# Autonomous Robot Navigation Based on Pattern Recognition Techniques and Artificial Neural Networks

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# Autonomous robot navigation based on pattern recognition techniques and artificial neural networks

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**Abstract.** The autonomous navigation of robots is one of the main problems among the robots due to its complexity and dynamism as it depends on environmental conditions as the interaction between themselves, persons or any unannounced change in the environment. Pattern recognition has become an interesting research line in the area of robotics and computer vision, however, the problem of perception extends beyond that of classification, main idea is training a specified structure to perform the classifying a given pattern. In this work, we have proposed the application of pattern recognition techniques and neural networks with back propagation learning procedure for the autonomous robots navigation. The objective of this work is to achieve that a robot is capable of performing a path in an unknown environment, through pattern recognition identifying four classes that indicate what action to perform, and then, a dataset with 400 images that were randomly divided with 70% for the training process, 15% for validation and 15% for the test is generated to train by neural network with different configurations. This purpose ROS and robot TurtleBot 2 are used. The paper ends with a critical discussion of the experimental results.

**Keywords**. Autonomous Robots, Artificial Neural Network, Pattern Recognition, Neuro-controllers, ROS, TurtleBot 2.



## 1 Introduction

Robotics, one of the most characteristic areas of Artificial Intelligence has been an amazing growth, has developed a lot of research regarding the autonomous mobile robots [1–3]. In the last years, advances in recent technologies in the area of robotics have made enormous contribution in different areas of application, robots have become a fundamental tool to produce, work and perform dangerous jobs on earth and beyond. Traditionally, applications of robotics [4] Were the focused mainly in the industrial sector, in the last two decades, the field of application of robotics has been extended to other sectors [5], for example, robots for construction [6, 7], domestic robots [8, 9], assistance robots [10–12], robots in medicine [13, 14], robots defense, rescue and security [15, 16], among others.

These investigations have been directed towards finding efficient and robust methods for controlling mobile robots. Today, can be considered a fully established scientific discipline, because they are emerging new areas of knowledge that attempt to improve the effectiveness, efficiency, performance and robustness in the autonomous robots navigation.

Computer vision has a multitude of applications in different areas, certainly, robotics is one of the main beneficiaries, because, there are many approaches to solve navigation of mobile robots, one of the most used techniques is the navigation based on image analysis. The computer vision field is formed by several techniques, and beside that, they are constantly combined with machine learning algorithms. In this research we have used a feedforward Scaled Conjugate gradient instead of Backpropagation, some researchers have used these techniques to solve other problems.

Khorrami et al. [17] have compared Continues Wavelet Transform (CWT) with the Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) as a way to improve the performance of a Multi-Layered Perceptron (MLP) and a Support Vector Machine (SVM). The training or learning algorithms used in MLP and SVM are Backpropagation (BP) and KernelAdatron (KA), respectively.

Alwakeel and Shabaan [18] have proposed a new face recognition system based on Haar wavelet transform (HWT) and Principal Component Analysis (PCA) using Levenberg-Marquardt backpropagation (LMBP) on a neural network. For face detection haar wavelet is used to form the coefficient matrix and PCA is used for extracting features. These features are used to train the classifier based on artificial neural networks. A comparison between the proposed recognition system using DWT, PCA and Discrete Cosine Transform (DCT) is performed.

In the study by Nazir et al. have presented a gender classification technique more efficiently than existing using the Discrete Cosine Transform (DCT) for feature extraction and sorting the features with high variance [19].

Sridhar et al. [20] have proposed a new method by combining of Discrete Cosine Transform and Probabilistic Neural Network for brain tumor classification. According to the results, these algorithms are more efficient and fast compared with other classifiers.

## 2 Formal Description of the Problem

The autonomous robot navigation based on computer vision is a wonderful resource, because any other information that can be extracted by a camera can provide a great help in getting the robot motion.

The aim of this work is to find a safe way able to guide the robot, from a initial position to the final position o target, through obstacle-free path within a given environment either known or unknown, trying to move with minimal cost. The environment must indicate which is the starting position and the position to which you want to reach (target). For this purpose, we have taking into account four different images corresponding to the main classes that indicate what action to perform as presented in Fig. 1.

