Technologies for autonomous operation in unstructured environments

Part I: Navigation

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Abstract

This paper describes the development of an autonomous navigation system suitable for robot navigation in an outdoor, unstructured environment. The navigation system uses a differential global positioning system (DGPS) receiver and digital charge coupled device (CCD) camera for navigation and a laser scanner for obstacle avoidance. The navigation algorithm was developed using a feed forward multi layer neural network. The network was trained using the quasi-Newton back propagation algorithm. Software was developed to simulate the performance and efficiency of the algorithm. The network was able to produce a path with a small MSE compared to the targeted path, which was developed using an experienced driver. The network produced acceptable results when tested under different kinds of roads and obstacles. The significance of the proposed research is that a new level of autonomous robot navigation in unstructured environment had been developed that has large application.

1. Introduction

A navigation system is the method for guiding a vehicle. Since the vehicle is in continuous motion, the navigation system should extract a representation of the world from the moving images and other sensory information that it receives. Several capabilities are needed for autonomous navigation. One is the ability to execute elementary goal achieving actions such as going to a given location or following a leader. Another is the ability to react to unexpected events in real time such as avoiding a suddenly appearing obstacle. Another capability is map formation such as building, maintaining and using a map of the environment. Another is learning which might include noting the location of an obstacle on the map so that they could be avoided in the future. Other learning capabilities might focus on the three-dimensional nature of the terrain and adapt the drive torque to the inclination of hills. Another capability is planning such as formation of plans that accomplish specific goals or avoid certain situations such as traps.

During the last fifteen years, a great deal of research has been done on the interpretation of motion fields as regards the information they contain about the 3-D world. In general, the problem is compounded by the fact that the information that can be derived from the sequence of images is not the exact projection of the 3D-motion field, but rather only information about the movement of light patterns, optical flow. About 40 years ago, Hubel and Wiesel (1962) studied the visual cortex of the cat and found simple, complex, and hyper complex cells. In fact, vision in animals is connected with action in two senses: “vision for action” and “action for vision” (Aloimonos, 1997).

The general theory for mobile robotics navigation is based on a simple premise. For a mobile robot to operate it must sense the known world, be able to plan its operations and then act based on this model. This theory of operation has become known as SMPA (Sense, Map, Plan, and Act).

SMPA was accepted as the normal theory until around 1984 when a number of people started to think about the more general problem of organizing intelligence. There was a requirement that intelligence be reactive to dynamic aspects of the unknown environments, that a mobile robot operate on time scales similar to those of animals and humans, and that intelligence be able to generate robust behavior in the face of uncertain sensors, unpredictable environments, an a changing world. This led to the development of the theory of reactive navigation by using Artificial Intelligence (AI) (Andreou and Charalambides, 1995).

1.1 Systems and Methods for mobile robot navigation

1.1.1 Odometry and Other Dead-Reckoning Methods

Odometry is one of the most widely used navigation methods for mobile robot positioning. It uses encoders to measure wheel rotation and/or steering orientation. Odometry has the advantage that it is totally self-contained, and it is always capable of providing the vehicle with an estimate of its position. The disadvantage of odometry is that the position error grows without bound unless an independent reference is used periodically to reduce the error.

1.1.2 Inertial Navigation

This method uses gyroscopes and sometimes accelerometers to measure rate of rotation and acceleration. Measurements are integrated once (or twice) to yield position (De la Escaler et al., 1996, Borenstein et al., 1997). Inertial navigation systems also have the advantage that they are self-contained. On the downside, inertial sensor data drifts with time because of the need to integrate rate data to yield position; any small constant error increases without bound after integration.

1.1.3 Active Beacon Navigation Systems

This method computes the absolute position of the robot from measuring the direction of incidence of three or more actively transmitted beacons (Jason et al., 1997, Premvuti and Wang, 1996). The transmitters, usually using light or radio frequencies must be located at known sites in the environment.

1.1.4 Landmark Navigation

In this method distinctive artificial landmarks are placed at known locations in the environment. The advantage of artificial landmarks is that they can be designed for optimal detect-ability even under adverse environmental conditions (Betke and Gurvits, 1997). As with active beacons, three or more landmarks must be "in view" to allow position estimation.

1.1.5 Map-based Positioning

In this method information acquired from the robot's onboard sensors is compared to a map or world model of the environment (Zelinsky and Y. Kuniyoshi, 1996, Kotani et al., 1998). If features from the sensor-based map and the world model map match, then the vehicle's absolute location can be estimated. The maps used in navigation include geometric and topological maps.

1.1.6 Global Positioning System (GPS)

GPS is a worldwide radio-navigation system formed from a constellation of 24 satellites and their ground stations (Trimble, 2001). GPS is funded by and controlled by the U. S. Department of Defense (DOD). Originally, it was designed for and is operated by the U. S. military. The system provides specially coded satellite signals that can be processed in a GPS receiver, enabling it to compute position, velocity and time. Four GPS satellite signals are used to compute positions in three dimensions and the time offset in the receiver clock (Dana, 1999).

The Space Segment of the system consists of the 24 satellites that orbit the earth in 12 hours. These space vehicles (SVs) send radio signals from space. There are often more than 24 operational satellites as new ones are launched to replace older satellites. The satellite orbits repeat almost the same ground track (as the earth turns beneath them) once each day. The orbit altitude is such that the satellites repeat the same track and configuration over any point approximately each 24 hours (4 minutes earlier each day). There are six equally spaced orbital planes and inclined at about fifty-five degrees with respect to the equatorial plane. This constellation provides the user with between five and eight SVs visible from any point on the earth (Dana, 1999).

