ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 2, February 2014

Microcontroller Based Neural Network Controlled Low Cost Autonomous Vehicle

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Abstract: The hurdle distance is measured using four ultrasonic Sensors which is equipped in vehicle. A low cost P89V51RD2-NP microcontroller is used in which a GPS receiver, a GSM modem and a RAM memory is interfaced. A GPS receiver is used for receive the goal position information, a GSM modem is used for changing destination place on run time and data is stored in a non-volatile RAM. The information is acquired from the sensors which is processed by the microcontroller and it generates commands for robot motion based on neutral network. The neutral network is a multi layer Feed forward network in which back-propagation training algorithm is used.

Keywords: Autonomous vehicle; ultrasonic sensors; compas; GPS receiver; GSM modem; nonvolatile RAM; tangent-sigmoid function approximation; neural network; microcontroller implementation

I. INTRODUCTION

Autonomous robots with mobile capability are finding their place in numerous application fields. Some typical examples of these application fields are factory automation [1], service application [2], hazardous environments such as dangerous zones in nuclear power stations [3], space exploration [4], material handling in hospital [5] and security guarding [6]. The key requirement for performing these tasks is navigation. Navigation is the ability of a mobile robot to reach the target safely without human assistance. Thus the main issues that need to be addressed in mobile robot navigation are reactive obstacle avoidance and target acquisition [7]. Vision based sensing for autonomous navigation is a powerful and popular method due to its ability to provide detailed information of environment which may not be available using combinations of other types of sensors [8] and has been addressed by many researchers. In [9], a lawn mower robot is developed that uses camera, differential GPS, IMU and wheel encoders for its navigation. The computation is carried on 1.3 GHz Mac Mini running Windows XP with 4GB of memory. In [10], an autonomous vehicle equipped with a digital video camcoder and GPS sensor is developed for IGVC competition. The vehicle uses a Toshiba Satellite 2415-S205-laptop computer running Windows XP with 2.0 Gigahertz Intel Pentium 4 processor and 256 MB RAM for image processing, navigational computation and issuing motor commands. In [11], experiments are carried out on a mobile robot Pioneer 2 DX equipped with a PTZ camera and a Pentium 233 MHz PC-104 on board computer with 64Mb of RAM to give it the ability to navigate based on textual messages which are used as landmarks in its way. In [12], mobile robot navigation is achieved with the help a camera mounted on the robot and pointing towards fluorescent tubes located above its desired path. A map of the lights based on odometry data is built in advance by the robot guided by an operator. The vision approaches though efficient provide a costly solution for navigation task because more processing power is required to run computationally complex image processing algorithms in real time. The other sensors of choice are range-based sensors e.g., ultrasonic sensors. Many systems have been implemented that use sonar for navigation [13,14,15]. These systems use sonar sensors to get the distance and heading to obstacles in robot environment. The main advantage in employing these sensors lies in their low computational requirement. Another requirement for navigation in complex, noisy and unpredictable environment is the selection of intelligent controller that can deal with these uncertainties and react robustly. The evolvement of soft-computing paradigms have provided a powerful tool to deal with mobile robot navigation process, which exhibits incomplete and uncertain knowledge due to the inaccuracy and imprecision inherent from the sensory system [7,16]. Among these methods, fuzzy logic and neural networks present a promising solution in decision making process for generating robot control commands. Neural navigators perceive their knowledge and skills from a demonstrating action and also suffer from a very slow convergence process and lack of generalization due to limited patterns to represent complicated environment [7]. However, neural networks that can be implemented with relatively modest computer hardware could be very useful. Some work done by the authors indicates that this approach may be successful [17,18,19]. Although the aforementioned techniques successfully solve the robot navigational problem, there always remains a need of lowering the system cost further without compromising much on its efficiency and reliability. In this paper, design of a low cost autonomous vehicle is presented for navigation inside the university campus. The navigation

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
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task is subdivided into hurdle avoidance seeking tasks. Hurdle avoidance is achieved with the help of four ultrasonic sensors. The range data from these sensors is fed to neural network running inside the microcontroller. To lower the computational burden on microcontroller, neural network is implemented with piecewise linear approximation of tangent-sigmoid activation function for neurons. Goal seeking behavior involves the data from compass, wheel encoder and GPS receiver which is processed by another microcontroller. Way point data for all stations is stored in a nonvolatile RAM. The main microcontroller fetches the desired data and generates motion commands for robot. A GSM modem is interfaced to the main controller for selecting start and goal stations for robot inside the university campus.