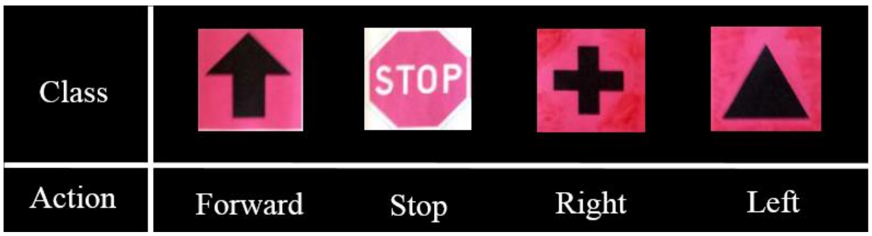


**Fig. 1.** Four classes that indicate the action to perform

## 3 Theoretical Foundations

In the last decades, pattern recognition has become an interesting research line in the area of robotics and computer vision. The classical techniques of pattern recognition more used are template matching, statistical classification, syntactic or structural matching and neural networks [21]. In this article, we have focused on the neural network approach to achieve an autonomous robot navigation using pattern recognition. The problem of perception extends beyond that of classification, main idea is training a specified structure to perform the classifying a given pattern.

Artificial neural networks (ANN's) have been studied since the 60's until today by various researchers in the scientific community to solve problems in many different application areas. Basically, the ANN's as its name indicates, are composed for a number of interconnected neurons, where its input parameters are the set of signals received from the environment, after, calculations are performed using an activation function and finally to obtain the output signal as shown in Fig.2. In this paper we have used supervised training using neural networks toolbox module of the mathematical software MATLAB. This process requires a set of training patterns, which are randomly propagated through the ANN to generate the output, using the backpropagation training algorithms.

### 3.1 Backpropagation algorithm

As is known, the "knowledge" acquired by neural networks is obtained through a learning algorithm, in which the weights are adjusted by iterations until to

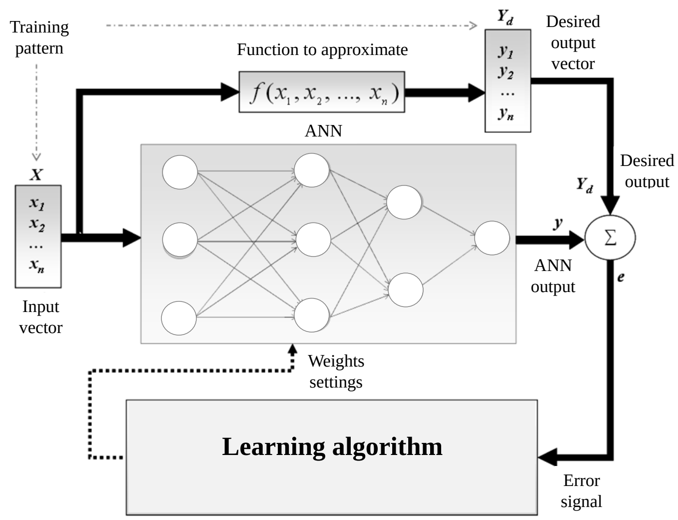


**Fig. 2.** General scheme of a neural network and representative diagram of supervised training.



achieve desired outputs within the accuracy level established. The backpropagation algorithm is the most used method in the literature, however, over time they have developed new techniques that are more stable and allow convergence faster, such as: gradient descent with momentum, gradient descent with adaptive learning rate, gradient descent with momentum and adaptive learning rate, resilient backpropagation, conjugate gradient backpropagation with fletcher-reeves update, conjugate gradient backpropagation with powell-beale restarts, BFGS quasi-newton backpropagation, scaled conjugate gradient backpropagation, among other. A brief description of these algorithms is presented in [22].

In this work, we used training algorithm Scaled Conjugate Gradient to train the multilayer feedforward network. We are trying to solve a simple pattern recognition problem using a network with backpropagation learning procedure, our task is to teach the neural network to recognize 4 images.