The Control Segment consists of a system of tracking stations located around the world, which measure signals from the SVs that are incorporated into orbital models for each satellite. The models compute precise orbital data (ephemeris) and SV clock corrections for each satellite. The Master Control station uploads ephemeris and clock data to the SVs. The SVs then send subsets of the orbital ephemeris data to GPS receivers over radio signals. GPS receivers convert SV signals into position, velocity, and time estimates (Dana, 1999).

The GPS signal contains some errors; the errors are a combination of noise, bias and blunders. In order to correct bias errors the differential GPS (DGPS) is evolved, where bias errors are corrected in the location of interest with measured bias errors at a known position. A reference receiver, or base station, computes corrections for each satellite signal.

DGPS implementations require software in the reference receiver that can track all SVs in view and form individual pseudo-range corrections for each SV. GPS receivers are used for navigation, positioning, time dissemination, and other research. Navigation receivers can be used for aircraft, ships, ground vehicles, and even for individuals (Dana, 1999).

1.2 Literature Review

Since many years of research has been done on mobile robots only a brief survey of related work will be presented.

Learning from the environment is also important for intelligent behavior. One approach that allows a robot to learn a model of its interaction with its operating environment in terms of experienced dynamics is described by Michaud, et al. (1998). Another approach in which the robot adapts to environmental changes by efficiently transferring a learned behavior in previous environments into a new one and effectively modifying it to cope with the new environment is described by Minati, et al. (1998). On the following a brief review for the literature in each of these systems will be presented

1.2.1 Vision based navigation

For an intelligent robot that must adapt to environmental changes in situations in which humans thrive, vision sensing is necessary. Vision-based navigation had been presented in the literature (Lee et al., 2001, Tomita and Tsugawa, 1994, Frohn and Seelen, 1989, Storjohann et al., 1990, Kabuka et al., 1990). Fork and Kabuka (1991) present a navigation system for automatic guided vehicles that uses an efficient double heuristic search algorithm for path location. Beccari, et al. (1997) described a vision-based line tracking system. A sensor composed of a fish-eye lens with a TV camera has been used by Kurata, et al. (1998), they used a reference target on a ceiling and hybrid image processing circuits, the experimental trial showed that the proposed system was valid for an indoor navigation (Kurata et al., 1998).

1.2.2 Sensor based navigation systems

Sensor based navigation systems that rely on sonar or laser scanners that provide one dimensional distance profiles have a great simplicity for collision and obstacle avoidance. In addition, range information can be used for constructing maps of the environment for short term reactive planning and long-term environmental learning.

1.2.3 Use of fuzzy logic

Fuzzy logic has also been used in navigation algorithms for mobile robots as described in (Wijesoma et al., 1999, Roth and Schilling, 1995, Tso et al., 1996, Castellano et al., 1996, Baranyi et al., 1998, Fung and Tso, 1998). A fuzzy logic based real time navigation controller is described by Mora, et al. (1998). Lin and Wang (1997) propose a fuzzy logic approach to guide an AGV from a starting point toward the target without colliding with any static obstacle as well as moving obstacles,. They also study other issues as sensor modeling and trap recovery. Kim, et al. (1998) used fuzzy multi-attribute decision-making in deciding which via-point the robot should proceed to at each step. The via-point is a local target point for the robot's movement at each decision step. A set of candidate via-points is constructed at various headings and velocities. Watanabe, et al. (1998) described a method using a fuzzy logic model for the control of a time varying rotational angle in which multiple linear models are obtained by utilizing the original non-linear model at some representative angles. New navigation strategies for intelligent mobile robot are described by Chio, et al. (1998).

1.2.4 Use of artificial neural networks

Artificial neural networks (ANN) have also been applied to mobile robot navigation. It had been considered for applications that focus on recognition and classification of path features during navigation. Kurd, et al. (1997)

propose the use of neural network controller that was trained using supervised learning as an indirect-controller to obtain the best control parameters for the main controller in use with respect to the position of the AGV. A method that uses incremental learning and classification based on a self-organizing ANN is described by Vercelli and Morasso (1998). Xue, and Cheung (1996) proposed a neural network control scheme for controlling active suspension. The presented controller used a multiplayer back propagation neural network and a prediction-correction method for adjusting learning parameters. Streilein, et al. (1998) described a novel approach to sonar-based object recognition for use on an autonomous robot. Dracopoulos and Dimitris (1998) present the application of multi-layer perceptrons to the robot path planning problem and in particular to the task of maze navigation. Zhu et al. (1998) present recent results of integrating omni-directional view image analysis and a set of adaptive back propagation networks to understand the outdoor road scene by a mobile robot.

The modern mechatronics or electro-mechanical engineering technologist must function in an increasingly automated world of design and manufacturing of today's products (Cicirelli, et al., 1998, Kruse and Wahl, 1998, Little et al., 1998, Arsenio, and Isabel, 1998). To navigate and recognize where it is, a mobile robot must be able to identify its current location. The more the robot knows about its environment, the more efficiently it can operate. Grudic, et al. (1998) used a nonparametric learning algorithm to build a robust mapping between an image obtained from a mobile robot's on-board camera, and the robot's current position. It used the learning data obtained from these raw pixel values to automatically choose a structure for the mapping without human intervention, or any a priori assumptions about what type of image features should be used.