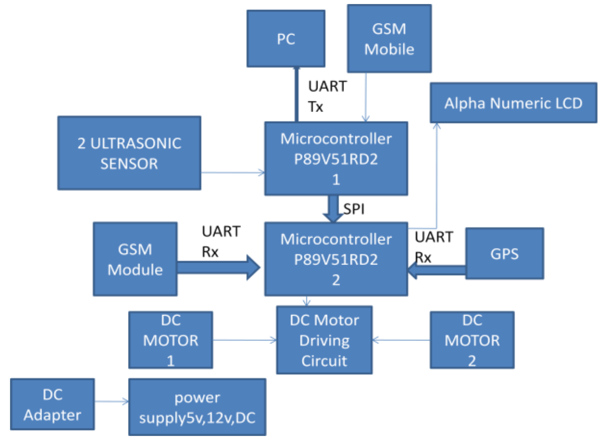

Figure 1. System Block Diagram

II. EXPERIMENTAL PROTOTYPE

The experimentation is carried out on a four wheeled mobile robot which is a modified form of a readily available RC car. The modification is done by adding extra circuitry in order to generate useful data for training the neural network. Steering information is obtained by connecting a potentiometer to the steering rod. Operational amplifiers, LM311, are then used as comparators to classify this information as being left, centre and right. The rear wheels information is classified as either forward or backward. In order to create a perceptual link with the environment, four ultrasonic sensors, SRF04, are mounted on the robot. Three sensors are mounted in front while one sensor is mounted on the rear side of the robot. The P89V51RD2 are 80C51 microcontrollers with 64kB flash and 1024 B of data RAM. A key feature of the P89V51RD2 is its X2 mode option. The design engineer can choose to run the application with the conventional 80C51 clock rate (12 clocks per machine cycle) or select the X2 mode (six clocks per machine cycle) to achieve twice the throughput at the same clock frequency.

The flash program memory supports both parallel programming and in serial ISP. Parallel programming mode offers gang-programming at high speed, reducing programming costs and time to market. ISP allows a device to be reprogrammed in the end product under software control. The capability to field/update the application firmware makes a wide range of applications possible.
The block diagram of the system is shown in Fig. 1 while the experimental prototype is shown in Fig. 2.

Figure 2. Experimental Prototype

III.NAVIGATION SYSTEM

Navigation problem is decomposed into obstacle avoidance and goal reaching problems.

A. Obstacle Avoidance

When a mobile robot is traveling towards its final target, it might face a variety of obstacles in its way. A

1) Gathering experimental data and pre-processing: A number of experiments are conducted to gather training and validation data with the help of ultrasonic sensors mounted on the robot. Used to detect the move of human or object. Suitable for indoor and outdoor burglar-proof application, vehicle burglar-proof application, ATM surveillance camera, warehouse surveillance camera, and safety warning application in dangerous site where voltage and temperature exist.. However in order to reduce the complexity, distance information from left and right ultrasonic sensor is divided into four regions: very near, near, far, very far and is represented by two bits for each sensor. Also, the distance information from centre and back ultrasonic sensor is divided into two regions: near and far and is represented by one bit for each sensor. The sensor placement with regions is shown in Fig. 3. Because the training data set also contains output commands, the control commands for motors are encoded in 4 bits with 2 bits representing the status of each motor.

Hurdle Data Set (H)=$\{(L_s,R_s,C_{os})$for $0\leq L_s, R_s,C_{os}< 3\}$ (1)
Motor Command Set (M)=$\{(S_m, R_m)$for $0\leq S_m, R_m \leq 3\}$ (2)
Training Data Set (T) = {(H, M)} (3)

During an experiment, car is run with the help of remote

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INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 1, January 2014

control and different sample values are collected corresponding to different environment conditions with each sample value being a packet consisting of 10 bits. These packets are then transferred by the microcontroller to PC through parallel port. A set of training examples is shown in table 1.

2) Neural network design: The neural network used is multi layer feed-forward network with back propagation learning algorithm and is designed using MATLAB® programming environment. The employed configuration contains 3 neurons in the input layer, 6 in the hidden layer and 4 in the output layer as shown in Fig. 4. The numbers of neurons in hidden layer are selected on trial and error basis. Three inputs to the neural network are distance information from 4 sensors. Centre and back sensors are combined to form one input while other two inputs are from left and right sensors. The outputs from the neural network are direct commands for motors. The activation function used for hidden layer is tangent-sigmoid function while pure linear function is employed in output layer. The output of a neuron can be expressed by the equation:

$$Y_i = T\,(\Sigma_j\,(X_j * W_{ij}) \quad (4)$$

where T is the transfer function which is made user selectable, either sigmoid, threshold or custom made. This equation will be applied to calculate the output of hidden and output layer. For hidden layer, (4) will be

$$H_j = \text{tansig}\,(\Sigma_i\,(X_i * W_{ij})),\ j = 1 \text{ to } 6,\ i = 1 \text{ to } 3 \quad (5)$$

