A Model of Environment Representation Architecture for Intelligent Robot

نموذج لتمثيل هيكلية البيئة للروبوت الذكي

By

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إقرار تفويض

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DEDICATION

Almighty Allah says “And remember! your Lord caused to be declared (publicly): "If ye are grateful, I will add more (favours) unto you; But if ye show ingratitude, truly My punishment is terrible indeed.”.

So all praise is for Allah, the exalted, for his favors that cannot be counted.

I dedicate this work to my Parents, my brother, my wife, my sisters, my relatives, my friends, and for all those who helped, supported and taught me.

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Abstract

This thesis presents a model of Environment Representation Architecture for Intelligent Robot. The model consists of a vehicle, an environment and landmarks. The proposed method is based on using Simultaneous Localization and Mapping based on Artificial Neural Network, back propagation algorithm, to be trained on predefined datasets on some environment.

The Finding in this thesis dun Using Artificial Neural on the Simultaneous Localization and Mapping enhances the obtained maps of the robot. Limitation of this thesis to test the proposed system, different maps with different datasets are required, however, these datasets, need expensive sensors, vehicles and GPS receivers to be built.

The Originality he contribution of this thesis, is the use of Artificial Neural Network Back Propagation algorithm on the Simultaneous Localization and Mapping algorithm to obtain enhanced results, enhanced maps and datasets obtained by the robot.

Using several methods of preparing data sets for the landmarks of an environment, SLAM was able to navigate and build its own map of landmarks based on them. In this work, the benefitted from previous approaches to design an enhanced SLAM system, which is based on Artificial Neural Network. However, by training this network on real dataset of environments, the proposed system was able to navigate an environment and build its own map accurately and without prerequisites.

Keywords

SLAM (Simultaneous Localization and Mapping)
ANN (Artificial Neural Network)
EKF (Extend Kalman Filter)

الخلاصة

هذه الرسالة تقدم نموذج لهيكلية تمثيل البيئة للروبوت الذكي. النموذج يتكون من سيارة، بيئة ومعالم. الطريقة المقترحة هي مبنية على استخدام التوطين ورسم الخرائط في وقت واحد بالاعتماد على الشبكات العصبونية الذكية، خوارزمية الانتشار الخلفي، ليتم تعليمها على مجموعات البيانات المعرفة مسبقا لنفس البيئة.

النتائج في هذه الرسالة تمت باستخدام الشبكات العصبونية الذكية والتوطين ورسم الخرائط في وقت واحد لتطوير الخريطة المبنية للبيئة عن طريق الروبوت. المحددات في هذه الرسالة تكمن في فحص النظام المقترح. خرائط مختلفة مع مجموعات بيانات مختلفة مطلوبة، مجموعات البيانات هذه تحتاج مجسات غالية الثمن، مركبات وأجهزة استقبال احداثيات ليتم بناؤها.

الجديد في هذه الرسالة هو استخدام الشبكات العصبونية الذكية طريقة الانتشار الخلفي في خوارزمية التوطين ورسم الخرائط في وقت واحد للحصول على نتائج محسنة، خرائط محسنة، ومجموعات بيانات مبنية عن طريق الروبوت.

استخدام العديد من الطرق لتحضير مجموعات بيانات لمعالم البيئة، طريقة سلام كانت قادرة على التنقل ورسم خرائط بناء على علامات البيئة. في هذا العمل استخدمنا من الطرق السابقة لتصميم نظام سلام متطور، مبني على الشبكات العصبونية الذكية، على أية حال، بتعليم هذه الشبكة على مجموعة بيانات حقيقية لبيئة، النظام المقترح يكون قادر على التنقل في البيئة وبناء خريطته الخاصة بشكل دقيق وبدون متطلبات سابقة.

Chapter One

Introduction

1.1 Overview

“Many natural systems of most creatures in the world are very rich topics for the scientific researchers, since that a simple individual behavior can cooperate to create a system able to solve a real complex problem and perform very sophisticated tasks” (Owaied 2007).

“Robots are designed to assist human beings to complete tasks. As described in many research journals and scientific fictions, researchers and the general public expect that one day robots can complete certain tasks independently and autonomously in this world” (Tan 2012).

There is currently a strong tendency to expand areas where robots functions, in office environments or domestic environments (service robots), types of applications are endless, starting from cleaning tasks, maintenance tasks, to the tasks of exploration and understanding. A robot can also be used as a museum guide. This is called, in general, interior robotics.

“Moreover, they usually have multiple sensors and actuators that allow for rich communication with the user. Of course, the task of designing and building a companion robot is highly complex” (Dastani 2012; Jules 2012).

"Mobile robots are currently more and more in use in a variety of environments including outdoors, in factories, in building automation, but also in homes. It has been previously shown that putting a mobile robot into a smart environment offers a whole new bunch of opportunities in the field of robotics, for example by optimizing velocities while maintaining safety in transportation tasks" (Arndt 2012; Berns 2012).

"Environment map building is closely linked with localization problem. Coherence and robustness of map actualizations depends on robustness of position estimation. In case of dynamical map building must be the localization with respect to already known map regions. Localization could be divided into global localization and position estimation. Global localization is performed with influence of global uncertainty which affects whole learnt" (Roman 2005).

Simultaneous Localization and Mapping (SLAM) algorithm, is an algorithm used by robots for map building, this work will be based on SLAM algorithm calculations to produce the mapped datasets and landmark. Artificial Neural Network (ANN) algorithms are very important for modern systems, which it can be trained and work without pre-requests. While SLAM requires pre-requests in order to build the robots landmarks and map. The proposed system in this work uses ANN to allow the robots to build its own map without pre-requests. Moreover, ANN enhances SLAM and allows the robot to map any environment.

1.2 The Problem Statement

Modeling of environment for use robotic systems has in fact become a major focus of contemporary autonomous robotic research. The following are the problems related to development of a model for general environment, these are:

1- How to build a robotic system capable of building map proximity form the original environment by identifying the characteristics of the environment and work in the any environment.

2- How to identify the relationships between required information for a robot related to an environment with the robot tasks.

1.3 Objectives of the Study

The objective of this thesis can be summarized into the following points:

1- Developing methods that allow robots to perform tasks automatically for representing the characteristics and information of an environment.

2- Developing model for representation architecture of static environment by enhancement for the SLAM algorithm by addition new methods.

1.4 Motivation

The main task of mobile robotics is autonomous work in environment. There are required as much information about environment as possible. Information about mobile robot environment representation is often named environment map, because actually it has in fact really form of map. Environment map building is closely linked with localization problem (Roman 2005).

Generally, the robots are evolved to perform tasks requiring some level of intelligence, for example moving around in an environment without running into things (lipson-n-2000).

The process of controller evolution consists of repeating cycles of controller fitness testing and selection that are roughly analogous generations in natural evolution. During each subsequent cycle, or generation, each of the robot controllers competes in an environment to perform the task for which the robots are being evolved (Nelson 2009).

1.5 Methodology

- Study the representation environment robot providers which provide to determine that most proper domain the intelligent.
- Selecting the environment representation domain, reviewing and analyzing existing robot and environment representation in depth.
- Create database in order to identifying and extracting information from various environment.
- Constructing the proposed model.
- Evaluating the proposed model.

1.6 Thesis Structure

The thesis includes six chapters:

Chapter one is content the idea of this work that consist of; the problem, the objective , and motivation of this studies.

Chapter two gives and overview of the terminology used introduces the basic concepts of mobile robots.

Chapter three is the literature survey and related works for the thesis,

Chapter four, will focus on the proposed model for the environment representation architecture.Chapter five will explain the implementation of the proposed model, and new approach of using ANN, to enhance the mapping process. In addition to results analysis. Conclusions of this work and future work will be in the six chapters.

Chapter Two

Terminology

2.1Overview

This chapter is introduction to the domain of localization in mobile robots. The issue of the location and value of the knowledge of the position and orientation of the robot, relative to its environment are presented. Different approaches to localization and associate sensors are stated. Localization in environment is addressed. The particular case of the location based on a model with the vision is also introduced in this chapter.

It is important to have a general idea of the concept of a mobile robot, in order to understand the interactions between different modules, which the study will refer in this work. For further coverage of this subject, volumes, (Murphy 2000) are recommended.

A mobile robot consists of hardware and software components. The hardware components, a mobile platform are attached to all other components such as sensors, actuators and power sources (batteries).

2.2 Components of Mobile Robot

2.2.1 Sensors

The sensors operable to acquire data from the environment. They typically installed on a mobile robot **(see Figure 2.1)** which shows, sonar's ultrasonic sensor, laser proximity sensor, encoder wheel (odometer), optical camera and microphone. The types collected of information and their accuracy vary greatly from one sensor to another. For example, **(Figure 2.2)** shows a laser proximity sensor (c) to better perceive the contours of environment (a) than a sonar (b) because the sensor offers better angular resolution and accuracy over distance.

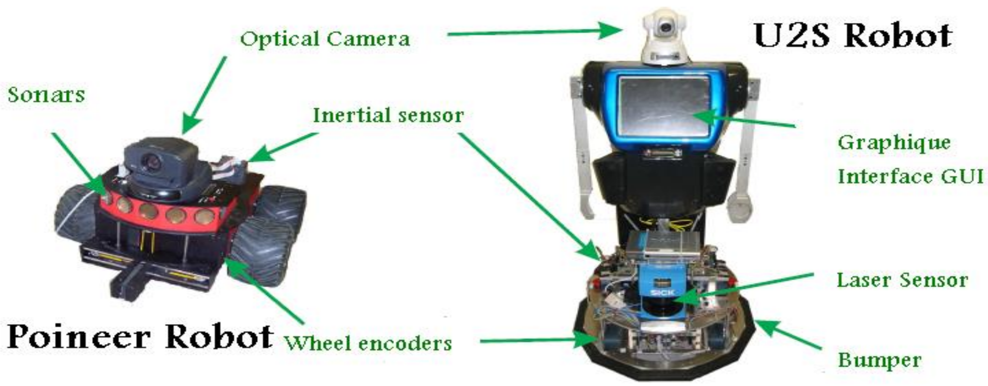
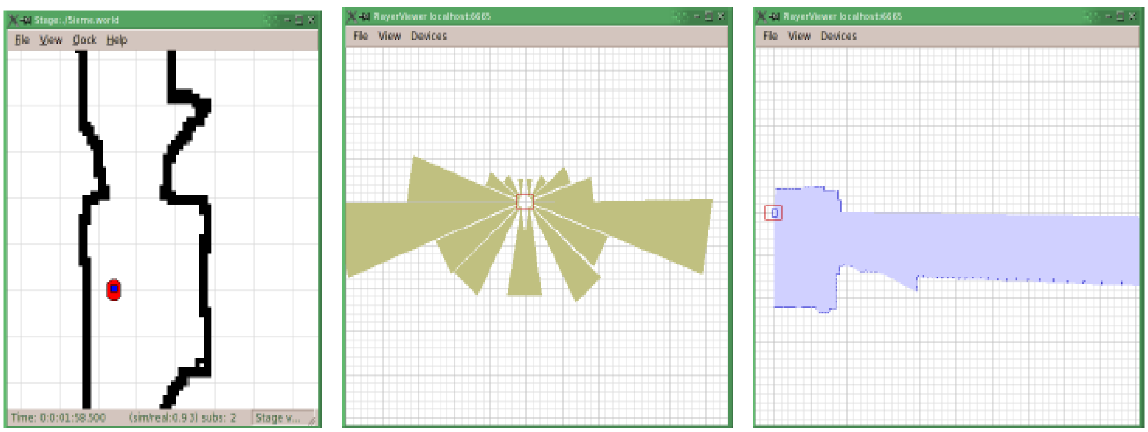


Figure 2.1: Typical sensor of a robot (Eric 2006)



(a) Simulator Stage (b) View of sonar (c) View of the laser

Figure 2.2: Preceptions of some sensors (Eric 2006)

2.2.2 Actuators

To move within a specific environment and interact with it, a robot should be equipped with actuators. For example, a robot is provided with one or more motors the wheels can be rotated to effect movement. Generally, the wheels of the robot are controlled by two actuators to control a forward speed and a rate of rotation. Usually, these commands are expressed in meters per second (m / s) and rotation in degrees per second (deg. / s).