In order to localize itself, a mobile robot tries to match its sensory information at any instant against a prior environment model or map (Feder et al., 1998). A probabilistic map can be regarded as a model that stores at each robot configuration the probability density function of the sensor readings at the robot configuration. Vlassis, et al. (1998) described a novel sensor model and a method for maintaining a probabilistic map in cases of dynamic environments.

1.2.5 Use of neural integrated fuzzy controller

A neural integrated fuzzy controller (NiF-T) that integrates the fuzzy logic representation of human knowledge with the learning capability of neural networks has been developed for nonlinear dynamic control problems. Ng, et al (1998), Daxwanger, et al. (1998) presented their neuro-fuzzy approach to visual guidance of a mobile robot vehicle.

1.2.6 Map-based navigation

While roadmaps has been used for robot path planning in static structured environment, Piaggio and Zaccaria (1998) had combine the use of dynamic analogical representation of the environment with a road map extraction method to guide the robot navigation and to classify the different regions of space in which the robot moves in order to use this approach in some real situations.

1.2.7 Navigation in unstructured environment

Some research had been conducted regarding robotics in unstructured environment. Martínez, et al. (2001) presented visual procedures especially tailored to the constraints and requirements of a legged robot that works with an un-calibrated camera, freely moving towards a stationary target in an unstructured environment. Kurazume and Shegeo (2000) proposed a new method called "Cooperative Positioning System (CPS)". Torras (1995) reviewed neural learning techniques for making robots well adapted to their surroundings. Yahja, et al. (2000) propose an on-line path planner for outdoor mobile robots using a framed-quadtrees data structure and an optimal algorithm to incrementally re-plan optimal paths. Baratoff, et al. (2000) designed a space-variant image transformation, called the polar sector map, which is ideally suited to the navigational tasks. Yu, et al. (2001) presented a hybrid evolutionary motion planning simulation system for mobile robots operating in unstructured environments, based on a new obstacle representation method named cross-line, a follow boundary repair approach, and a hybrid evolutionary motion planning algorithm. Yan, et al. (1997) presents an attempt to devise and develop a domain-independent reasoning system (DIRS) scheme for handling dynamic threats, and uses the scheme for automated route planning of military vehicles in an unstructured environment.

Computer vision and image sequence techniques was proposed for obstacle detection and avoidance for autonomous land vehicles that can navigate in an outdoor road environment, the object shape boundary is first extracted from the image. After the translation from the vehicle location in the current cycle to that in the next cycle is estimated, the position of the object shape in the image of the next cycle is predicted, then it is matched with the extracted shape of the object in the image of the next cycle to decide whether the object is an obstacle (Chen and Tsai, 2000). Jarvis (1996) report some preliminary work regarding an autonomous outdoor robotic vehicle navigation using flux gate compass, differential global positioning systems and range sensing and distance transform based path planning. An adaptive navigation method suited for the complex natural environments had been proposed based on a multi-purpose perception system that manages different terrain representations, the paper focuses on the functions deal with the navigation planning ad the robot self-localization which have been integrated within the robot control system (Devy et al., 1995). Krishna and Kalra (2001) proposed incorporating cognition and remembrance capabilities in a sensor-based real-time navigation algorithm to enhance the robots performance by providing for a memory-based reasoning whereby the robot's forthcoming decisions are also affected by its previous experiences during the navigation apart from the current range inputs. A fuzzy classification scheme coupled to Kohonen's self-organizing map and fuzzy ART network (Krishna and Kalra, 2001).

1.3 Research Outline

Most of the previous research that has been conducted in this area covered the navigation in a structured indoor environment; however, in our application and in a lot of other important applications, the environment is no longer structured. Most of the times there is no prior knowledge regarding the environment or the path, presence of wild terrain and unpredictable obstacles. The literature available is insufficient in those kinds of applications.

In this research, we propose the development of a defensive military robot with learning capability. This robot needs to navigate in an unstructured environment to some specific location of interest that will generally be very difficult for the human to reach, detect the location of objects such as land mines and destroy them. It can also perform any kind of surveillance, collect some samples or take photos, and finally, return to the base after accomplishing its mission. Due to the intensity of the research, it will be described in a series of papers and in this paper the navigation and obstacle avoidance in an unstructured environment will be addressed.

The proposed navigation algorithm that is proposed uses a differential GPS and vision system for tracking the path, a laser scanner for obstacle detection, and a feed forward multi layer neural network for developing the robot path; the network is trained using a quasi-Newton back propagation algorithm. To permit the widest exploration of the proposed algorithm, an analytical and simulation approach will be presented. The simulations have been developed for a two-dimensional world with a mobile ground vehicle using Matlab software. This work will be continued and extended where possible to full three-dimensional simulations.

Some challenges that this research is trying to solve are:

- Effective navigation and obstacle avoidance algorithms for an unstructured outdoor environment.
- Control algorithms that are capable of dealing with all the inputs and deciding the optimal course of action.
- Sensory devices capable of giving the proper description of the environment to the controller.

Similar operations that are performed by humans are very limited, due to the following:

- The limited capabilities of humans, in terms of force, speed of operations and tolerance to any kind of poisonous gas or low-level radiation.
- Most of the conditions are dangerous to humans and their lives.
- Hence, the robot can be more effective, faster and can work in many difficult and dangerous situations.