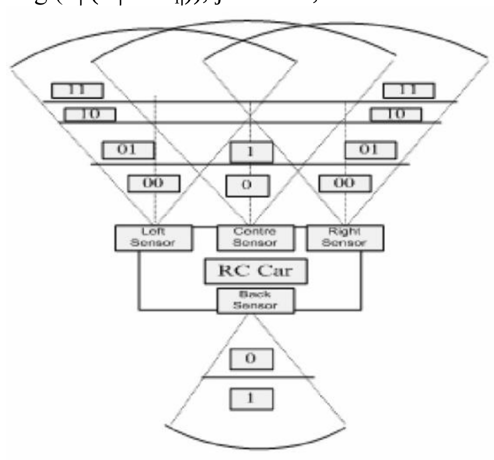

Figure 3. Regions Corresponding to Sensor Values

TABLE I
RULES FOR TRAINING EXAMPLES

Rule	SL	SR	SCo	LT	RT	FD	BK
Forward	3	3	3	0	0	1	0
F. Right	2	3	3	0	1	1	0
F. Left	3	1	3	1	0	1	0
B. Right	1	0	3	0	1	0	1
B. Left	0	2	3	1	0	0	1
Stop	0	3	0	0	0	0	0

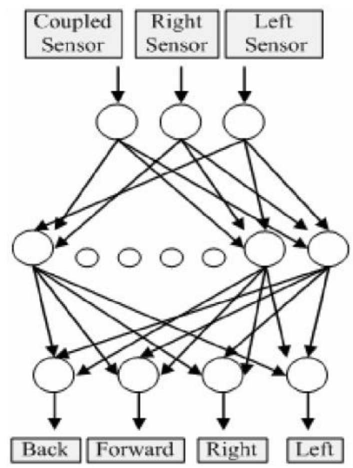

Figure 4. Neural Network Structure

Experimental data is divided into two sets: training data set and validation data set. During training, for each sample value, error is calculated between the desired output ‘H’ and network calculated output ‘Y’:

$$E = H\text{-}Y \quad (6)$$

The error is minimized by using back propagation training algorithm. The algorithm minimizes the error by updating the weights and biases of the network. For a tangent-sigmoid function, new weights are calculated according to the relation:

$$W_{new} = W_{old} + \eta\,(1 - \alpha)\,\Delta W + \alpha\,\Delta W_{old} \quad (7)$$

where ΔW is the weight correction factor and α is the momentum factor used for convergence of network output to desired behavior by speeding up the iterative process. After performance goal is met in training phase, the network is tested with validation data set. This data set is used to avoid over-fitting the network to the training data. The training error graph showing the performance of network is shown in Fig. 5.

3) Neural network implementation: After offline training in MATLAB®, the neural network is implemented using 89C52 microcontroller. Keeping in view the low memory and processing power of the microcontroller, tangent-sigmoid function is converted into piecewise linear function for implementation using microcontroller and the converged weights are converted into integer form.

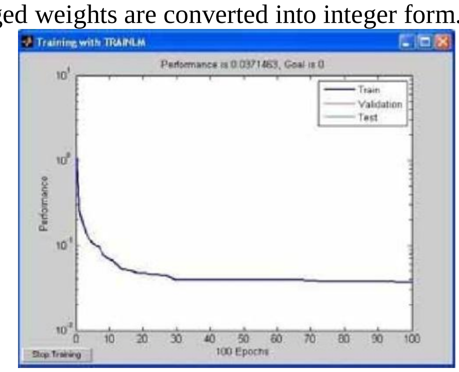

Figure 5 training Error Graph

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A comparison of actual tangent-sigmoid function and its approximation is shown in Fig. 6.