2.2.3 Software Models

In order for a mobile robot to operate, several software components are involved. These components can be used to interpret the data collected by the sensors to extract information or to treat high-level commands in order to generate other lower level commands. The most frequently used components are positioning modules, navigation, and vision, audio and sequential activities of the robot.

2.2.3.1 Location

One of the most important functions for a robot is the ability to locate its position in its environment. Using data provided by the sensors, the module consider the current location of the robot position. Typically, this position is expressed by a tuple (X, Y) representing a position and an orientation of a two dimensions plane. The location can be calculated using technology based on the Markov theory for decision processes (Fox 1999), using sampling techniques Monte Carlo (particle filters) (thrun 2001), or other methods.

2.2.3.2 Vision

By analyzing the images captured by the cameras, a large amount of information are extracted. For example, by using a segmentation algorithm (Gongalez 2001), one can recognize color objects in addition to estimate their relative position (angle) relative to the view of the camera. Using three-dimensional vision techniques (Truco 1998), it is also possible to estimate certain distances in the environment. It can also recognize symbols, characters and read messages (tetourn 2001), such as direction signals posters in a corridor or conference badges.

2.2.3.3 Navigation

A navigation module is responsible for moving a robot from its current position to a desired destination safely and efficiently. In addition to including perception features of the environment and location, the navigation module is also responsible to find a path connecting the positions of origin and destination, form a list of intermediate points to, and to guide the robot through the developed path.

2.3 Control Loop

A mobile robot is controlled by a control loop, as shows in **(Figure 2.3).** Iteratively, this loop is read data received by the sensors; interpreter calculates the motor commands and sends them to the actuators. Typically, this loop is executed about ten times per second; the frequency can vary depending on the types of sensors and actuators used. The control loop is not unique, depending on the architecture used; it can be decomposed into several sub-loops control arranged in different ways.

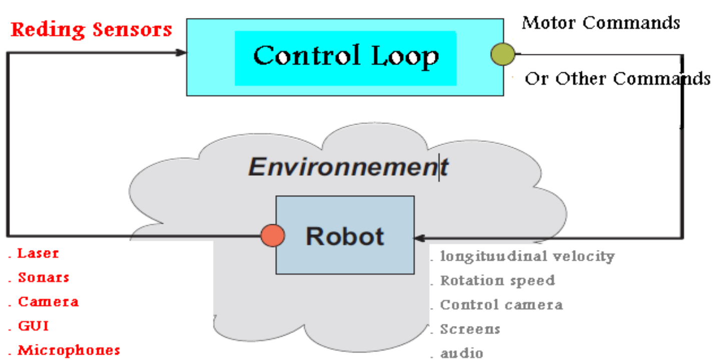


Figure 2.3: Control Loop

2.4 Localization in Mobile Robots: Techniques and Sensors

Whatever the domain of applications for which they are intended a mobile robot to be used, they must include a system for a certain level of autonomy in localization and navigation. To simplify, it must be able to answer three types of questions: “Where am I?”, “Where I go?”, and “how to get there?”.The first question raises the issue of localization. The other two are related to planning and navigation of the path itself. The performance of the last two tasks is closely related to the first one (Nicolas 2010).

2.4.1 Odometry

In navigation, odometry is the use of data from the movement of actuators to estimate change in position over time through devices such as rotary encoders to measure wheel rotations. This is one of the most used mobile robotic systems because it has many benefits such as financial cost, a high level of measurement sampling, a very good short-term accuracy and great ease of implementation .The basic idea of this system is the integration of the increment of the position calculated through encoders mounted on the wheels, over time (Maimone 2007).

2.5 Methods for Calculating the Position and Orientation

2.5.1 Trilateration (or Multilateration)

A GPS receiver uses trilateration (a more complex version of triangulation) to determine its position on the surface of the earth by timing signals from three satellites in the Global Positioning System. The GPS is a network of satellites that orbit the earth and send a signal to GPS receivers providing precise details of the receiver's location (www.mio.com).

Figure 2.6: Show Trilateration form from three Satellites (David 2009).

2.6 Artificial Neural Networks (ANN).

A neural network consists of a set of neurons connected together by weighted connections. It is characterized mainly by the type of units used and by its topology. There are two types of specific neurons in a network: neurons receiving input data from the outside world (the situation) and the output neurons providing the result of the performed treatment (the evaluation). The other units are generally qualified to caches. However, this distinction is not required, and all neurons can communicate very well in both directions with the outside (hidden) (Mirza 2009).

Neural networks have seen an explosion of interest over the last few years and are being successfully applied across an extraordinary range of problem domains, in areas as diverse as Nance, medicine, engineering, geology and physics (Statsoft 2010).

It all started way back in 1943 when McCullock and Pitts proved that neuron can have two states and that those states could be dependent on some threshold value.

2.6.1 Using Artificial Neural Networks

ANN model is able to be used as an arbitrary function approximation mechanism that 'learns' from observed data. The model depending on the data representation and the application.

2.6.1.1 Learning the Algorithm

One of the main attractions of the ANN for the learning capabilities that possess some models. The automatic modification of the connection weights or more rarely in the number and organization of neurons is defined generally by learning to adapt to end processing performed by the network to a particular task.

Thanks to very good generalization capabilities of the neural network, reinforcement learning can process a problem with a huge number of possible states.

2.6.1.2 Robustness

The ANN result can be robust depending on whether the model, cost function and learning algorithm are selected appropriately, or not.

2.6.2 Architecture of ANN

It is made up from an input, output and one or more hidden layers. Each node from input layer is connected to a node from hidden layer and every node from hidden layer is connected to a node in output layer. There is usually some weight associated with every connection.

Input layer represents the raw information that is fed into the network. This part of network is never changing its values. Every single input to the network is duplicated and send down to the nodes in hidden layer.

Hidden Layer accepts data from the input layer. It uses input values and modules them using some weight value, this new value is than send to the output layer but it will also be modified by some weight from connection between hidden and output layer.

Output layer process information received from the hidden layer and produces an output. This output is than processed by activation function. In this figure (2.8) represent architecture of a simple ANN (Mirza 2009).

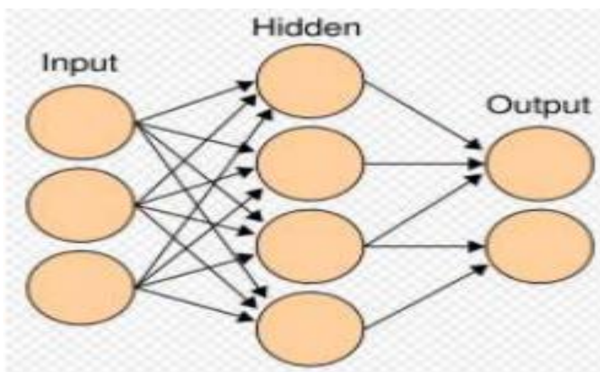


Figure 2.8: Artificial Neural Network (Mirza 2009)

2.6.3 Number of Nodes and Layers

Choosing number of nodes for each layer will depend on problem ANN is trying to solve, types of data network is dealing with, quality of data and some other parameters. Number of input and output nodes depends on training (Rojas 2005).

2.6.4 Setting Weights

The way to control ANN is by setting and adjusting weights between nodes. Initial weights are usually set at some random numbers and then they are adjusted during NN training.

If results of ANN after weights updates are better than previous set of weights, the new values of weights are kept and iteration goes on. Finding combination of weights that will help us minimize error should be main aim when setting weights. This will become bit more clear once the learning rate (Fogel 2002).

2.6.5 Running and Training ANN

Running the network consist of a forward pass and a backward pass. In the forward pass outputs are calculated and compared with desired outputs. Error from desired and actual output are calculated. In the backward pass this error is used to alter the weights in the network in order to reduce the size of the error. When training ANN, we are feeding network with set of examples that have inputs and desired outputs. If we have some set of 1000 samples, we could use 100 of them to train the network and 900 to test our model (Rojas 2005).

2.6.6 Activation Function

Activation function is usually used for hidden layer because it depending on the input value (Michael 2005).

$$\text{Activation function} = \sum^{i} Xi\ Wi$$

SUM is collection of the output nodes from hidden layer that have been multiplied by connection weights, Added to get single number and put through activation function, Xi input value, Wi weight value. Input to sigmoid is any Value between number while the output can only be a number between 0 and 1 (Dspguide 2010).

2.6.7 Back Propagation (BP) Algorithm

One of the most popular NN algorithms is back propagation algorithm. Claimed that BP algorithm could be broken down to four main steps. After choosing the weights of the network randomly, the back propagation algorithm is used to compute the necessary corrections. Basic formula for BP algorithm. The algorithm can be decomposed in the following four steps (Rojas 2005):

1- Feed-forward computation.
2- Back propagation to the output layer.
3- Back propagation to the hidden layer.
4- Weight updates

The algorithm is stopped when the value of the error function has become small.

2.6.7.1 Feed-Forward Computation

Feed forward computation or forward pass is two-step process. The First part is getting the values of the hidden layer nodes.

The second part is using those values from hidden layer to compute value or values of output layer.

2.6.7.2 Back Propagation to the Output Layer

Next step is to calculate error of node. Once error is known, it will be used for backward propagation and weights adjustment. Error is propagated from output layer to the hidden layer. This is where learning rate

2.6.7.3 Back Propagation to the Hidden Layer

Now errors has to be propagated from hidden layer down to the input layer. This is bit more complicated than propagating error from output to hidden layer. This will be calculated multiplying new weight value with error for the node value.

2.6.7.4 Weight Updates

Important thing is not to update any weights until all errors have been calculated and using new weights to see if error has decreased**.**

Chapter Three

Literature Review and Related works

3.1 Overview

In this chapter, the related of this work will be mentioned and discussed in addition to the previous studies that have relationship with this study. Many researchers have spent their time trying to develop what will be called Humanoid Robot. Researches obtained in developing intelligent robots that simulate the human being on his functionalities and duties many new points to this subject. Now humanoid robots are here. They think like humans do, move like humans do, and even sacrifice themselves for man's sake.

3.2 Literature Review

Inherent topology of the environment perceived by a robot is a key prerequisite of high-level decision-making. This is achieved through the construction of a concise representation of the environment that endows a robot with the ability to operate in a coarse-to-fine strategy. This proposes a novel topological segmentation method of generic metric maps operating concurrently as a path-planning algorithm (Mario 2012).