In addition, the algorithms that will be developed in this research can be utilized in numerous applications including the discovery robot or explorer robot, undersea vehicles, passenger transport in urban areas, personal robots, and for many unstructured applications as in construction and agriculture. Actually, they are also needed for any robot that is working in real time applications, since all of these applications have varying amounts of uncertainty.

The design of the robot will be presented in the next section followed by a description of the algorithm used for the navigation, and then the results of the simulations will be presented, finally a conclusion will be given.

2. Robot Design

The defensive military robot is a robot that is designed to navigate in an unstructured environment, as in a field or any region without specified road marks. The robot needs to have intelligence to perform perception, vehicle control, obstacle avoidance, position location, path planning, and navigation. The robot must navigate to the target location and then perform the intended activities like locating and destroying land mines and any other surveillance activities. During this quest, the robot may encounter a variety of difficulties including navigation difficulties, health difficulties, and being captured by the enemy.

In case of navigation difficulties like impassable terrain, wild animals, holes, boulders, dangerous locations or bad weather the robot need to be equipped with a navigation system that is capable of overcoming all these obstacles to reach its target location.

Regarding the health problems occurring when facing hazards like any kind of poison gases, low-level radiation, or pumps, which are usually impossible for humans to overcome, the robot can be build to be immune to them. Finally, when captured, a robot could destroy itself, thus improving the security of combat information (ThinkQuest Project, 1998).

The robot will have a set of operating systems. Each system will enable the robot to perform in a specific situation. The operating systems are:

- Navigation and obstacle avoidance

- Locating and destroying land mines
- Surveillance activities
- Health monitoring
- Self-destruction

The proposed research will be implemented on Bearcat III Robot; however, the available systems will be modified accordingly to fit the new research.

The robot will be able to sense the environment from the inputs of the vision and sensory system. Then it will make decisions using the central control system. Finally, it will make control actions by the use of the motion control system, locating and destroying land mines system and the surveillance system. The supplementary systems that will enable it to perform the control actions are the motion control system, mechanical system, and the power system. The central control system will choose which system to operate in that particular situation. The main components of the robot are shown in Fig. 1.

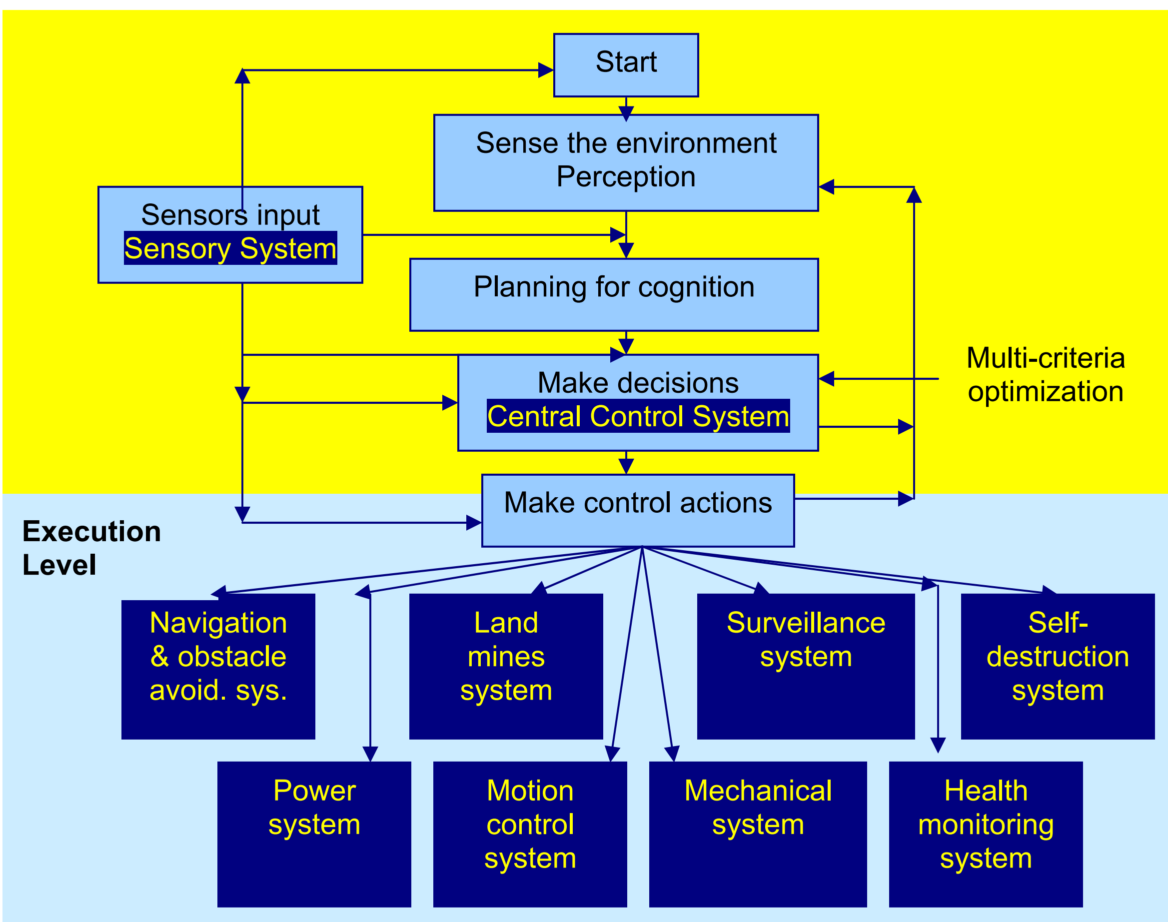

Figure 1: The structure of the control system.

