ROAD FOLLOWING FOR AUTONOMOUS VEHICLE NAVIGATION USING A CONCURRENT NEURAL CLASSIFIER

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ABSTRACT
The paper presents an original approach for visual identification of road direction of an autonomous vehicle using a neural network classifier called *Concurrent Self-Organizing Maps* (CSOM), representing a winner-takes-all collection of neural modules. We present the experimental results obtained by computer simulation of our model. The path to be identified has been quantized in 5 output directions. For training and testing the neural model, we captured and labeled a road image data set which has been divided in two lots: 30 images for training and other 30 images for test. We have also performed, trained and tested a real time neural path follower based on CSOM model, implemented on a mobile robot (car toy).

KEYWORDS: road following, concurrent self-organizing maps, autonomous vehicle navigation.

1. INTRODUCTION
The goal of autonomous vehicle navigation is to bring computer vision and robotics to the common man by creating systems that make the task of driving easier and safer. A key system requirement in the domain of driving is the ability to adapt to changing conditions, since the appearance of the car's surroundings can change dramatically depending on environmental conditions and the type of road the car is on. The automatic detection of the path to be followed by the vehicle in autonomous navigation has proven to be a formidable task when dealing with outdoor scenes. Most of the model-based road following systems have a tendency to break down when environmental variables such as road width and lightning conditions change, and in the presence of external noise.

Connectionist approaches have shown promise in autonomous navigation, and specifically in autonomous road following. One of the first successful implementation architecture for visual road following was ALVINN (*Autonomous Land Vehicle in a Neural Network)* developed by Pomerleau [1] at Carnegie Mellon University, Pittsburgh, USA. ALVINN is based on a feedforward network (multilayer perceptron), where the network is fed directly with image data at a low resolution level. ALVINN is a perceptron system which learns to control the NAVLAB vehicles by watching a person drive. ALVINN's architecture consists of a single hidden layer backpropagation network. The input layer of the network is a 30x32 unit two dimensional "retina" which receives input from the vehicle video camera. Each input neuron is fully connected to a layer of five hidden units which are in turn fully connected to a layer of 30 output units. The output layer is a linear representation of the direction the vehicle should travel in order to keep the vehicle on the road. ALVINN is the most successful development of the ARPA UGV (*Unmanned Ground Vehicle*) program. ALVINN has been demonstrated on several test vehicles driving at speeds of up to 70 mph, and for distances of over 90 miles without human intervention. ALVINN was originally designed as part of an unmanned vehicle for the modern battlefield, performing reconnaissance, surveillance as well as nuclear, biological, and chemical (NBC) detection missions [2]. However, it was adapted for civilian use, as part of the *Intelligent Vehicle Highway System* (IVHS) initiative.

In order to confer to the autonomous vehicle the ability to robustly and transparently navigate between many different road types, the same team lead by Pomerleau designed an improved a variant of ALVINN called MANIAC (*Multiple ALVINN Networks In Autonomous Control)* [3]. MANIAC is composed of several ALVINN networks, each trained for a single road type that is expected to be encountered during driving.

A few approaches for visual identification of road direction of an autonomous vehicle using radial basis function (RBF) neural networks have been performed and reported by Rosenblum and Davis [4] as well as by Neagoe *et al* [5].

The well known *road detection and tracking* algorithm (RDT), developed at the Universität der Bundeswehr München (UBM), has been adapted for following unpaved paths (dirt road detection) and contour lines [6].

Road detection is also a key issue for autonomous driving in urban traffic. He *et al* [7] have proposed a road-area detection algorithm based on color images.

Recently, Dahlkamp *et al* [8] have presented a method for identifying drivable surfaces in difficult unpaved and offroad terrain conditions as encountered in the DARPA Grand Challenge robot race. Instead of relying on a static, pre-computed road appearance model, this method adjusts its model to changing environments.

Within this paper we present an original neural approach to road image recognition for autonomous path following. It is based on the neural network model of *Concurrent Self-Organizing Maps* (CSOM) [9], [10], representing a winner-takes-all collection of neural modules. Each module is an artificial neural network called Self-Organizing Map (SOM) [11], [12], trained to recognize a specific class of road images. We have quantized the path to be followed in five classes (directions). A dataset of five class road images has been built; the results of computer simulation of CSOM road image classifier are given. We have also performed and tested a real time neural path follower based on CSOM model, implemented on a mobile robot (car toy).

2. CONCURRENT SELF ORGANIZING MAPS ARCHITECTURE FOR ROAD FOLLOWING

2.1 CSOM Architecture

Concurrent Self-Organizing Maps (CSOM) is a collection of small SOM modules, which use a global winner-takes-all strategy. Each SOM module is trained to correctly recognize the road images of one class only, corresponding to a specific road direction; the number of modules equals the number "M" of classes. For automatic road detection, we have considered M = 5 classes (SOM modules), corresponding to the number of five quantized road directions: *sharp left, wide left, straight ahead, wide right, sharp right*. We have chosen a circular SOM architecture for each module. The CSOM training technique is a supervised one, but for any individual module, the SOM specific training algorithm is used. We built M=5 training pattern sets and we used the SOM training algorithm independently for each of the "M" neural modules. Namely, each SOM module is trained with the pattern set characterized by the corresponding class label. For example, the SOM module number 3 is trained with the image road subset labeled "straight ahead". CSOM model for road direction training is shown in Fig. 1.