Hybrid sensing system for mobile robot localization in large-scale indoor environments. The system operates in two sensing modes, either Omni-directional vision or laser scanning, according to the environmental characteristics. For a structured corridor environment, the vision information is adopted to track the robot pose with a predefined hybrid metric-topological map Yan (2012).

Algorithm for topological mapping cited in (Ananth 2011), which is the problem of finding the graph structure of an environment from a sequence of measurements. This algorithm, called Online Probabilistic Topological Mapping, systematically addresses the problem by constructing the posterior on the space of all possible given measurements topologies Ranganathan, et al.

Appearance based mapping goes towards richer semantic representations of the environment. This method may allow autonomous systems to perform higher-level tasks and provide better human-robot interaction Rituerto (2011).

Artificial neural networks multilayer feed forward, which are training using and Extended Kalman Filter (EKF) algorithm one and training Back propagation algorithm standard way then compare them by using two types of data which are the original data represent time delay of the network (Aria phone) for telephone communications and simulation data. The results confirm that EKF approach is faster to the period time steps to train the neural networks compared to the second way Sharif (2010).

Mention that a system which combines single-camera SLAM with established methods for feature recognition. Besides using standard salient image features to build an on-line map of the camera's environment, this system is capable of identifying and localizing known planar objects in the scene, and incorporating their geometry into the world map Gawley, et al (2008).

SLAM is a key process in several robotic contexts. In this paper the researcher attempts to explore the realization of non-metric SLAM using a visual information based approach relying on the detection of morphologically independent images. The selected images are proposed as the landmarks for localization, building simultaneously a qualitative map of the environment. Ivan, et al (2007).

SLAM continues to draw considerable attention in the robotics community due to the advantages it can offer in building autonomous robots. It examines the ability of an autonomous robot starting in an unknown environment to incrementally build an environment map and simultaneously localize itself within this map Chen, (2007).

Mobile-robot map building is the task of generating a model of an environment from sensor data. Most existing approaches to mobile robot mapping either build topological representations or generate accurate, metric maps of an environment. Benson, et al. introduced relational object maps, which is a new approach to building metric maps that represent individual objects such as doors or walls Benson, (2006).

Techniques for mobile robots to efficiently explore and model their environment. While much existing research in the area of SLAM focuses on issues related to uncertainty in sensor data, our work focuses on the problem of planning optimal exploration strategies Benjamín, (2006).

Topological representation, with their building and with their linked problems. One of the main problems not even during map building, but even by using the prebuilt map, is localization problem Roman, (2005).

Describes a scalable algorithm for the SLAM problem. SLAM is the problem of acquiring a map of a static environment with a mobile robot. The vast majority of SLAM algorithms are based on the extended Kalman filter (EKF) Sebastian, (2004).

The effectiveness of the system in real robot tests in unmodified indoor environments using a learning vision system. Results are shown for two test environments; a large corridor loop and the complete floor of an office building Michael, (2003) .

3.3 Related Works

In this part, three examples that will be discussed that were studied to help to apply the ANN with the illustrated approach, in addition to the advantages and disadvantages of each of them.

In the following examples, which used navigation systems based on modernized utility vehicle with the described sensors. The laser and the Global Positioning System (GPS) antenna are mounted on the front of the vehicle. In this system, given parameters were used, like the positions of landmarks, speeds and GPS readings in the ground (Environment Extern). Although this environment is very rich in terms of the number of natural sites, so the need of another type of landmark that is validated at the sensor for the significant reduction of the location error is highly important.

3.3.1 Nebot's 2000

The advantages of this approach is that it is not necessary to survey the position of the beacons; it is obtained while the vehicle navigates where the system builds a map and localizes it itself. The accuracy of this map is determined by the initial uncertainty of the vehicle.

On the other hand, the disadvantage of it consist in the uncertainty in position is not reduced below the initial uncertainty. Since they used the same number of beacons, there is no enhancement when compared to the absolute navigation algorithm. The only way the uncertainty can be reduced is by incorporating additional information that is not correlated to the vehicle position, such as GPS position information or recognizing a beacon with known position.

3.3.2 Kantor 2002

The advantage of this method is that it bounded most of errors by 95% confidence bounds estimated by the filter. It is also important to note that the localizer is able to estimate the position of the vehicle with an error. This is a very important achievement considering the systematic errors presented in the surveying and detection of the landmarks and vehicle model errors.

The disadvantage of the approach is that it has systematic errors due to slip and steering nonlinearities. It can be reduced using larger number of beacons or with the addition of artificial landmarks as will be shown later.

3.3.3 Jose 2006

The advantage of this method is that it is not required to add the beacons to the environment. The most relevant navigation features are obtained during the running time or the driving of the vehicle. Where the vehicle builds a navigation map of the environment maintains it and localizes it itself. The accuracy of this map is determined by the initial uncertainty of the vehicle. Moreover, all the landmarks are consistent with the actual errors.

The uncertainty in the position becomes significantly smaller than the SLAM with beacons only. This is due to a larger number of landmarks that incorporate more information to the filter.

However, the disadvantages of this approach existed in the complexity of the feature extraction, which was not investigated; moreover, it does not address the integrity issues of the algorithm when working in larger areas of operations.

3.4 The Relationship between this study and the Previous Study

After studying the three proposed algorithms and concluded the advantages and disadvantage of each of them and how one is a solution of the other, an algorithm including all previous benefits and enhanced using the ANN is proposed.

This study is meeting with the three previous studies, (Nebo'ts 2000, Kantor 2002, Jose 2006), because dealing with SLAM. Nebot's 2000 use SLAM with artificial beacons, Kantor using SLAM with beacon at known Locations , Jose 2006 using SLAM with Natural features in Outdoor Environments , and in this studies using SLAM with ANN.

As it was defined in the previous section, ANN has a very good generalization ability of the neural network, reinforcement learning that can deal with a problem with large states possible. Results can be robust depending on the model, the cost function and Learning algorithm.

Chapter Four

Proposed Model for the Environment Representation Architecture

4.1 Overview

The proposed model for the environment representation architecture consists of five parts; these are Organize Object in environment, landmark, localization, algorithm SLAM , and operation of ANN form the environment , as seen in figure 4.1.

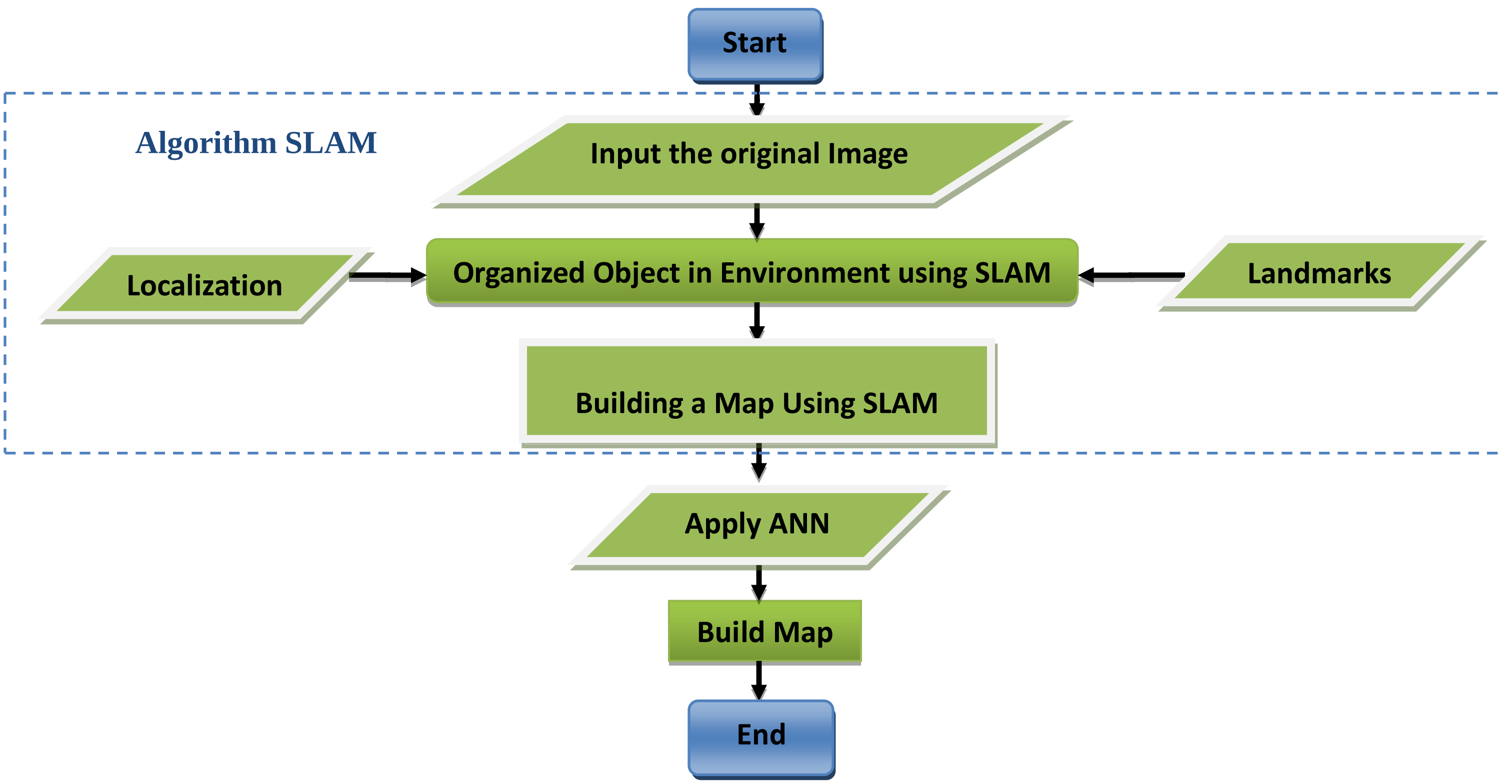


Figure 4.1: Flow chart of Development Representation an Environment for Robot

4.2 The Environment

In this work one type of environment that is static. The static environment is the environment that does not change and can be easily dealt with by an intelligent agent.

Using SLAM for construction of a map for the environment for a priori data or put the update on a given map in a known environment using vehicle without forgetting to keep its track of the position.

In the following subsections are the brief descriptions for SLAM objectives, building a map and locating the vehicle simultaneously.

4.2.1 SLAM Objectives

SLAM makes a vehicle capable to move in an environment with unknown location, moreover, it allows the vehicle to map this environment simultaneously, and use this map to calculate vehicle location. Figure 4.2 presents how to do SLAM using internal representations for the positions of landmarks (map) and the vehicle parameters, always takes the zero starting position.

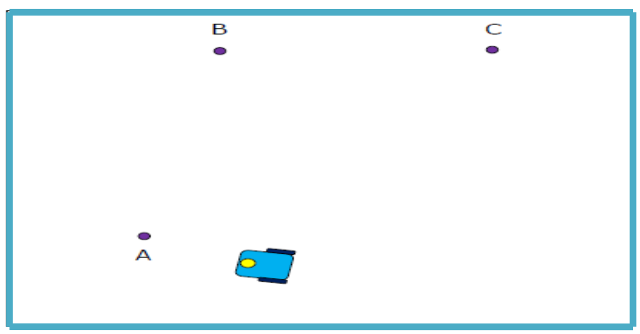


Figure 4.2: SLAM Behavior (Margarita 2011)

Localization and mapping are coupled, each has a relationship with the other and usually they are considered together to have good results. Figure 4.3 presents Localization of Automatic Guided Vehicle.