2.1 The navigation system

The navigation system is responsible for guiding the robot. The navigation system should extract a representation of the world from the moving images and other sensory information that it receives. Several capabilities are required for autonomous navigation. Over the years, all kinds of technologies were tried to simplify the task but each one had its own disadvantages regarding working in unstructured environments (Trimble, 2001).

The navigation system that will be developed for the defensive military robot must take into consideration that the robot needs to be able to navigate in unstructured environment. The unstructured environment that usually confronts with the military robot is an open outdoor wild terrain with usually no landmarks and some stationary or moving obstacles. Hence, the pre-mentioned methods cannot be used. On the other hand, GPS works in any open area; hence, DGPS is suggested for the navigation system.

The robot will be supplied with crawler, which makes it capable of navigating through any open wild terrain.

2.2 The sensory devices

The robot is supplied with a Galil DMC Motion Controller, a sensor system that is based on a micro-controller interfaced with a rotating ultrasonic transducer, vision system, and encoders. Point or line tracking is achieved through the medium of a digital CCD camera. Image processing is done by an Iscan (Iscan, 1993) tracking device. This device finds the centroid of the brightest or darkest region in a computer-controlled window, and returns its X, Y image coordinates as well as size information. This system enables the robot to navigate through the landmarks.

Just as with a human being, the robot may have some obstacles on its path while navigating. In order for the robot to reach its target safely, it needs to sense these obstacles and avoid them. Obstacle avoidance is one of the key problems in computer vision and mobile robotics. There has been a considerable research devoted to the obstacle detection problem for mobile robot platforms and intelligent vehicles. Laser scanners have been used for many years for obstacle detection and are found to be most reliable and provide accurate results. They operate by sweeping a laser beam across a scene and at each angle, measuring the range and returned intensity. The robot senses its location and orientation using the integrated vision system and the SICK laser scanner (LMS 200). The laser provides fast single- line laser scans and is used to map the location and size of possible obstacles. With these inputs, the central control system can control the steering speed and steering decisions of the robot on an obstacle course. The scans were made using a scan-oriented approach rather than a pixel-oriented approach because of the faster refreshing rate and the laser scanner giving a clear field of view of the coordinates of every point along x and y-axis (Sexena, 2001). The system is designed to perform mainly with fixed obstacles, for the case of moving obstacles, which are assumed not so many; the robot will stop and wait until these obstacles will free the robot path. If these obstacles stop and remain stand still the robot will avoid them using the same algorithm it uses for a fixed obstacle. Further experimentation, however, will be conducted for the detection and avoidance of the moving obstacles.

The robot will be supplied with a DGPS receiver in order to make it capable to navigate in the places where there are no landmarks.

2.3 Navigation algorithm

During navigation in an unstructured environment there are two possible cases:

1. There are landmarks, stationary obstacles and a low possibility for moving obstacles.
2. There are no landmarks, stationary obstacles and a low possibility for moving obstacles.

For the first case, the robot will find its path using the digital CCD camera and the image processing will be done by an Iscan (Iscan, 1993) tracking device. For the second case, which is the common case for a military robot, the robot will use the DGPS receiver to capture information about its path. GPS position information X, Y, and Z coordinates will be used to plan the robot path. The algorithm used first connects the GPS points and then uses artificial neural network (ANN) to find the best path for the robot.

2.3.1 ANN architecture

2.3.1.1 ANN input: The inputs to the ANN are:

3. The lower boundary of the path, which is developed by connecting between the GPS points for the lower boundary.
4. The upper boundary of the path, which is developed by connecting between the GPS points for the lower boundary.
5. The position of the fixed obstacles a long the path collected from the laser scanner.

2.3.1.2 ANN output: The output of the ANN will be the robot path that needs to be within the lower and upper boundary avoiding any obstacles along the path.

2.3.1.3 ANN layers architecture: The architecture for ANN was selected based on the simple rules of thump and trial and error. Trials were conducted on simulation software developed using Matlab for the robot navigation. The ANN used was a feed forward network that has five layers, the layers architecture are shown in Table 1.

Layer	Number of neurons	Activation function
First layer	3	Log-sigmoid
Second layer	7	Log-sigmoid
Third layer	12	Log-sigmoid
Fourth layer	8	Log-sigmoid
Fifth layer (Output layer)	1	Linear

Table 1: ANN layers architecture.

2.3.1.4 ANN training

The network was trained using back propagation training algorithm. Back propagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. The term back propagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. The back propagation training algorithm used was a Broyden, Fletcher, Goldfarb, and Shanno (BFGS) quasi-Newton algorithm, which is a high performance algorithm that can converge from ten to one hundred times faster than the common gradient descent algorithms. The Newton's method is an alternative to the conjugate gradient methods for fast optimization; it uses standard numerical optimization techniques (Matlab, 2002).

