	3.015847	2.982339	3.020451	3.000457
3.02433	3.015271	2.964121	3.013644	2.975482	3.018799	2.996102
3.023954	3.013469	2.943	3.011142	2.967625	3.016873	2.991198
3.023554	3.011442	3.023454	3.008289	2.958616	3.01467	2.985617
3.023054	3.009115	3.022553	3.005061	2.936119	3.012193	2.979236
3.022503	3.006487	3.021402	3.001407	2.905514	3.00934	2.971904
3.021877	3.003459	3.020076	2.997278	3.022928	3.006162	2.96347
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3.020351	2.996052	3.016797	2.987269	3.020301	2.998405	2.913246
3.019425	2.986093	3.014821	2.981188	3.018674	2.9937	3.023204
3.018374	2.972479	3.012593	2.974256	3.016672	2.98842	3.022378
3.017198	3.023929	3.010041	2.966273	3.014445	2.982439	3.021277
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3.008239	3.019275	2.991223	3.020651	2.997829	2.905038	3.011793
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3.011793	3.021953	3.002584	2.910969	3.009115	2.968751	3.017273
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3.007163	3.019475	2.9942	3.021852	3.002183	2.93757	3.013244
3.00431	3.017974	2.989146	3.020401	2.998029	2.907141	3.010792
2.997178	3.016272	2.983365	3.018774	2.9933	3.023204	3.008014
2.987394	3.014345	2.976733	3.016848	2.987944	3.022103	3.004886
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3.023729	3.009641	2.950208	3.012143	2.974907	3.019325	2.997278

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3.007589	2.956439	3.021102	3.016497	8.405397	8.38305	8.47051
3.00446	3.02428	3.020276	3.015046	8.39356	8.356674	8.47051
3.000957	3.023754	3.019375	3.011492	8.380297	8.323041	8.47051
2.996953	3.023029	3.018224	3.006387	8.365333	8.468458	8.470335
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2.987018	3.021527	3.015621	3.02483	8.330924	8.466181	8.470335
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2.30567439	1.678175178	1.914544547	1.607613914	1.969354119	1.991983259	1.977410663
2.280663719	1.721193924	1.928815399	1.726138761	1.973542545	1.993561563	1.981894183
2.209845971	1.299110521	1.937024592	1.838007948	1.977503202	1.994983088	1.984459171
2.154399625	1.773008552	1.944234757	1.855536358	1.980394106	1.851724506	1.987084761