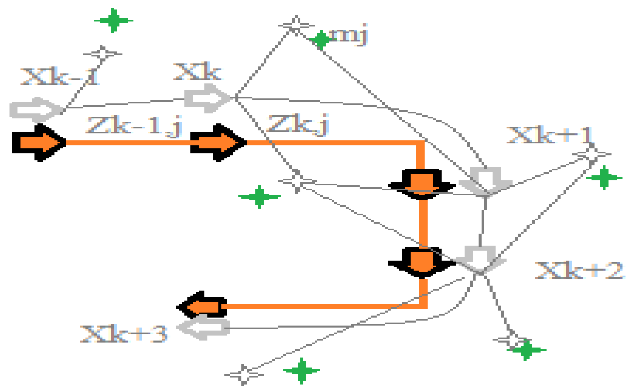


Figure 4.3: Localization of Automatic Guided Vehicle (Drexel Lap 2011)

4.2.2 Building a Map Using SLAM

The building of map using SLAM is depending on the vehicle locations based on measurement of landmark location.

4.2.3 Vehicle Locating Using SLAM

It is in reliance on information map from the beginning and of the measurements of landmarks location, it is also based on observation of landmarks to determine the vehicle location at time.

4.3 Landmarks

Landmarks are important for place or objects identification. Landmark is natural or artificial. Artificial landmarks are better for detection and identification, but it is necessary to make changes in environment to add new artificial landmarks. Natural landmarks it is more complicated task, because must be chosen which information about place or object in environment is important. Identification marks must be chosen so, that detection, identification and recognition of places or objects in environment is possible.

There are two activities for to represent the landmark, these are the motion of Landmark, which is to place a vehicle in an environment containing many of landmarks, and the observation Landmark by taking the measurement of the landmarks location in relation of the vehicle position using a sensor as seen in Figure 4.4.

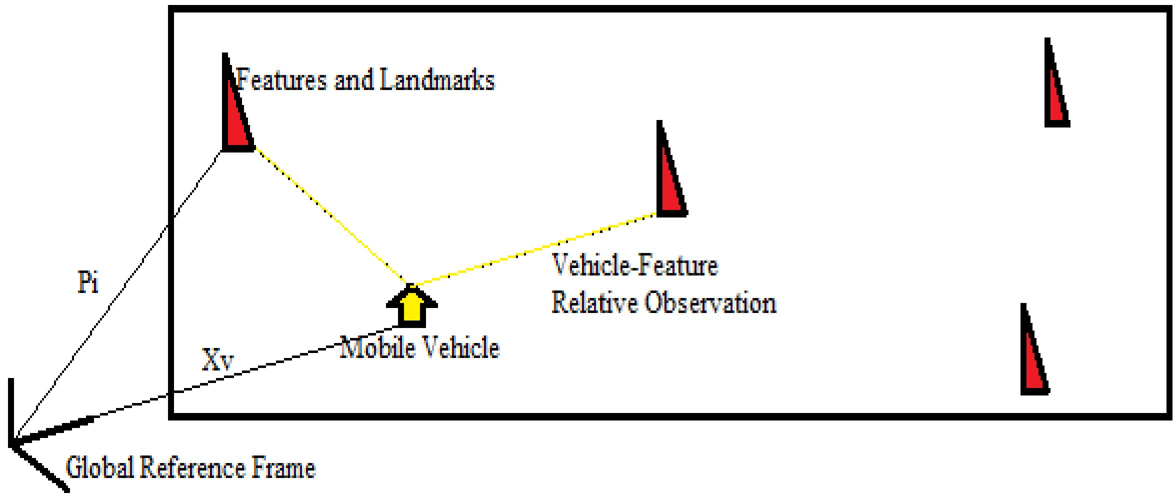


Figure 4.4: The Motion Model and the Observation Landmark Model (Drexel Lap 2011).

4.4 Organize Object in Environment

The environment can contain different objects and these objects have many properties and can be organized in different methods. The objects in the environment can be either unstructure.

The unstructured objects in environment are not organized sequentially .This means that they do not have intelligent code linked the object in environment and the agent cannot through this code detect the position of target then directly go to target.

4.5 Task of Robot in the Environment

There are many methods can be used for task robot (access) in the environment. EKF-SLAM is important solution method, newer alternatives, which offer much potential, have been proposed including the use of the information-state form (Thurn 2004).EKF representation used to describe the vehicle motion model as a set of samples of a more general non-Gaussian probability distribution.

4.5.1 Extend Kalman Filter

4.5.1.1 Filtering

Is the operation of estimating the state of a dynamical system from partial and noisy observations.

Extended Kalman Filter consists of a set of discrete equations for estimating the states of a system compared to measured data. Since the system model is nonlinear, the Extended Kalman Filter was chosen. The implementation of Extended Kalman Filter is done in two steps and in a cyclic manner. As shown in **(Figure 4.5).**

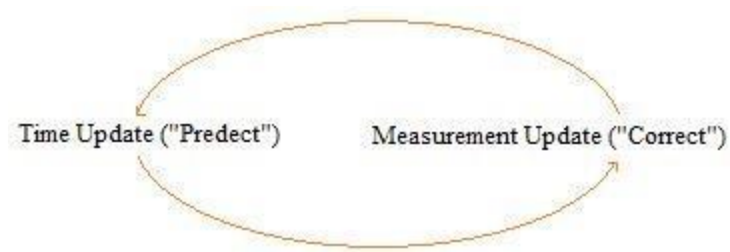


Figure 1 4.5: The Implementation of EKF (Drexel Lap 2011).

4.5.1.2 EKF Process

As soon as the SLAM process has the principle data, it can be resumed as three steps:

1. Update the current state estimate using the odometry data (Prediction).
2. Update the estimated state using re-observing landmarks. (Observation).
3. Add new landmarks to the current state. (Measure).

4.5.2 The System State: Xstate

Xstate is a matrix contains the position of the robot**, x, y** and **theta,** where x and y are the position of each landmark. It is important to represent matrix as a vertical matrix to make sure that all the equations will work well. The size of **Xstate** is initially (1,3).

4.5.2.1 The Covariance Matrix: Mpred

The covariance matrix Mpred contains the covariance on the robot position, on the landmarks, between robot position and landmarks and finally it contains the covariance between the landmarks.

4.5.2.2 The Kalman Gain: K

The Kalman gain K allows to know how much the observed landmarks are true. Moreover, how much gain is wanted from the new knowledge they provide.

Suppose that the robot can be moved a known distance, for example 10cm, to the right, the Kalman gain can be used with relation of landmarks to find out how much corrections of the position is needed. This may only be a distance, as short as5 cm, because the landmarks are not completely trusted, but rather, find a best solution between the odometry and the true landmark.

The Kalman Filter gain can be low if the range measurement device is bad, compared to the odometry performance of the robot. On the other hand, it can be high when the range of measurement device is very good, compared to the odometry performance of the robot.

4.5.3The Jacobian of the Measurement Model: H

The Jacobian of the measurement model is closely related to the measurement model. The measurement model is to compute an expected range and bearing of the measurements (observed landmark positions).

4.5.4 The Measurement Noise: R and V

The measurement range is Gaussian noise proportional to the range and bearing. It is calculated as VRV^t.Where V and R is a 2 by 2 identity matrix and R with numbers only in the diagonal. This constituted of three steps:

Step 1: Prediction

Is to update a state with calculating an estimate of the new position of the robot using the given data.

This should be updated in the first x, y and,θ (Xstate). Jn matrix is needed to be updated, every iteration. In addition to the value of Q. At the end, the new covariance for the robot position is calculated. The robot to feature cross correlations is needed to be updated also.

Step 2: Observation

Re-observed landmarks are good way to calculate the displacement of the robot compared to what the robot position is, and the robot position can be updated using the associated landmarks because the obtained estimation for the robot position is not completely exact due to the odometry errors from the robot. This step is performed for each re-observed landmark. Delaying the incorporation of new landmarks until the next step will decrease the computation cost needed for this step, since the covariance matrix, Mpred, and the system state, state, are smaller.

Step 3: Measure

In this step, the state vector Xstate and the covariance matrix MPred are updated with new landmarks, so the robot has more landmarks that can be matched. The robot - landmark covariance is the transposed value of the robot landmark covariance.

Finally, using the SLAM process make a robot ready to move again, observe landmarks, associate landmarks, update the system state using odometry, update the system state using re-observed landmarks and add new landmarks.

4.6 Localization

The localization means considering the positions of robot and an object in environment. The specified position and target can be inserted as parameter to the robot through predefined format of commands. To work localization the robot uses SLAM to work localization and mapping simultaneously, and use EKF to reduce the noise using the artificial neural networks.

Chapter Five

The Implementation of the Proposed Model

5.1 Overview

In the previous chapter, the SLAM process is studied, in which the work was developed new design of the proposed idea. In this chapter, the proposed algorithm will be explained, and the new approach of using ANN, to enhance the mapping process. In this chapter, the implementation of the proposed methodology was explained, showing the algorithms and the equations used in it. The evaluation of this contributed approach was explained, which proofed the proposed solutions to the problems under study. The results of the evaluation showed enhanced map regarding to the accuracy, process time and uncertainty.

5.2 Modeling Vehicle Coordinated System

To position the used vehicle several parameters as shown in (Figure 5.1). In (Figure 5.1) explain vehicle navigation in the environment, that means the robot's ability to determine position in environment and then to plan a path towards goal location.

Navigation can be defined as the combination of the three fundamental competences: localization, path planning, map-building.

Robot localization denotes the robot's ability to determined its position and orientation in environment. Path planning is effectively an extension of localization, in that it requires the determination of the robot's current position and a position of a goal location. Map building can be in the shape of a metric map or any way. In This study use steering control alpha is defined in vehicle coordinate frame; the laser sensor is located in the front of the vehicle and returns range and bearing related to objects at distances of up to 50 meters, high intensity reflection can be obtained by placing high reflectivity beacons in the area of operation.

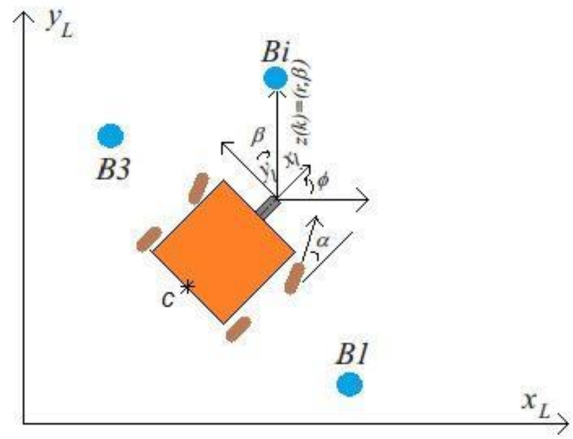


Figure 5.1 Vehicle Coordinated System (Jose 2006)

These landmarks are labeled as Bi(i=1..n) and measured with respect to the vehicle coordinates (x_1, y_1), that is $z(k) = (r$, b , I) , where r is the distance from the beacon to the laser, b is the sensor bearing measured with respect to the vehicle coordinate frame and I is the intensity information. In this figure 5.1 is always changing because it represents a mechanism of the vehicle in the environment for determine positioning and draw path.