The basic step of Newton's method uses the Hessian matrix (second derivatives) of the performance index at the current values of the weights and biases. Newton's method often converges faster than conjugate gradient methods. Unfortunately, it is complex and expensive to compute the Hessian matrix for feed forward neural networks. There is a class of algorithms that is based on Newton's method, but which doesn't require calculation of second derivatives. These are called quasi-Newton (or secant) methods. They update an approximate Hessian matrix at each iteration of the algorithm. The update is computed as a function of the gradient. The quasi-Newton method that has been most successful in published studies is the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update. This algorithm has been implemented in this paper (Matlab, 2002). The performance function used is the mean square error (MSE). MSE is the average squared error between the network outputs and the target outputs. The weights and biases of the network were automatically initialized to small random numbers by the software.

The training data was a simulated road boundary that was developed using typical GPS data. Two sets of experiment were tried. In the first set six obstacles were imposed to the path, while in the second set of experiments seventeen obstacles were used.

The target used for training the network is developed based on the judgment of an experienced driver on how to navigate the road without hitting any of the obstacles. The road boundary is represented by lines, while the obstacles are represented by circles. The robot path is represented by a line, which represents the position of the robot center of gravity and a distance of half the width of the robot. Some clearance is always to be kept between the robot path and the obstacles or the road boundary during navigation. The road consists of 1000 points. The simulated road boundary with the two sets of obstacles and the target are shown in Fig. 2 and Fig. 3.

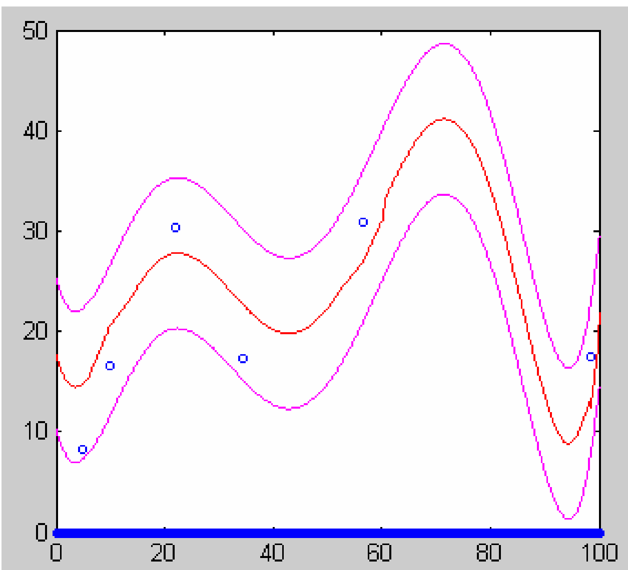

Figure 2: The simulated road boundary with the first set of obstacles (six obstacles) and the target.

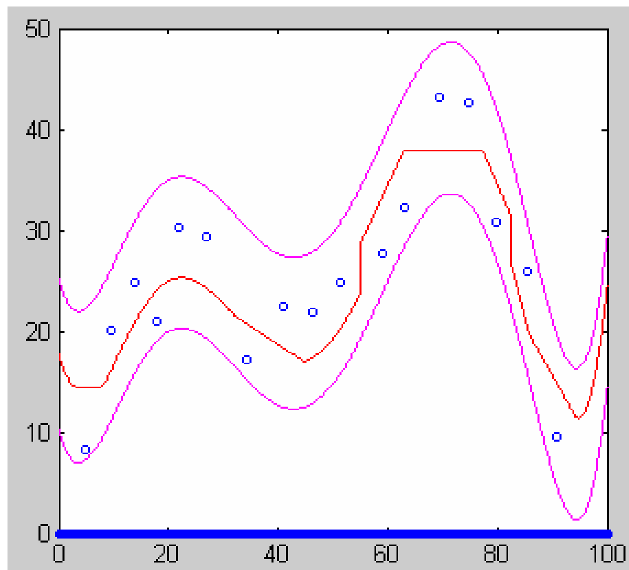

Figure 3: The simulated road boundary with the second set of obstacles (seventeen obstacles) and the target.

The network trained in a very small time and was able to produce the target with a MSE of 1.33 *10-4 in the first case and 4.86*10-4 in the second case. The training performance is shown in Fig. 4 and Fig. 5 respectively.

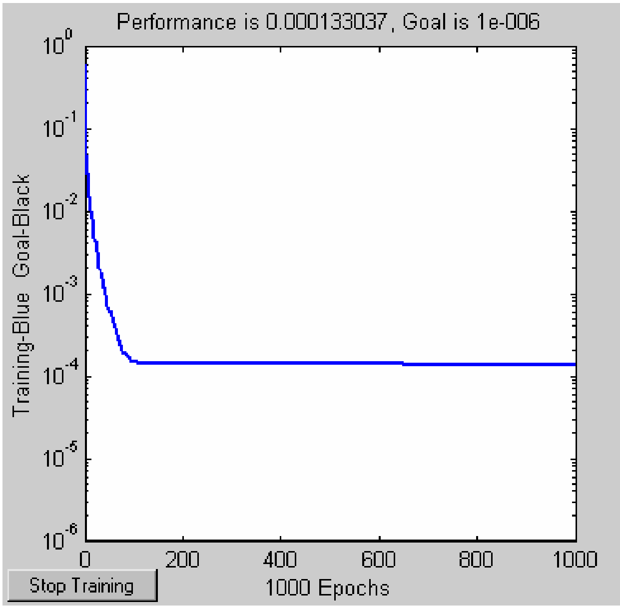

Figure 4: The training performance of the network versus epochs for the road with six obstacles.