## 4 Implementation tools

The Robot Operating System (ROS) is a development platform open source for robotic systems. Provides a range of services and libraries that greatly simplify the creation of complex applications for robots. ROS allows the use of different programming languages. Officially supported Python, C++ and Lisp, besides many others. Currently, the library is dedicated to the Ubuntu operating system that is completely stable, although it is also adapting to other operating systems like Fedora, Mac OS X, Arch, OpenSUSE, Slackware, Debian and Microsoft

Windows. At present, there are many groups using ROS to power their robots, some examples are: Care-O-bot 3, iRobot Create, Aldebaran Nao and TurtleBot 2 [24, 25].

Turtlebot 2 is a mobile robot of differential kinematics is programmed with ROS and can be used for multiple applications, is an open robotics platform designed specifically for education and research (see Fig. 3).


**Fig. 3.** Turtlebot 2 equipped with a sensor in 3D, bumpers and Kinect Xbox 360, it can navigate in indoor and outdoor environments



## 5 Experimental Results

To carry out the development of this work we have performed in two stages, in order to obtain an effective solution to the problem proposed. The first stage, consisted of the acquisition of data or images obtained from TurtleBot 2 by controller Openni, in order to obtain the characteristics of the patterns to recognize. For best results in the acquisition of images, we performed a median filter and binarized the image to perform operations on it. Subsequently, we proceeded to reduce noise removing objects smaller than 300 pixels and we identified the total of objects found in the image using the integrated function in Matlab bwlabel.

Once we have recognized objects, in the second stage, we obtain the exact coordinates where the object is located in the image, in order to remove the object from the image and analyze it using the neural network. To carry out the training process of the neural network we have generated a dataset, obtaining 100 examples of each image with rotation variations and applying the technique of Discrete Cosine Transform (DCT) [23], where we get a vector that starts with the most significant values of the image and ends with the least significant.

At the end, we obtained a dataset with 400 images that were randomly divided with 70% for the training process, 15% for validation and 15% for the test. After that dataset is integrated, we have proceeded with the creation of the neural network using a structure optimized for pattern recognition. The neural network of the present design consists of three layers with 4 neurons each, 4 neurons in the hidden layer with a sigmoid activation function, 4 output neurons using SoftMax function and the algorithm scaled conjugate gradient backpropagation for training, and finally, there are 300 inputs to the network as shown in Fig. 4.

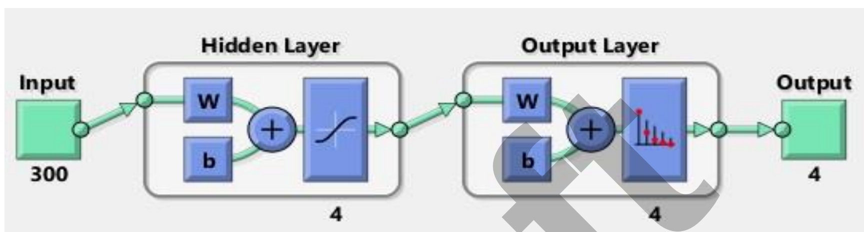


**Fig. 4.** Neural network structure



We have conducted several experiments to evaluate the performance index, we considered some variants for the neural network configuration, specifically, the number of neurons in the hidden layer was modified. In table 1 shows the training results for 3, 4 and 150 neurons in the hidden layer respectively.

| | **Samples** | **CE** | **%E** |
|---|---|---|---|
| Training | 280 | 1.08021-0 | 6.78571e-0 |
| Validation | 60 | 2.76247e-0 | 10.0000e-0 |
| Testing | 60 | 2.75740e-0 | 10.0000e-0 |
| | | | |
| Training | 280 | 3.21172e-0 | 0 |
| Validation | 60 | 9.20532e-0 | 0 |
| Testing | 60 | 9.2148e-0 | 0 |
| | | | |
| Training | 280 | 3.09154e-0 | 0 |
| Validation | 60 | 9.33340e-0 | 0 |
| Testing | 60 | 7.11894e-0 | 0 |

**Table 1.** Training results for 3, 4 and 150 neurons in the hidden layer respectively.

Fig. 5 presents four confusion matrices: the training, validation and test. The fourth confusion matrix is obtained from the data of the three matrices previously mentioned. It can be seen that 100% correct classification for the entire dataset was obtained.