(Figure 5.2) shows the kinematic parameters of the vehicle. This figure does not change (fixed) explains measurements between the landmarks of the environment and the landmarks of the vehicle and between measurements components of the vehicle.

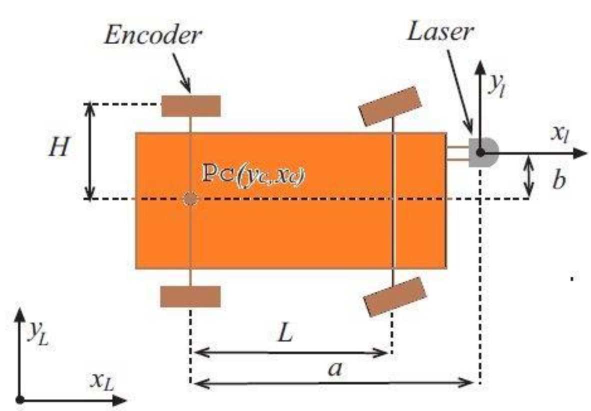


Figure 5.2 Kinematics parameters (Jose 2006)

Suppose that the vehicle is controlled through the vehicle velocity v_c and the steering angle α. Then to predict the trajectory of the back axle center C, the below equation should be followed.

Because the laser is located in the front of the vehicle, the translation of the center of the back axle, the transformation data is defined by the orientation angle, the velocity is generated by the encoder and translated to the center of the axle.

5.3 Implementation Organization of Objects in an Environment

The Organization of Objects in an Environment will be implemented as abstract data types according to the types of the environment (unstructured). The unstructured implemented as group of classes, each class presents unstructured landmarks, and group of link lists of landmarks.

In this study, the objects in the environment were represented by landmarks which are specifically implemented for the objects in order to test the performance of the robot which will avoid it during its trip. The dataset for the landmarks that represent the unstructured objects were extracted from the complete dataset which contains the environment landmarks and the vehicle initial position. This dataset were taken from similar research (Nebot 2000).

5.4 Implementation the Environment (Map Building)

In this method, using Back-propagation ANN to make the robot estimate the locations of landmarks accurately. In this works has been trained the ANN on the SLAM landmark equation results and the true landmarks from the dataset. Initially the vehicle starts at an unknown position with predefined uncertainty and obtains measurements using the ANN relative to its position. The ANN output and the sensor information are used together to incrementally build and maintain a navigation map and localization respecting the map.

5.5 Implementation of the Landmark

Landmarks are the set of objects that leads the robot in the environment. These landmarks originally built using sensors and GPS, in which the GPS reads the coordinates of the sensors to build the landmark dataset. These landmarks represent the maneuvers or the turning points that the robot uses during its trip.

Several international universities and research groups who study the field of environment mapping, built their own landmarks inside their lap environment. In this study, a pre-prepared dataset of landmark was used to apply the algorithm on it.

Sample of the used artificial landmarks are shown in the below table. In this function can be loaded the landmark.

Table 5.1 The Original Coordinates of Landmarks

X	Y
2.8953	**-4.0353**
9.9489	6.9239
12.4595	-4.7855
4.0361	11.6744
2.2772	5.5880
2.9600	7.8134
-3.6468	-2.1185

2.8116	-14.2272
1.9698	-23.4219
-5.4175	-22.2045
-4.6090	-14.1417
-3.5045	-10.3083
7.3714	15.3067
14.6249	13.6736
5.7161	16.4315

5.6 Implementation of Localization

In this study, the localization process depends on the artificial neural network, specifically the back propagation algorithm that was used in the study. Back propagation was used due to its functionality in the feedback and its performance on the error reduction. This neural network algorithm is the core of the proposed system which connects the previous sections together to be trained and finally tell the robot the best decision.

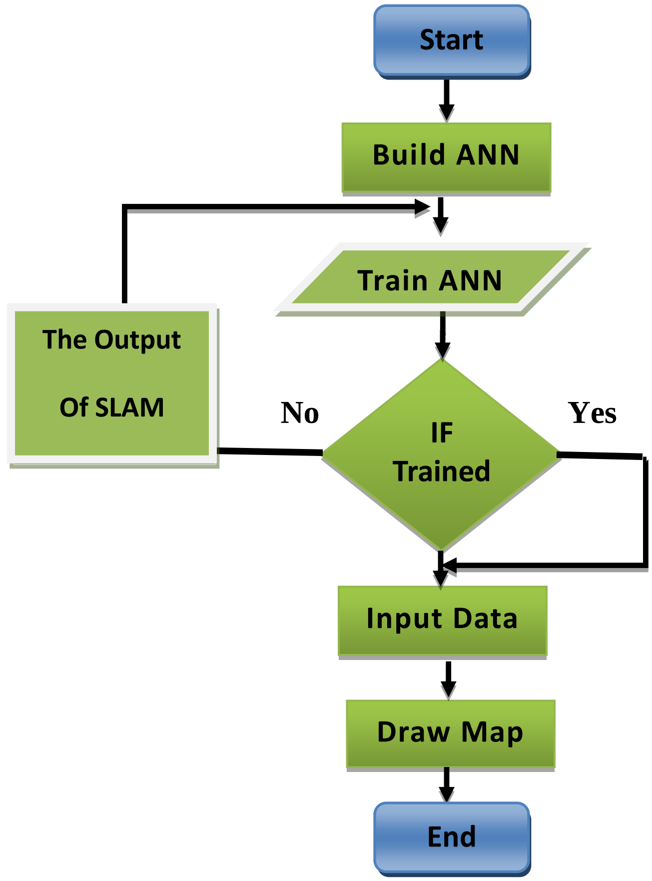


Figure 5.3 Flow Chart the Proses Localization

5.7 Implementation Task of Robot in Environment

After studying the SLAM algorithms and methods, the work is propose an enhanced SLAM algorithm based on Artificial Neural Network. In this algorithm used the equations of the SLAM landmark equations to train a neural network; a landmark dataset is also used from Drexel Autonomous System Lab datasets, which where scanned using SICK scanner (Drexel).

In this algorithm, a known dataset of landmarks is proposed, GPS coordinates of this map, due to the egg, and chicken problem in SLAM, a dataset of landmarks is needed for localization while an accurate robot navigations and estimations are required to build that map. The flow chart that implement task of robot in environment is shown below:

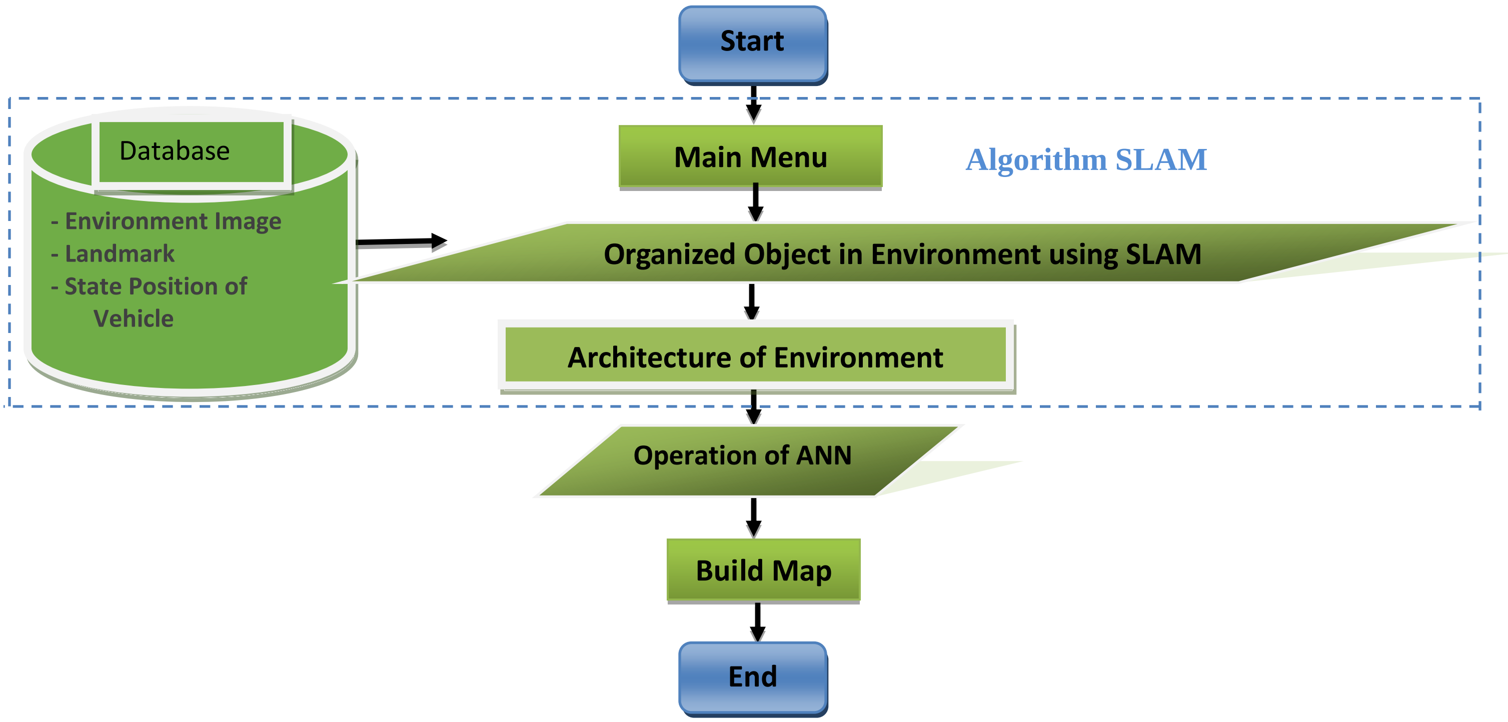


Figure 5.4 Flow chart Implementation Task Robot in Environment to Build Map

The output results of the SLAM system now are the calculated landmarks with their reference positions and building a map as seen in Figure 5.5 and table 4.2.

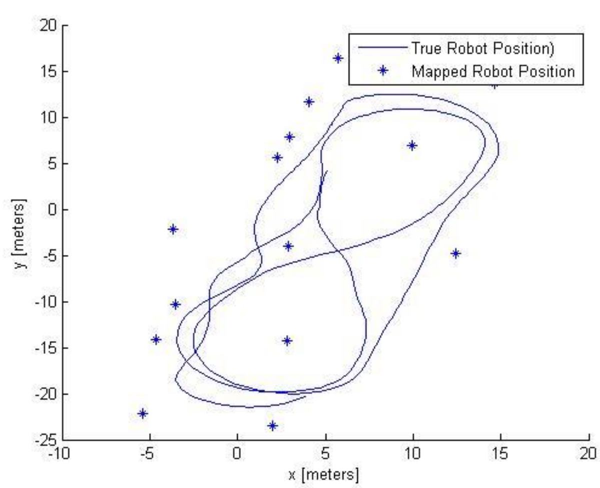


Figure 5.5: The Result Map from SLAM

Table 5.2 Represent the Original Landmark and Result SLAM

The Original Landmark		Result SLAM	
X	Y	X	Y
12.4595	-4.7855	12.7469	-4.5523
-3.6468	-2.1185	-3.4058	-2.4774
2.8953	-4.0353	3.1617	-4.1894
2.8116	-14.2272	3.4410	-14.3665
1.9698	-23.4219	2.6571	-23.5377
-5.4175	-22.2045	-4.6989	-22.1780
-4.6090	-14.1417	-3.8439	-14.1231
-3.5045	-10.3083	-2.7557	-10.3124
2.2772	5.5880	2.4300	5.3932
7.3714	15.3067	7.4179	15.1981
9.9489	6.9239	10.1005	6.8314
2.9600	7.8134	3.1211	7.6474
4.0361	11.6744	4.1137	11.5021
14.6249	13.6736	14.6718	13.6532
5.7161	16.4315	5.7266	16.2963

Together with the landmark equations, the neural network is trained to obtain enhanced results of SLAM landmarks, and then enhanced robot maps. In order to obtain the needed result to model this process initially.

