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# INTRODUCTION

The Artificial Neural Networks (ANNs) are based on the behavior of the brain. So, they can be considered as intelligent systems. In this way, the ANNs are constructed according to a brain, including its main part: the neurons. Moreover, they are connected in order to interact each other to acquire the followed intelligence. And finally, as any brain, it needs having memory, which is achieved in this model with their weights.

So, starting from this point of view of the **ANNs**, we can affirm that these systems are able to learn difficult tasks. In this article, the task to learn is to distinguish between different kinds of **traffic signs**. Moreover, this **ANN** learning must be done for **traffic signs** that are not in perfect conditions. So, the learning must be robust against several problems like rotation, translation or even vandalism. In order to achieve this objective, an intelligent extraction of information from the images is done. This stage is very important because it improves the performance of the **ANN** in this task.

## BACKGROUND

The **Traffic Sign Classification** (**TSC**) problem has been studied many times in the literature. This problem is solved in (Perez, 2002, Escalera, 2004) using the correlation between the **traffic sign** and each element of a database, which involves large computational cost. In (Hsu, 2001), Matching Pursuit (MP) is applied in two stages: training and testing. The training stage finds a set of the best MP filters for each **traffic sign**, while the testing one projects the unknown traffic sign to different MP filters to find the best match. This method also implies large computational cost, especially when the number of elements grows up. In recent works (Escalera, 2003, Vicen, 2005a, Vicen, 2005b), the use of **ANNs** is studied. The first one studies the combination of the Adaptive Resonance Theory with **ANNs**. It is applied to the whole image, where many **traffic signs** can exist, which involves that the **ANN** complexity must be very high to recognize all the possible signs. In the last works, the **TSC** is constructed using a **preprocessing** stage before the **ANN**, which involves a computational cost reduction in the classifier.

**TSCs** are usually composed by two specific stages: the *detection* of **traffic signs** in a video sequence or image and their *classification*. In this work we pay special attention to the classification stage. The performance of these stages highly depends on lighting conditions of the scene and the state of the **traffic sign** due to deterioration, vandalism, rotation, translation or inclination. Moreover, its perfect position is perpendicular to the trajectory of the vehicle, however many times it is not like that. Problems related to the **traffic sign** size are of special interest too. Although the size is normalized, we can find signs of different ones, because the distance between the camera and the sign is variable. So, the classification of a **traffic sign** in this environment is not easy.

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The objective of this work is the study of different classification techniques combined with different **preprocessings** to implement an intelligent **TSC** system. The **preprocessings** considered are shown below and are used to reduce the classifier complexity and to improve its performance. The studied classifiers are the k-Nearest Neighbor (k-NN) and an **ANN** based method using **Multilayer Perceptrons** (**MLPs**). So, this work tries to find which are the best **preprocessings**, the best classifiers and which combination of them minimizes the error rate.

# INTELLIGENT TRAFFIC SIGN CLASSIFICATION

An intelligent **traffic sign** classification can be achieved taking into account two important aspects. The first one focus on the extraction of the relevant information of the input **traffic signs**, which can be done adaptively or fixed. The second one is related with the classification core. From the point of view of this part, **ANNs** can play a great role, because they are able to learn from different environments. So, an intelligent combination of both aspects can lead us to the success in the classification of **traffic signs**.

# Traffic Sign Classification System Overview

The **TSC** system and the blocks that compose it are shown in figure 1. Once the *Video Camera* block takes a

video sequence, the *Image Extraction* block makes the video sequence easy to read and it is the responsible to obtain images. The *Sign Detection and Extraction Stage* extracts all the **traffic signs** contained in each image and generates the small images called blobs, one per possible sign. Figure 1 also shows an example of the way this block works. The *Color Recognition Stage* is the responsible to discern among the different predominant color of the **traffic sign**: blue, red or others. Once the blob is classified according to its predominant color, the *TSC Stage* has the responsibility to recognize the exact type of signal, which is the aim of this work. This stage is divided in two parts: the **traffic sign preprocessing** stage and the **TSC** core.

## **Database Description**

The database of blobs used to obtain the results presented in this work is composed of blobs with only noise and nine different types of blue traffic signs, which belong to the international traffic code. Figure 2.a (Normal Traffic Signs) shows the different classes of traffic signs considered in this work, which have been collected by the **TSC** system presented above. So, they present distortions due to the problems described in previous sections, which are shown in figure 2.b (Traffic Signs with problems). The problems caused by vandalism are shown in the example of class S<sub>o</sub>. The problems related to the blob extraction in the Sign Detection and Extraction Stage (not a correct fit in the square image) are shown in the examples of classes  $S_{2}$ ,  $S_{4}$  and  $S_{0}$ . Examples of signs with problems of rotation, translation or inclination are those of classes  $S_4$ ,  $S_6$  and

Figure 1. Traffic sign classification system



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