**Fig. 5.** Confusion matrix



Fig. 6 shows the evolution of the performance index obtained when the best performance in the validation was achieved, it is observed that not show any major mistake with training, this is, the validation curve is greater than the test. If the test curve had increased significantly before the validation curve, then it is possible that occurred overfitting.

Fig. 7 shows a sequence of images with the implementation in the Turtlebot 2, it can clearly see how the robot uses the data and characteristics of the environment to conduct a successful autonomous navigation, using pattern recognition techniques and neural networks.

## 6 Conclusions and further research work

In this paper we have applied pattern recognition techniques and neural networks for autonomous navigation of robots. According to the results of the simulation

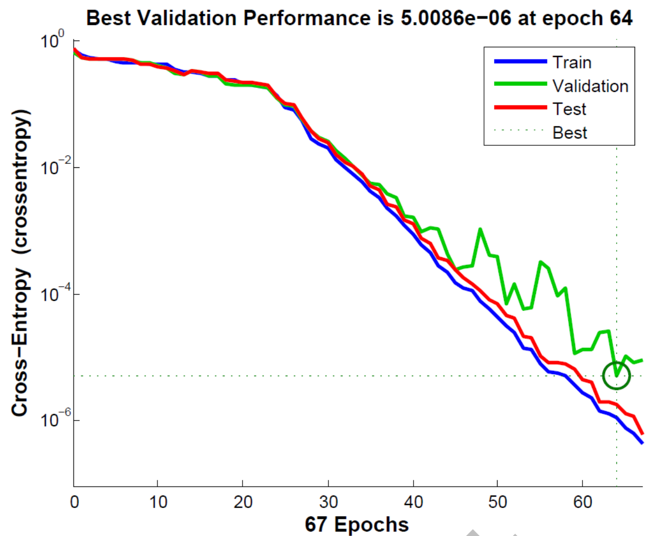


**Fig. 6.** Performance



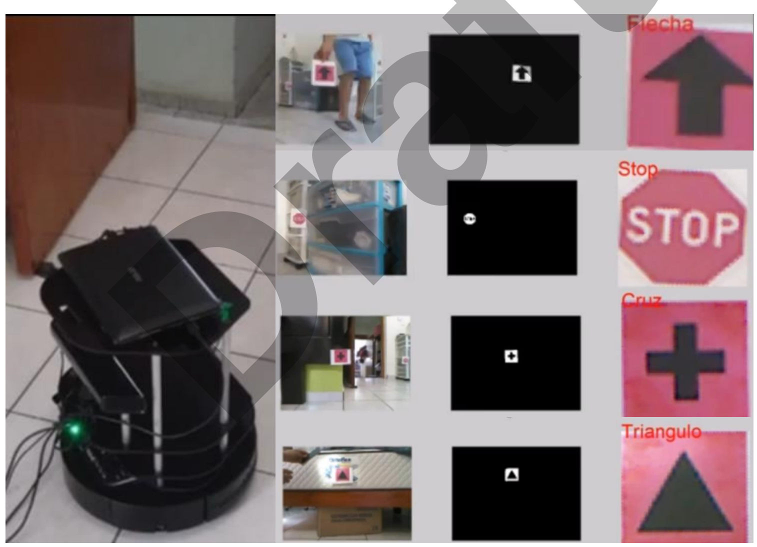


**Fig. 7.** Implementation in the turtlebot 2: the robot is able to recognize the four classes into the environment

on the performance index, we can conclude that a greater amount of data entering the network can generate an overfiting affecting the generalization of the network, because it tends to identify the images only when exactly replicate the conditions in which they were taken.

It has been verified that the algorithm is not affected by changes of scale and image rotation due to preprocessing performed, an important factor to obtain a better learning performance of the network is enlightenment, because when improving lighting conditions the coefficients generated by the DCT are more consistent.

Finally, experiments on the TurtleBot 2 were favorable, the robot was able to recognize patterns successfully. However, we considered it would be interesting to make a comparison with other training techniques in order to obtain a better learning performance, as well as the evaluation with different activation functions.

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