Here a pseudo-code to obtain a landmarks after using SLAM algorithm

```
j = 1;
for i = 4:2:numStates
   res = [Xstate(i,k),Xstate(i+1,k)]
   result(j,1) = res(1,1);
   result(j,2) = res(1,2);
   j = j+1;
end
```

MSE=1/2(t-y)^2

T=Real value (landmark)

Y= actual value (output of ANN)

Here input landmarks and targets Results (OUT)

```
net = feedforwardnet(30,'trainrp');
net.trainParam.epochs = 50000;
net.trainParam.show = 10;
net.trainParam.goal = 0.001;
net.performFcn = 'msereg';
net = train(net,landmarks,result);
OUT = net(landmarks);
plot(GPSLon(1:560),GPSLat(1:560));
plot(Xstate(1,1:k),Xstate(2,1:k),'g');
plot(landmarks(:,1),landmarks(:,2),' * ')
```

$plot(OUT(:,1), OUT(:,2), 'r*');$

After explaining the proposed approach and methodology, in addition to the experiment and evaluation of this approach, in the next section, the result obtained will show and discuss them.

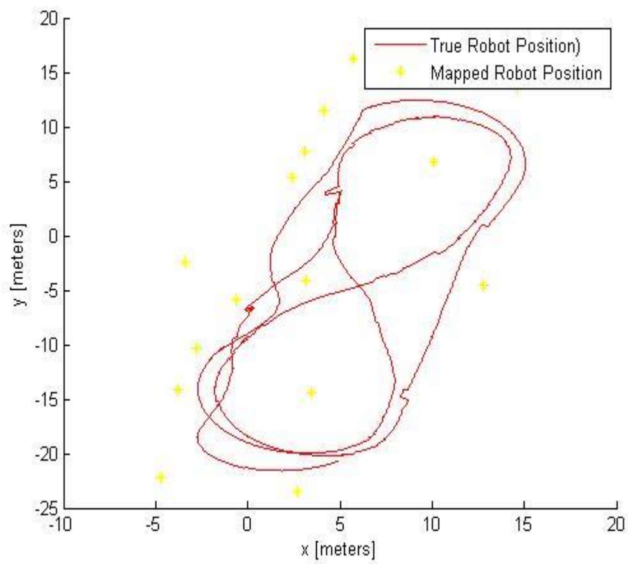


Figure 5.6: Building Map Using SLAM

Table 5.3 Result SLAM and Result ANN

Result SLAM		Result ANN	
X	Y	X	Y
12.7469	-4.5523	12.7458	-4.5565
-3.4058	-2.4774	-3.4060	-2.4775
3.1617	-4.1894	3.1614	-4.1883
3.4410	-14.3665	3.4416	-14.3665
2.6571	-23.5377	2.6598	-23.5397
-4.6989	-22.1780	-4.6974	-22.1774
-3.8439	-14.1231	-3.8444	-14.1219
-2.7557	-10.3124	-2.7562	-10.3115
2.4300	5.3932	2.4301	5.3934
7.4179	15.1981	7.4178	15.1993
10.1005	6.8314	10.1020	6.8306
3.1211	7.6474	3.1220	7.6476
4.1137	11.5021	4.1140	11.5027
14.6718	13.6532	14.6719	13.6533
5.7266	16.2963	5.7253	16.2987

Table 5.4 Ituration Result SLAM and Result ANN

Result SLAM		Result ANN	
X	**Y**	**X**	**Y**
12.7469	-4.5523	12.7450	-4.5515
-3.4058	-2.4774	-3.4060	-2.4774
3.1617	-4.1894	3.1632	-4.1937
3.4410	-14.3665	3.4386	-14.3696
2.6571	-23.5377	2.6602	-23.5361
-4.6989	-22.1780	-4.6984	-22.1785
-3.8439	-14.1231	-3.8448	-14.1224
-2.7557	-10.3124	-2.7517	-10.3110
2.4300	5.3932	2.4302	5.3933
7.4179	15.1981	7.4172	15.1978
10.1005	6.8314	10.1009	6.8314
3.1211	7.6474	3.1210	7.6469
4.1137	11.5021	4.1144	11.5022
14.6718	13.6532	14.6721	13.6532
5.7266	16.2963	5.7288	16.2964

Table 5.5 Iteration Result SLAM and Result ANN

Result SLAM		Result ANN	
X	Y	X	Y
12.7469	-4.5523	12.7457	-4.5429
-3.4058	-2.4774	-3.4055	-2.4768
3.1617	-4.1894	3.1629	-4.1912
3.4410	-14.3665	3.4414	-14.3680
2.6571	-23.5377	2.6582	-23.5337
-4.6989	-22.1780	-4.7011	-22.1768
-3.8439	-14.1231	-3.8469	-14.1245
-2.7557	-10.3124	-2.7571	-10.3127
2.4300	5.3932	2.4317	5.3928
7.4179	15.1981	7.4164	15.1998
10.1005	6.8314	10.1019	6.8299
3.1211	7.6474	3.1201	7.6480
4.1137	11.5021	4.1072	11.5030
14.6718	13.6532	14.6715	13.6531
5.7266	16.2963	5.7278	16.2968

Table 5.6 Iteration Result SLAM and Result ANN

Result SLAM		Result ANN	
X	Y	X	Y
12.7469	-4.5523	12.7416	-4.5581
-3.4058	-2.4774	-3.4060	-2.4775
3.1617	-4.1894	3.1569	-4.1922
3.4410	-14.3665	3.4426	-14.3649
2.6571	-23.5377	2.6555	-23.5371
-4.6989	-22.1780	-4.7003	-22.1781
-3.8439	-14.1231	-3.8386	-14.1210
-2.7557	-10.3124	-2.7577	-10.3157
2.4300	5.3932	2.4312	5.3952
7.4179	15.1981	7.4175	15.1984
10.1005	6.8314	10.1039	6.8323
3.1211	7.6474	3.1231	7.6461
4.1137	11.5021	4.1149	11.5034
14.6718	13.6532	14.6718	13.6532
5.7266	16.2963	5.7269	16.2944

Table 5.7 Iteration Result SLAM and Result ANN

Result SLAM		Result ANN	
X	**Y**	**X**	**Y**
12.7469	-4.5523	12.7425	-4.5565
-3.4058	-2.4774	-3.4060	-2.4775
3.1617	-4.1894	3.1614	-4.1883
3.4410	-14.3665	3.4416	-14.3665
2.6571	-23.5377	2.6598	-23.5397
-4.6989	-22.1780	-4.6974	-22.1774
-3.8439	-14.1231	-3.8444	-14.1219
-2.7557	-10.3124	-2.7562	-10.3115
2.4300	5.3932	2.4301	5.3934
7.4179	15.1981	7.4178	15.1993
10.1005	6.8314	10.1020	6.8306
3.1211	7.6474	3.1220	7.6476
4.1137	11.5021	4.1140	11.5027
14.6718	13.6532	14.6719	13.6533
5.7266	16.2963	5.7253	16.2987

Table 5.8 Iteration Result SLAM and Result ANN

Result SLAM		Result ANN	
X	**Y**	**X**	**Y**
12.7469	-4.5523	12.7515	-4.5462
-3.4058	-2.4774	-3.4057	-2.4773
3.1617	-4.1894	3.1593	-4.1904
3.4410	-14.3665	3.4465	-14.3611
2.6571	-23.5377	2.6556	-23.5344
-4.6989	-22.1780	-4.7018	-22.1711
-3.8439	-14.1231	-3.8443	-14.1240
-2.7557	-10.3124	-2.7544	-10.3151
2.4300	5.3932	2.4302	5.3934
7.4179	15.1981	7.4161	15.1921
10.1005	6.8314	10.1020	6.8325
3.1211	7.6474	3.1219	7.6474
4.1137	11.5021	4.1146	11.5045
14.6718	13.6532	14.6716	13.6527
5.7266	16.2963	5.7250	16.2927

Table 5.9 Iteration Result SLAM and Result ANN

Result SLAM		Result ANN	
X	Y	X	Y
12.7469	-4.5523	12.7421	-4.5558
-3.4058	-2.4774	-3.4064	-2.4769
3.1617	-4.1894	3.1649	-4.1921
3.4410	-14.3665	3.4405	-14.3675
2.6571	-23.5377	2.6520	-23.5382
-4.6989	-22.1780	-4.7047	-22.1749
-3.8439	-14.1231	-3.8452	-14.1225
-2.7557	-10.3124	-2.7540	-10.3144
2.4300	5.3932	2.4320	5.3947
7.4179	15.1981	7.4161	15.1964
10.1005	6.8314	10.0941	6.8394
3.1211	7.6474	3.1213	7.6445
4.1137	11.5021	4.1115	11.4999
14.6718	13.6532	14.6718	13.6536
5.7266	16.2963	5.7273	16.3006

5.8 Results and Comparisons

The navigation system was tested with a utility vehicle retrofitted with the described sensors. The utility car used for the experiment is shown in **(Figure 5.7).**

Figure 5.7: Utility car used for the experiments (Nebot 2000)

In the experiment, using the dataset contains the true landmarks and GPS coordinates for his map was taken from Drexel Autonomous System Lab datasets, which where scanned using SICK scanner (Drexel), in this study used the vehicle model and sensor pose, mentioned earlier. The “stars” in the map represent potential natural landmarks and the “circles” are the artificial reflective beacons. Although this environment is very rich with respect to the number of natural landmarks, the data association becomes very difficult since most of the landmarks are very close together. The evaluated of this algorithm by using MATLAB® R2013a. The resulted map is shown in the below **(Figure 5.8).**

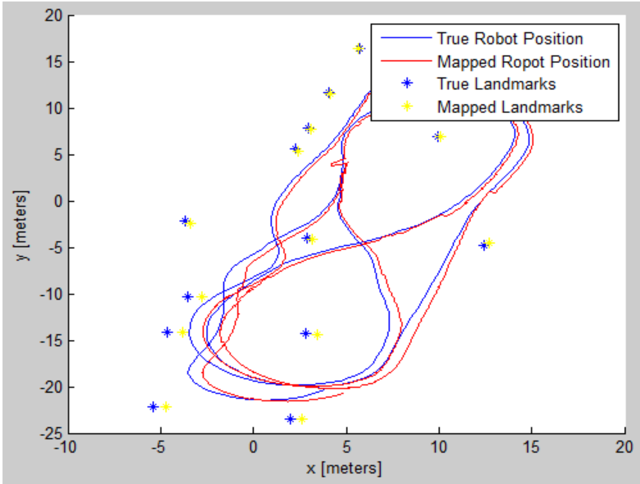


Figure 5.8 True and Robot Maps

As it is shown in **(Figure 5.8),** above, in this work was reached for mapping the landmarks and the environment, the robot followed the same direction, but with small error margin. The ANN error histogram is shown in the below **(Figure 5.9).**

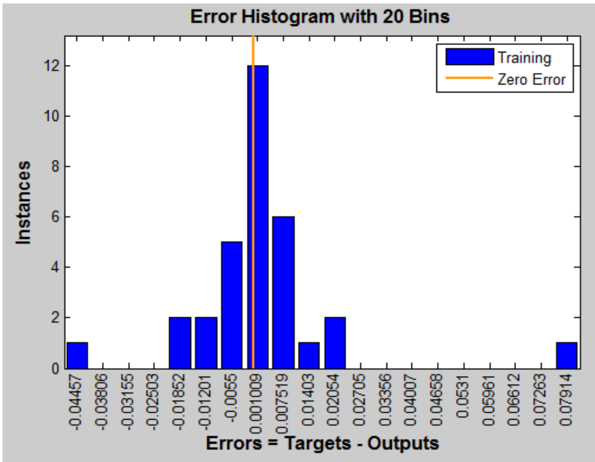


Figure 5.9: ANN Model Error Histogram

The performance plot is shown in **(Figure 5.10),** below.