1.989110704	1.997951037	target =100*	0.425 0.45	0.325 0.35	0.225 0.25	0.6 0.1 0.125
1.990671553	1.998515392	[0.1 0.125	0.475 0.5 0.55	0.375 0.4	0.275 0.3	0.15 0.175 0.2
1.992088003	1.781315977	0.15 0.175 0.2	0.6 0.1 0.125	0.425 0.45	0.325 0.35	0.225 0.25
1.993113057	1.953262456	0.225 0.25	0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4	0.275 0.3
1.994108139	1.948571298	0.275 0.3	0.225 0.25	0.6 0.1 0.125	0.425 0.45	0.325 0.35
1.994966085	1.961911119	0.325 0.35	0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4
1.995650285	1.979433822	0.375 0.4	0.325 0.35	0.225 0.25	0.6 0.1 0.125	0.425 0.45
1.996235992	1.981141731	0.425 0.45	0.375 0.4	0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55
1.997128484	1.988525202	0.475 0.5 0.55	0.425 0.45	0.325 0.35	0.225 0.25	0.6 0.1 0.125
1.997715039	1.989335444	0.6 0.1 0.125	0.475 0.5 0.55	0.375 0.4	0.275 0.3	0.15 0.175 0.2
1.81664855	1.990470011	0.15 0.175 0.2	0.6 0.1 0.125	0.425 0.45	0.325 0.35	0.225 0.25
1.940023839	1.993450339	0.225 0.25	0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4	0.275 0.3
1.958379615	1.993941262	0.275 0.3	0.225 0.25	0.6 0.1 0.125	0.425 0.45	0.325 0.35
1.966213515	1.994743933	0.325 0.35	0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4
1.975240355	1.995963643	0.375 0.4	0.325 0.35	0.225 0.25	0.6 0.1 0.125	0.425 0.45
1.980639931	1.996317685	0.425 0.45	0.375 0.4	0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55
1.985081686	1.996722289	0.475 0.5 0.55	0.425 0.45	0.325 0.35	0.225 0.25	0.6 0.1 0.125
1.986521518	1.997514557	0.6 0.1 0.125	0.475 0.5 0.55	0.375 0.4	0.275 0.3	0.15 0.175 0.2
1.988458353	1.99776114	0.15 0.175 0.2	0.6 0.1 0.125	0.425 0.45	0.325 0.35	0.225 0.25
1.99122581	1.99842984	0.225 0.25	0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4	0.275 0.3
1.991613489	1.998715849	0.275 0.3	0.225 0.25	0.6 0.1 0.15	0.425 0.45	0.325 0.35
1.993266271	2.687690432	0.325 0.35	0.275 0.3	0.175 0.2	0.475 0.5 0.55	0.375 0.4
1.994704721	1.975269642	0.375 0.4	0.325 0.35	0.225 0.25	0.6 0.1 0.125	0.425 0.45
1.994894684	1.977388704	0.425 0.45	0.375 0.4	0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55
1.995887495	1.982115673	0.475 0.5 0.55	0.425 0.45	0.325 0.35	0.225 0.25	0.6 0.1 0.125
1.996680323	1.98986558	0.6 0.1 0.125	0.475 0.5 0.55	0.375 0.4	0.275 0.3	0.15 0.175 0.2
1.99685127	1.988949958	0.15 0.175 0.2	0.6 0.1 0.125	0.425 0.45	0.325 0.35	0.225 0.25
1.997626491	1.991183929	0.225 0.25	0.15 0.175	0.475 0.5 0.55	0.375 0.4	0.275 0.3
1.998246868	1.994653062	0.275 0.3	0.2 0.225 0.25	0.6 0.1 0.125	0.425 0.45	0.325 0.35
1.91169894	1.995876139	0.325 0.35	0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4
1.936937174	1.996699578	0.375 0.4	0.325 0.35	0.225 0.25	0.6 0.1 0.125	0.425 0.45
1.95700887	1.996698746	0.425 0.45	0.375 0.4	0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55
1.971042028	1.99744864	0.475 0.5 0.55	0.425 0.45	0.325 0.35	0.225 0.25	0.6 0.1 0.125
1.97880183	1.997801998	0.6 0.1 0.125	0.475 0.5 0.55	0.375 0.4	0.275 0.3	0.15 0.175 0.2
1.982567628	1.998066479	0.15 0.175 0.2	0.6 0.1 0.125	0.425 0.45	0.325 0.35	0.225 0.25
1.984715572	1.998361708	0.225 0.25	0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4	0.275 0.3
1.988817138	1.998585547	0.275 0.3 0.3	0.225 0.25	0.6 0.1 0.125	0.425 0.45	0.325 0.35
1.989308694	1.998795117	25 0.35 0.375	0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4
1.992444953	1.999196333	0.4 0.425 0.45	0.325 0.35	0.225 0.25	0.6 0.1 0.125	0.425 0.45
1.993679764	1.999511057]	0.475 0.5 0.55	0.375 0.4	0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55
1.994484502	;	0.6 0.1 0.125	0.425 0.45	0.325 0.35	0.225 0.25	0.6 0.1 0.125
1.9947969		0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4	0.275 0.3	0.15 0.175 0.2
1.996069842		0.225 0.25	0.6 0.1 0.125	0.425 0.45	0.325 0.35	0.225 0.25
1.996284265		0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4	0.275 0.3
1.997118647		0.325 0.35	0.225 0.25	0.6 0.1 0.125	0.425 0.45	0.325 0.35
1.997253323		0.375 0.4	0.275 0.3	0.15 0.175 0.2	0.475 0.5 0.55	0.375 0.4