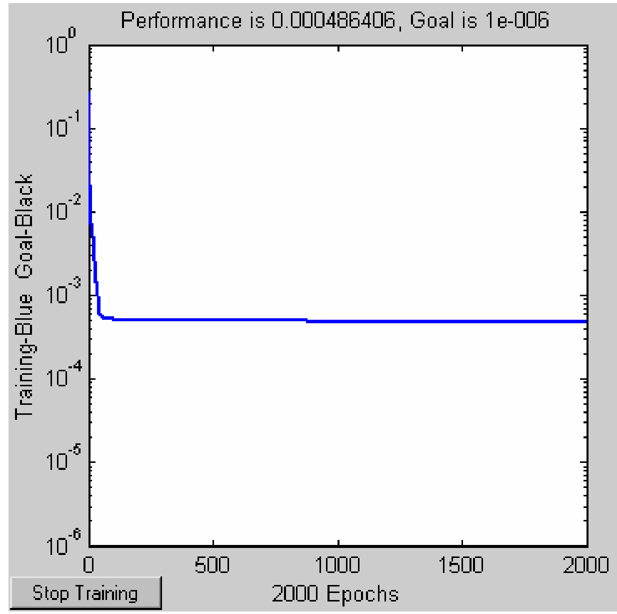

Figure 5: The training performance of the network versus epochs for the road with seventeen obstacles.

2.4 Results

After training the network, the same road applied to the network, the output from the network is shown in Fig. 6 and Fig. 7 respectively.

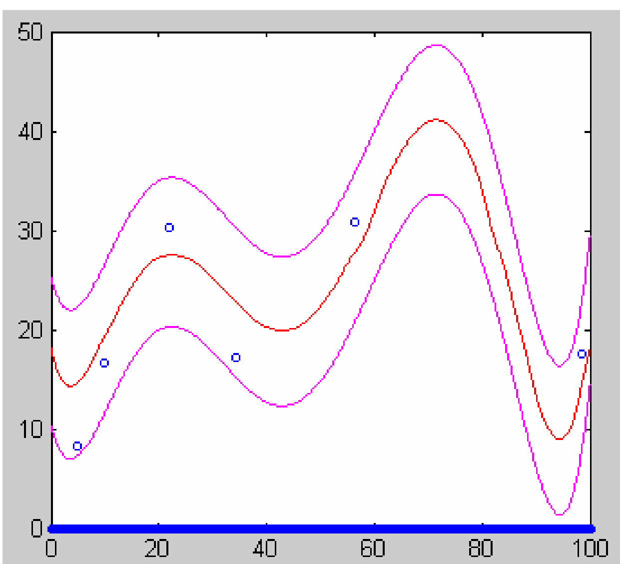

Figure 6: The output of the network for the original road with six obstacles.

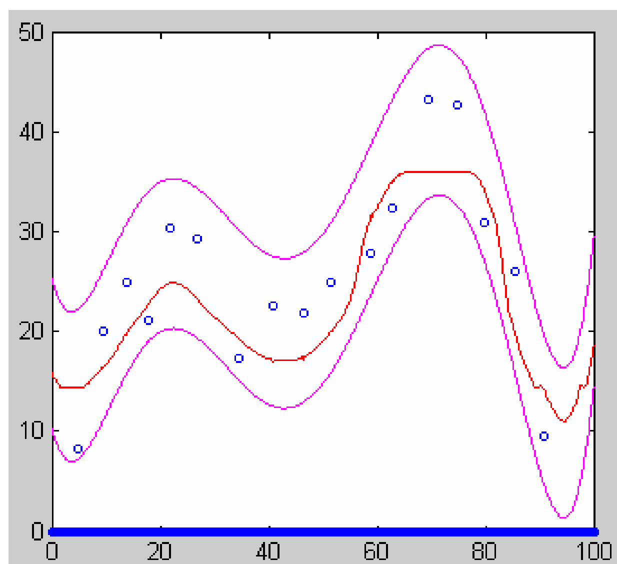

Figure 7: The output of the network for the original road with seventeen obstacles.

As shown in the figures the network was able to produce a good path that is within the road boundaries and avoiding all the obstacles, actually, in the second case the network output is even smoother than the target in some points.

To test the learning capability of the network, two different roads were given to the network; one with few obstacles and the other one with many obstacles. The roads are shown in Fig. 8 and Fig. 9 respectively. The outputs of the network for these roads are shown in Fig 10 and Fig. 11 respectively.

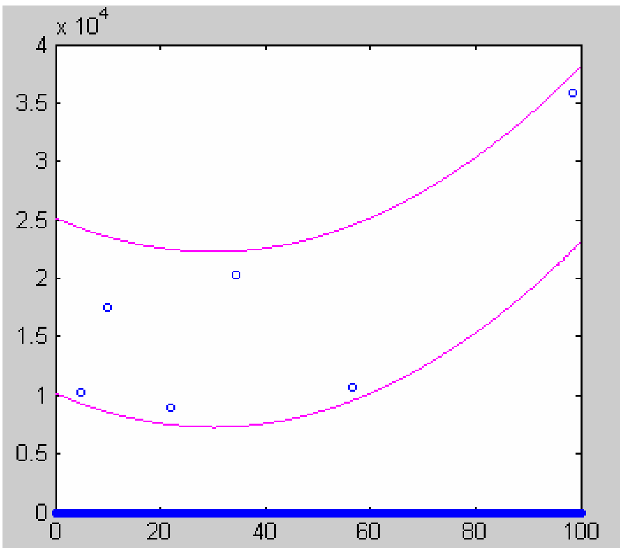

Figure 8: The second road boundary applied to the network.