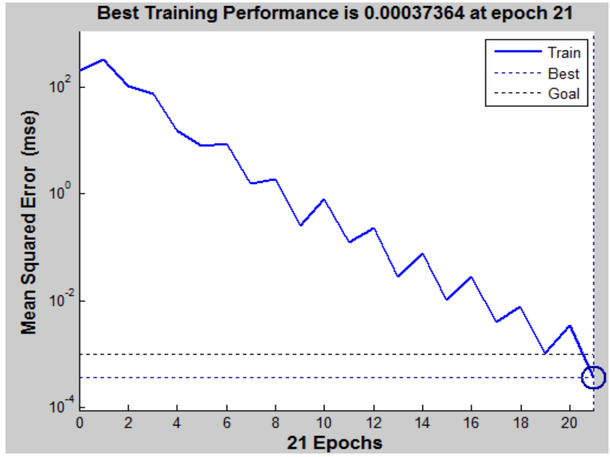


Figure 5.10: Performance Plot

From the error histogram and the plots above, it is noticed that good results of landmarks mapping is reached, which is very close to the true landmarks position. Based on that, very good results of environment mapping have been obtained, as shown in **(Figure 5.9)** above, the model mapped line is very close with the true line.

It can be noticed from the figures above, that very good results in comparison to the previous works are reached, some of them discussed previously. Using ANN enhanced the accuracy of the map, which is noticed from **(figure 5.8)**, where the mapped landmarks and routs are almost the same. Moreover, using ANN enhanced the speed of map building which is very important achievement especially in real time applications, or in robots that use this information to build their decisions.

The systematic error found in Nebot's work (Nebot 2000), was solved by the proposed approach, because, using ANN, depends only on the initial values that were used during the training phase, it considers previous landmarks in order to build the next route, but on the other hand, it does not accumulate the previous error. The table is show of the compression between the work of SLAM and ANN:

Table 5.10 The Compression for the Original Landmark and the Result from SLAM and ANN and The Error of SALM and the Error of ANN

The Original Landmark		Result SLAM		Result ANN		The Error of SLAM		The Error of ANN	
12.4595	-4.7855	12.7469	-4.5523	12.7458	-4.5565	0.0412	0.0271	0.0409	0.0262
-3.6468	-2.1185	-3.4058	-2.4774	-3.4060	-2.4775	0.0290	0.0644	0.0289	0.0644
2.8953	-4.0353	3.1617	-4.1894	3.1614	-4.1883	0.0354	0.0118	0.0354	0.0117
2.8116	-14.2272	3.4410	-14.3665	3.4416	-14.3665	0.1980	0.0097	0.1984	0.0097
1.9698	-23.4219	2.6571	-23.5377	2.6598	-23.5397	0.2361	0.0067	0.2380	0.0069
-5.4175	-22.2045	-4.6989	-22.1780	-4.6974	-22.1774	0.2581	0.0003	0.2592	0.0001
-4.6090	-14.1417	-3.8439	-14.1231	-3.8444	-14.1219	0.2926	0.0011	0.2923	0.0001
-3.5045	-10.3083	-2.7557	-10.3124	-2.7562	-10.3115	0.2803	0.0001	0.2799	0.0001
2.2772	5.5880	2.4300	5.3932	2.4301	5.3934	0.0116	0.0189	0.0116	0.0189
7.3714	15.3067	7.4179	15.1981	7.4178	15.1993	0.010	0.0042	0.0010	0.0042
9.9489	6.9239	10.1005	6.8314	10.1020	6.8306	0.0014	0.0137	0.0010	0.0043
2.9600	7.8134	3.1211	7.6474	3.1220	7.6476	0.0129	0.0148	0.0131	0.0137
4.0361	11.6744	4.1137	11.5021	4.1140	11.5027	0.0300	0.0001	0.0030	0.0147
14.6249	13.6736	14.6718	13.6532	14.6719	13.6533	0.0010	0.0010	0.0010	0.0002
5.7161	16.4315	5.7266	16.2963	5.7253	16.2987	0.0001	0.0091	0.0001	0.0088
				The Average of Error		0.0941	0.0152	0.0770	0.0124

Table 5.11 The Compression for the Original Landmark and the Result from SLAM and Iteration ANN and The Error of SALM and Iteration the Error of ANN

The Original Landmarks		Result SLAM		Result ANN		The Error of SLAM		The Error of ANN	
12.4595	**-4.7855**	12.7469	-4.5523	12.7450	-4.5515	0.0412	0.0271	0.0407	0.0273
-3.6468	**-2.1185**	-3.4058	-2.4774	-3.4060	-2.4774	0.0290	0.0644	0.0289	0.0640
2.8953	**-4.0353**	3.1617	-4.1894	3.1632	-4.1937	0.0354	0.0118	0.03508	0.0120
2.8116	**-14.2272**	3.4410	-14.3665	3.4386	-14.3696	0.1980	0.0097	0.1965	0.0101
1.9698	**-23.4219**	2.6571	-23.5377	2.6602	-23.5361	0.2361	0.0067	0.02383	0.0857
-5.4175	**-22.2045**	-4.6989	-22.1780	-4.6984	-22.1785	0.2581	0.0003	0.2585	0.0003
-4.6090	**-14.1417**	-3.8439	-14.1231	-3.8448	-14.1224	0.2926	0.0011	0.2920	0.0001
-3.5045	**-10.3083**	-2.7557	-10.3124	-2.7517	-10.3110	0.2803	0.0001	0.02833	0.0001
2.2772	**5.5880**	2.4300	5.3932	2.4302	5.3933	0.0116	0.0189	0.0117	0.0189
7.3714	**15.3067**	7.4179	15.1981	7.4172	15.1978	0.010	0.0042	0.0010	0.0059
9.9489	**6.9239**	10.1005	6.8314	10.1009	6.8314	0.0014	0.0137	0.0115	0.0042
2.9600	**7.8134**	3.1211	7.6474	3.1210	7.6469	0.0129	0.0148	0.0928	0.0138
4.0361	**11.6744**	4.1137	11.5021	4.1144	11.5022	0.0300	0.0001	0.0030	0.0148
14.6249	**13.6736**	14.6718	13.6532	14.6721	13.6532	0.0010	0.0010	0.0011	0.0002
5.7161	**16.4315**	5.7266	16.2963	5.7288	16.2964	0.0001	0.0091	0.0001	0.0091
				The Average of Error		0.0941	0.0152	0.0683	0.0144

Table 5.12 The Compression for the Original Landmark and the Result from SLAM and Iteration ANN and The Error of SALM and Iteration the Error of ANN

The Original Landmarks		Result SLAM		Result ANN		The Error of SLAM		The Error of ANN	
12.4595	**-4.7855**	12.7469	-4.5523	12.7457	-4.5429	0.0412	0.0271	0.0409	0.0294
-3.6468	**-2.1185**	-3.4058	-2.4774	-3.4055	-2.4768	0.0290	0.0644	0.0291	0.0641
2.8953	**-4.0353**	3.1617	-4.1894	3.1629	-4.1912	0.0354	0.0118	0.0358	0.0121
2.8116	**-14.2272**	3.4410	-14.3665	3.4414	-14.3680	0.1980	0.0097	0.1491	0.0099
1.9698	**-23.4219**	2.6571	-23.5377	2.6582	-23.5337	0.2361	0.0067	0.2369	0.0062
-5.4175	**-22.2045**	-4.6989	-22.1780	-4.7011	-22.1768	0.2581	0.0003	0.2565	0.0003
-4.6090	**-14.1417**	-3.8439	-14.1231	-3.8469	-14.1245	0.2926	0.0011	0.2903	0.0001
-3.5045	**-10.3083**	-2.7557	-10.3124	-2.7571	-10.3127	0.2803	0.0001	0.2830	0.0001
2.2772	**5.5880**	2.4300	5.3932	2.4317	5.3928	0.0116	0.0189	0.0117	0.0180
7.3714	**15.3067**	7.4179	15.1981	7.4164	15.1998	0.010	0.0042	0.0009	0.0038
9.9489	**6.9239**	10.1005	6.8314	10.1019	6.8299	0.0014	0.0137	0.0100	0.0050
2.9600	**7.8134**	3.1211	7.6474	3.1201	7.6480	0.0129	0.0148	0.0128	0.0138
4.0361	**11.6744**	4.1137	11.5021	4.1072	11.5030	0.0300	0.0001	0.0030	0.0146
14.6249	**13.6736**	14.6718	13.6532	14.6715	13.6531	0.0010	0.0010	0.0010	0.0002
5.7161	**16.4315**	5.7266	16.2963	5.7278	16.2968	0.0001	0.0091	0.0001	0.0070
				The Average of Error		0.0941	0.0152	0.0709	0.0123

Table 5.13 The Compression for the Original Landmark and the Result from SLAM and Iteration ANN and The Error of SALM and Iteration the Error of ANN