0.425 0.45	0.375 0.4	0.325 0.35	0.275 0.3	0.225 0.25	0.15 0.175 0.2	0.6 0.1 0.125
0.475 0.5 0.55	0.425 0.45	0.375 0.4	0.325 0.35	0.275 0.3	0.225 0.25	0.15 0.175 0.2
0.6 0.1 0.125	0.475 0.5 0.55	0.425 0.45	0.375 0.4	0.325 0.35	0.275 0.3	0.225 0.25
0.15 0.175 0.2	0.6 0.1 0.125	0.475 0.5 0.55	0.425 0.45	0.375 0.4	0.325 0.35	0.275 0.3
0.225 0.25	0.15 0.175 0.2	0.6 0.1 0.125	0.475 0.5 0.55	0.425 0.45	0.375 0.4	0.325 0.35
0.275 0.3	0.225 0.25	0.15 0.175 0.2	0.6 0.1 0.125	0.475 0.5 0.55	0.425 0.45	0.375 0.4
0.325 0.35	0.275 0.3	0.225 0.25	0.15 0.175 0.2	0.6 0.1 0.125	0.475 0.5 0.55	0.425 0.45
0.375 0.4	0.325 0.35	0.275 0.3	0.225 0.25	0.15 0.175 0.2	0.6 0.1 0.125	0.475 0.5 0.55
0.425 0.45	0.375 0.4	0.325 0.35	0.275 0.3	0.225 0.25	0.15 0.175 0.2	0.6];
0.475 0.5 0.55	0.425 0.45	0.375 0.4	0.325 0.35	0.275 0.3	0.225 0.25	
0.6 0.1 0.125	0.475 0.5 0.55	0.425 0.45	0.375 0.4	0.325 0.35	0.275 0.3	
0.15 0.175 0.2	0.6 0.1 0.125	0.475 0.5 0.55	0.425 0.45	0.375 0.4	0.325 0.35	
0.225 0.25	0.15 0.175 0.2	0.6 0.1 0.125	0.475 0.5 0.55	0.425 0.45	0.375 0.4	
0.275 0.3	0.225 0.25	0.15 0.175 0.2	0.6 0.1 0.125	0.475 0.5 0.55	0.425 0.45	
0.325 0.35	0.275 0.3	0.225 0.25	0.15 0.175 0.2	0.6 0.1 0.125	0.475 0.5 0.55	

(Table 2: Training Data Table)

After training and learning process is completed, this neural network model along with its peripheral components (sensors and stepper motors) can be used in an AGV in unknown and unconstructed environment. This can be implemented in real space time co-ordinate because of the precise output generated by the decision making system. The outputs were obtained similar to the target matrix. Thus the system is capable of navigating a vehicle replacing a human and there is no room for error in this domain which is generally present in a human driver domain. The training of neural network ended with a mean square error of $\sim 10e-3$. This can be further decreased by training the neural network for more number of epochs which would enhance the performance of the model.

INPUTS				OUTPUT
D_Left	D_Right	D_Front	Heading_angle	Steering Angle
0.9641818	3.021877	8.462978	1.406949757	9.24
0.9635322	3.020101	8.458799	1.587584249	11.98
0.9626826	3.017974	8.453994	1.747647304	14.37
0.961733	3.015496	8.448214	1.876352901	17.13
0.9606336	3.012618	8.441557	1.989234575	20.65
0.9593344	3.00934	8.43405	2.093322907	23.2
0.9578852	3.005637	8.425566	2.185945383	24.56
0.9562362	3.001458	8.416132	2.271935887	29.04
0.9543872	2.996778	8.405397	2.351751677	31.85
0.9522384	2.991498	8.39356	2.429188946	33.16

(Table 3: Output Data Table)

CHAPTER 7

Conclusion and Scope for Future Work

7 Conclusion and Scope for Future Work:

An aerial and a grounded prototype were developed, which were guided by the developed ANN model. These prototypes were equipped with proximity sensors which fed the ECU with analog signals regarding the topology of the environment. Then the output of the ECU is fed to the hardware control system of the prototypes. For grounded prototype the hardware consists of servo motors, chain drive mechanism, and rack & pinion gear system. In aerial vehicle the output is fed to the receiver which then manipulates the rpm of the rotor through ESC.

The performance of the prototypes can be vastly improved by further optimization of the ANN. This can be done by reducing the Mean Square Error. Numerous algorithms are available for this optimization. Further, the proximity sensors maybe replaced by LASER sensors, which are more precise and reliable. Use of LASER sensors, would provide analog signals similar to the proximity sensors. Hence, the ANN model would remain vastly unaffected.

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