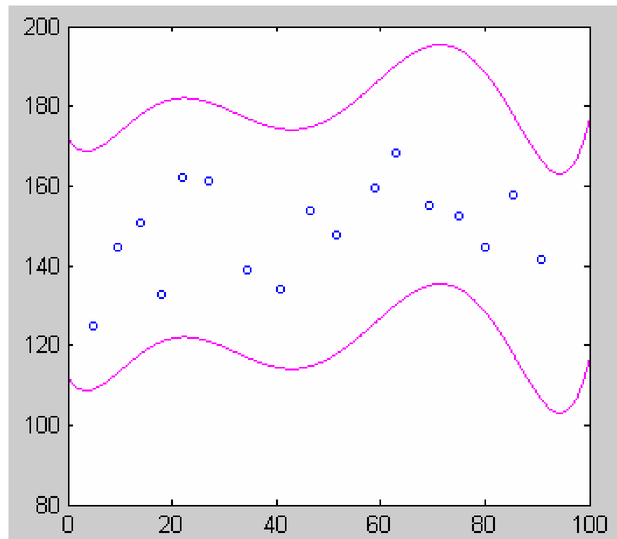

Figure 9: The third road boundary applied to the network.

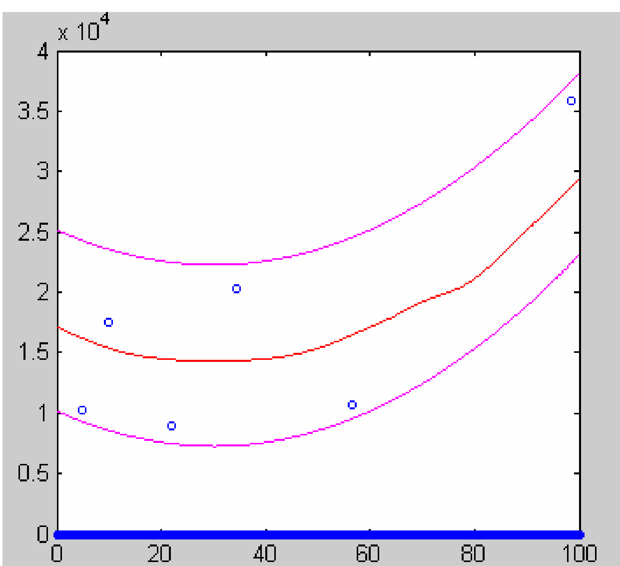

Figure 10: The output of the network for the second road boundary.

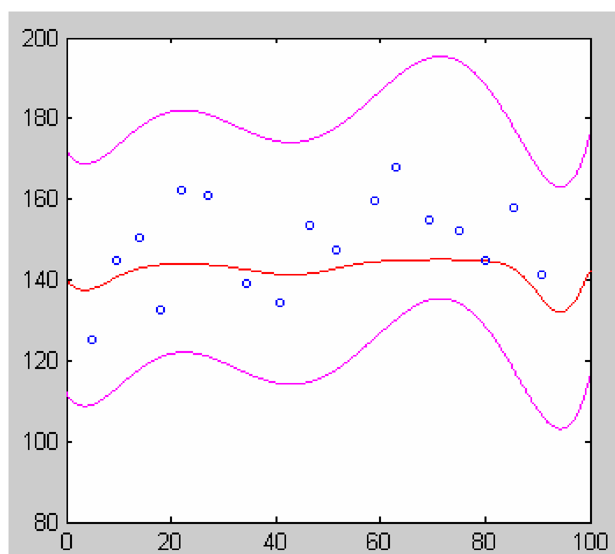

Figure 11: The output of the network for the third road boundary.

As shown in the figures the network performance was excellent for the second road where a few number of obstacles are present, however, for the third road the network succeeds in finding a good path but it hits one of the obstacles.

3. Conclusion

In this paper the development of an autonomous navigation system suitable for robot navigation in out door, unstructured environment is presented. The navigation system suggested uses digital CCD cameras for navigating if there are landmarks and a DGPS receiver in cases where there are no landmarks. A laser scanner is used to detect the presence of an obstacle. The navigation algorithm was developed using a feed forward neural network with five layers; the network was trained using quasi-Newton back propagation algorithm. Software has been developed to simulate the performance and efficiency of the algorithm. The network was trained on road with less number of obstacles and on another road with many obstacles and the network was able to produce the output within a MSE of $1.33 * 10^{-4}$ and $4.86 * 10^{-4}$ from the target that was developed using an experienced driver. The network has been tested under different kind of roads and obstacles and produced very good results on paths with a small number of obstacles; for the path with many obstacles the network had some difficulties in dealing with the obstacles in some parts of the path. The network performance can be modified by incorporating some rules regarding how to deal with the obstacles. This can be done by incorporating fuzzy logic into the neural network. Neuro-fuzzy systems combine the advantages of fuzzy systems and neural networks. Fuzziness can be introduced to the neural nets by either using a fuzzy input or a fuzzy output, or using a fuzzy training data. Neural network learning provides a good way to adjust the expert's knowledge and automatically generates additional fuzzy rules and membership functions to meet certain specifications and reduces design time and costs. Further experiments will be conducted using a neuro-fuzzy architecture.

The significance of the proposed research is that a new level of autonomous robot navigation that has large application in unstructured environment has been developed.

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