The Original Landmarks		Result SLAM		Result ANN		The Error of SLAM		The Error of ANN	
12.4595	**-4.7855**	12.7469	-4.5523	12.7416	-4.5581	0.0412	0.0271	0.0397	0.0258
-3.6468	**-2.1185**	-3.4058	-2.4774	-3.4060	-2.4775	0.0290	0.0644	0.0289	0.0644
2.8953	**-4.0353**	3.1617	-4.1894	3.1569	-4.1922	0.0354	0.0118	0.0342	0.0123
2.8116	**-14.2272**	3.4410	-14.3665	3.4426	-14.3649	0.1980	0.0097	0.1990	0.0001
1.9698	**-23.4219**	2.6571	-23.5377	2.6555	-23.5371	0.2361	0.0067	0.2350	0.0001
-5.4175	**-22.2045**	-4.6989	-22.1780	-4.7003	-22.1781	0.2581	0.0003	0.2571	0.0001
-4.6090	**-14.1417**	-3.8439	-14.1231	-3.8386	-14.1210	0.2926	0.0011	0.2967	0.0001
-3.5045	**-10.3083**	-2.7557	-10.3124	-2.7577	-10.3157	0.2803	0.0001	0.02788	0.0001
2.2772	**5.5880**	2.4300	5.3932	2.4312	5.3952	0.0116	0.0189	0.0118	0.0185
7.3714	**15.3067**	7.4179	15.1981	7.4175	15.1984	0.010	0.0042	0.0001	0.0001
9.9489	**6.9239**	10.1005	6.8314	10.1039	6.8323	0.0014	0.0137	0.0120	0.0001
2.9600	**7.8134**	3.1211	7.6474	3.1231	7.6461	0.0129	0.0148	0.0133	0.0139
4.0361	**11.6744**	4.1137	11.5021	4.1149	11.5034	0.0300	0.0001	0.0001	0.0002
14.6249	**13.6736**	14.6718	13.6532	14.6718	13.6532	0.0010	0.0010	0.0001	0.0001
5.7161	**16.4315**	5.7266	16.2963	5.7269	16.2944	0.0001	0.0091	0.0001	0.0010
				The Average of Error		0.0941	0.0152	0.0707	0.0091

Table 5.14 The Compression for the Original Landmark and the Result from SLAM and Iteration ANN and The Error of SALM and Iteration the Error of ANN

The Original Landmarks		Result SLAM		Result ANN		The Error of SLAM		The Error of ANN	
12.4595	**-4.7855**	12.7469	-4.5523	12.7425	-4.5565	0.0412	0.0271	0.0412	0.0263
-3.6468	**-2.1185**	-3.4058	-2.4774	-3.4060	-2.4775	0.0290	0.0644	0.0289	0.0644
2.8953	**-4.0353**	3.1617	-4.1894	3.1614	-4.1883	0.0354	0.0118	0.0354	0.0117
2.8116	**-14.2272**	3.4410	-14.3665	3.4416	-14.3665	0.1980	0.0097	0.1984	0.0001
1.9698	**-23.4219**	2.6571	-23.5377	2.6598	-23.5397	0.2361	0.0067	0.2380	0.0001
-5.4175	**-22.2045**	-4.6989	-22.1780	-4.6974	-22.1774	0.2581	0.0003	0.2592	0.0001
-4.6090	**-14.1417**	-3.8439	-14.1231	-3.8444	-14.1219	0.2926	0.0011	0.2923	0.0010
-3.5045	**-10.3083**	-2.7557	-10.3124	-2.7562	-10.3115	0.2803	0.0001	0.2799	0.0001
2.2772	**5.5880**	2.4300	5.3932	2.4301	5.3934	0.0116	0.0189	0.0116	0.0189
7.3714	**15.3067**	7.4179	15.1981	7.4178	15.1993	0.010	0.0042	0.0001	0.0001
9.9489	**6.9239**	10.1005	6.8314	10.1020	6.8306	0.0014	0.0137	0.0117	0.0001
2.9600	**7.8134**	3.1211	7.6474	3.1220	7.6476	0.0129	0.0148	0.0011	0.0137
4.0361	**11.6744**	4.1137	11.5021	4.1140	11.5027	0.0300	0.0001	0.0001	0.0147
14.6249	**13.6736**	14.6718	13.6532	14.6719	13.6533	0.0010	0.0010	0.0001	0.0001
5.7161	**16.4315**	5.7266	16.2963	5.7253	16.2987	0.0001	0.0091	0.0001	0.0001
				The Average of Error		0.0941	0.0152	0.0712	0.0101

Table 5.15 The Compression for the Original Landmark and the Result from SLAM and Iteration ANN and The Error of SALM and Iteration the Error of ANN

The Original Landmarks		Result SLAM		Result ANN		The Error of SLAM		The Error of ANN	
12.4595	**-4.7855**	12.7469	-4.5523	12.7515	-4.5462	0.0412	0.0271	0.0420	0.0286
-3.6468	**-2.1185**	-3.4058	-2.4774	-3.4057	-2.4773	0.0290	0.0644	0.0290	0.0634
2.8953	**-4.0353**	3.1617	-4.1894	3.1593	-4.1904	0.0354	0.0118	0.0348	0.0120
2.8116	**-14.2272**	3.4410	-14.3665	3.4465	-14.3611	0.1980	0.0097	0.2015	0.0001
1.9698	**-23.4219**	2.6571	-23.5377	2.6556	-23.5344	0.2361	0.0067	0.2351	0.0001
-5.4175	**-22.2045**	-4.6989	-22.1780	-4.7018	-22.1711	0.2581	0.0003	0.2561	0.0001
-4.6090	**-14.1417**	-3.8439	-14.1231	-3.8443	-14.1240	0.2926	0.0011	0.2923	0.0001
-3.5045	**-10.3083**	-2.7557	-10.3124	-2.7544	-10.3151	0.2803	0.0001	0.2813	0.0001
2.2772	**5.5880**	2.4300	5.3932	2.4302	5.3934	0.0116	0.0189	0.0117	0.0189
7.3714	**15.3067**	7.4179	15.1981	7.4161	15.1921	0.010	0.0042	0.0001	0.0001
9.9489	**6.9239**	10.1005	6.8314	10.1020	6.8325	0.0014	0.0137	0.00117	0.0001
2.9600	**7.8134**	3.1211	7.6474	3.1219	7.6474	0.0129	0.0148	0.0131	0.0137
4.0361	**11.6744**	4.1137	11.5021	4.1146	11.5045	0.0300	0.0001	0.0001	0.0144
14.6249	**13.6736**	14.6718	13.6532	14.6716	13.6527	0.0010	0.0010	0.0001	0.0001
5.7161	**16.4315**	5.7266	16.2963	5.7250	16.2927	0.0001	0.0091	0.0001	0.0001
				The Average of Error		0.0941	0.0152	0.0703	0.0100

Table 1 5.16 The Compression for the Original Landmark and the Result from SLAM and Iteration ANN and The Error of SALM and Iteration the Error of ANN

The Original Landmarks		Result SLAM		Result ANN		The Error of SLAM		The Error of ANN	
12.4595	**-4.7855**	12.7469	-4.5523	12.7421	-4.5558	0.0412	0.0271	0.0399	0.0263
-3.6468	**-2.1185**	-3.4058	-2.4774	-3.4064	-2.4769	0.0290	0.0644	0.0288	0.0642
2.8953	**-4.0353**	3.1617	-4.1894	3.1649	-4.1921	0.0354	0.0118	0.0363	0.0122
2.8116	**-14.2272**	3.4410	-14.3665	3.4405	-14.3675	0.1980	0.0097	0.1977	0.0001
1.9698	**-23.4219**	2.6571	-23.5377	2.6520	-23.5382	0.2361	0.0067	0.2326	0.0001
-5.4175	**-22.2045**	-4.6989	-22.1780	-4.7047	-22.1749	0.2581	0.0003	0.2540	0.0001
-4.6090	**-14.1417**	-3.8439	-14.1231	-3.8452	-14.1225	0.2926	0.0011	0.2916	0.0001
-3.5045	**-10.3083**	-2.7557	-10.3124	-2.7540	-10.3144	0.2803	0.0001	0.2816	0.0001
2.2772	**5.5880**	2.4300	5.3932	2.4320	5.3947	0.0116	0.0189	0.0119	0.0186
7.3714	**15.3067**	7.4179	15.1981	7.4161	15.1964	0.010	0.0042	0.0001	0.0001
9.9489	**6.9239**	10.1005	6.8314	10.0941	6.8394	0.0014	0.0137	0.0105	0.0001
2.9600	**7.8134**	3.1211	7.6474	3.1213	7.6445	0.0129	0.0148	0.0130	0.0142
4.0361	**11.6744**	4.1137	11.5021	4.1115	11.4999	0.0300	0.0001	0.0001	0.0152
14.6249	**13.6736**	14.6718	13.6532	14.6718	13.6536	0.0010	0.0010	0.0001	0.0002
5.7161	**16.4315**	5.7266	16.2963	5.7273	16.3006	0.0001	0.0091	0.0001	0.0001
				The Average of Error		0.0941	0.0152	0.0700	0.0097

5.9 The Developed Application

After studying the SLAM algorithms and methods, this work is enhanced SLAM algorithm based on ANN. In this method, using Back-propagation ANN to make the robot estimate the locations of landmarks accurately.

In this algorithm used the equations of the SLAM landmark equations to train a neural network; a landmark dataset is also used from Drexel Autonomous System Lab datasets, which where scanned using SICK scanner (Drexel) as seen below:

The original landmark → SLAM algorithm → result of SLAM (build map using
(Input) SLAM)

In this works has been trained the ANN on the SLAM landmark equation results as seen below:

Result of SLAM → operation ANN → result of ANN (build map using ANN)
(Input)

In the experiment, using the dataset contains the true landmarks and GPS coordinates for his map was taken from Drexel , in this study used the vehicle model and sensor pose, mentioned earlier. The “stars” in the map represent potential natural landmarks and the “circles” are the artificial reflective beacons. Although this environment is very rich with respect to the number of natural landmarks, the data association becomes very difficult since most of the landmarks are very close together.

The evaluated of this algorithm by using MATLAB® R2013a. The systematic error found in Nebot’s work, was solved by the proposed approach, because, using ANN, depends only on the initial values that were used during the training phase, it considers previous landmarks in order to build the next route, but it does not accumulate the previous error

Chapter Six

Conclusions and Future Work

6.1 Overview

In this work, a model of environment representation architecture is represented for intelligent robot. Autonomous mobile robot must be able to describe the environment in which it operates. To do this, the robot must be able to locate and construct a map of the environment if it does not exist. With this information, it can for example avoid obstacles and then navigate safely. This capability is a mandatory step in the road towards complete independence.

6.2 Conclusion

Conclusion summarize in the following points:

1- The proposed solution of this thesis. It concerns the localization of a vehicle and an environmental mapping simultaneously.

2- In the literature, this problem is the acronym for SLAM. To solve this problem, many solutions exist. These methods use different representations of the environment but also different methods of estimation.

3- The last two chapters of this manuscript offer a state of the non-exhaustive but full of art approaches discussed. This study has led to a new Simultaneous Localization and Mapping algorithm based on Artificial Neural Network, which resulted in high accuracy navigation and mapping.

4- The design of this algorithm, in addition to the modeling aspects are presented with an implementation of it. Modeling SLAM using landmarks does not require any landmarks surveying.

5- The results showed that the use of landmarks in this thesis, ANN could deliver accurate results considering the initial vehicle uncertainty. Obtaining the maps are relative to the initial coordinates of the vehicle, which gives more reliability to the resulted maps. In case of using GPS, it is noticed that the vehicle uncertainty needs to be incorporated.

6- Achieving results of this thesis, by using the ANN, the algorithm was able to estimate the position of the landmarks and the position of the vehicle with high accuracy.

6.3 Future Works

This study focused on mapping a static environment using automated robot, this mapping process or environment modeling process was based on ANN. Future work on this field is suggested to implement the same approach on dynamic environment. To study the dynamic environment, more parameters should be taken in account.

Dynamic environment contains dynamic or mobile objects, which are more complex than static or stationary objects. These variable parameters require different SLAM equations. Moreover, they require different method for obtaining the dataset. However, this dynamic environment mapping more likely to be enhanced using ANN, considering the obtained results on this work.

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