B. Goal Reaching

Goal reaching task combines information from compass, wheel encoders, GPS receiver and GSM mode. The flow chart for this task is shown in Fig. 7. The vehicle is initialized with the start and goal locations by using SMS service of GSM network GPS-634R" is a highly integrated smart GPS module with a ceramic GPS patch antenna. The antenna is connected to the module via an LNA. The module is with 51 channel acquisition engine and 14 channel track engine, which be capable of receiving signals from up to 65 GPS satellites and transferring them into the precise position and timing information that can be read over either UART port or RS232 serial port. Small size and high-end GPS functionality are at low power consumption, Both of the LVTTL-level and RS232 signal interface are provided on the interface connector, supply voltage of 3.6V~6.0V is supported. The smart GPS antenna module is available as an off-the-shelf component, 100% tested. The smart GPS antenna module can be offered for OEM applications with the versatile adaptation in form and connection. Additionally, the antenna can be tuned to the final systems' circumstances.. The heading algorithm is described as:

ROBOT-HEADING( )
$\Theta_D \leftarrow$ Destination Angle
$\Theta_M \leftarrow$ Maximum Angle
while Destination Not Reached
  do $\Theta_C \leftarrow$ Current Angle
    if $\Theta_D > \Theta_C$
      then $\Theta_1 \leftarrow \Theta_D - \Theta_C$
        $\Theta_2 \leftarrow (\Theta_M - \Theta_D) + \Theta_C$
    if $\Theta_D > \Theta_C$
      then $\Theta_1 \leftarrow \Theta_C - \Theta_D$
        $\Theta_2 \leftarrow (\Theta_M - \Theta_C) + \Theta_D$
    if $\Theta_2 > \Theta_1$
      then
        repeat RIGHT-AND-FORWARD( )
          until NO-OBSTACLE( )
    if $\Theta_1 > \Theta_2$
      then
        repeat LEFT-AND-FORWARD( )
          until NO-OBSTACLE( )

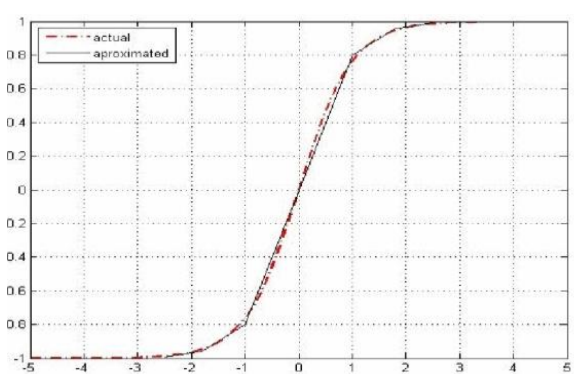

Figure 6. Comparison of Tangent-Sigmoid Function and Approximated

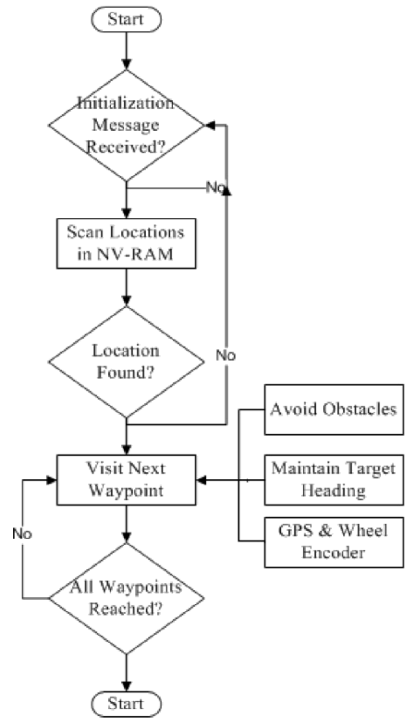

Figure 7. Goal Reaching Behaviour

During navigation, if the obstacle avoidance system detects an obstacle, the control commands for avoiding the obstacle will override the normal commands provided by goal reaching system. In this case, vehicle will travel more distance than desired. The extra distance traveled by vehicle after avoiding the obstacle is recorded. Then knowing the current and destination (active waypoint) vehicle orientation, a new path is generated along with new distance to be traveled to reach that waypoint. When the vehicle reaches within 5 meter of current waypoint, position value is read with the help of GPS receiver and new waypoint is loaded.

IV. RESULTS

Ten experiments are performed with the designed vehicle for transportation of computer accessories inside the university campus and the success rate is found to be 80%. More refined algorithms are needed that will account for errors in odometry system and path generation for increasing the efficiency of the system further e.g., vector pursuit algorithm can be employed for path tracking. Shortest pathalgorithms can also be used for reducing the navigation time.

V. CONCLUSIONS

In this paper, design of a low cost autonomous vehicle based on neural network is presented for mining areas, forestareas and military areas. Equipped with various sensors, the vehicle has the capability of navigating in complex environments avoiding the obstacles in its way and reaching the target. The complexity of the system is reduced by making it modular i.e., more modules can easily be added to system by setting their priority level in the main controller.

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