For the recognition, the test vector has been applied in parallel to each previously trained SOM module. The neural module providing the minimum distance neuron is decided to be the winner and its index becomes the class index that the pattern belongs to (see Fig. 2).

2.2 Road image dataset

We have captured and labeled 60 real road color images; we have divided the whole dataset into two lots: 30 images for training and 30 images for test. We have considered six pictures for each road direction (both six for training lot and also six for test).

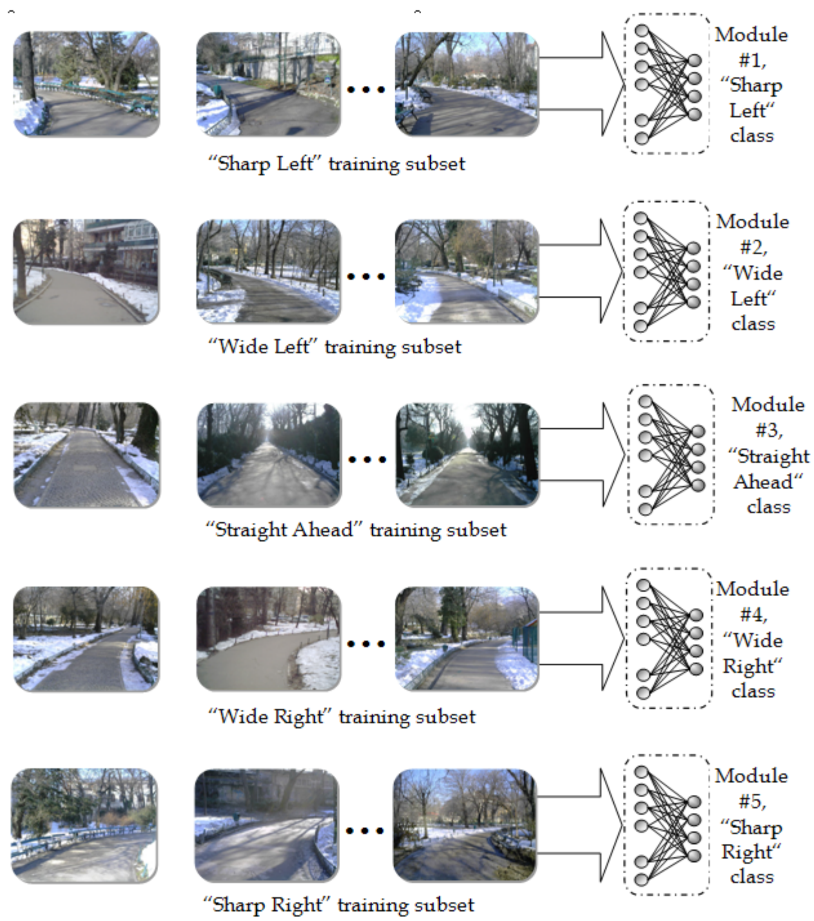

Figure 1. The training phase of the CSOM road following system.

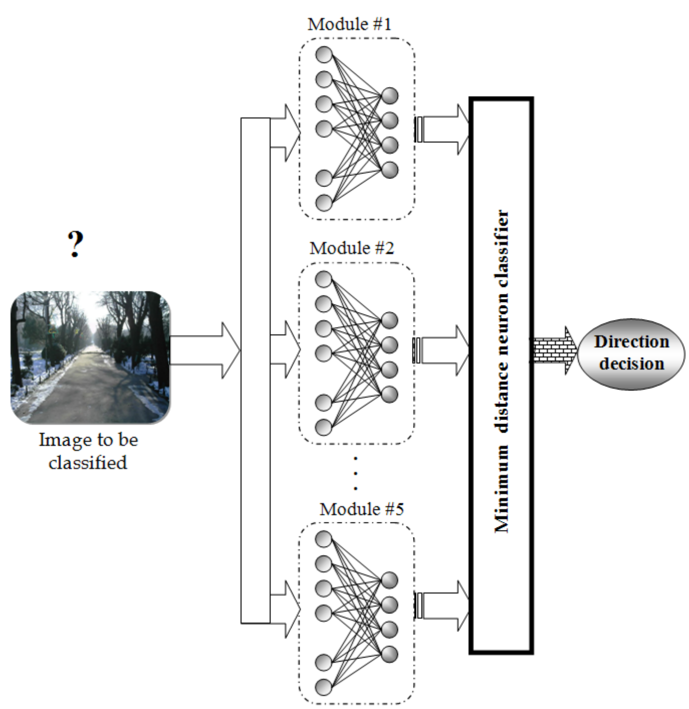

Figure 2. The recognition phase of the CSOM road following system.

The road images have been captured in the winter, at a resolution of 640 x 480 color pixels, represented by their RGB components. To reduce the computational effort, resolution was reduced to 160 x 120 pixels, by averaging on blocks of 4 x 4 pixels. This is why the dimensionality of the vectors applied to any SOM module input is of 19200. The number of neurons per module has been modified from 2 to 40.

2.3 Computer simulation results

Each of the five SOM modules has been trained with its corresponding subset of six road images. Figs. 3 and 4 show the results of the proposed neural road follower model based on CSOM using a test lot of 30 images, six pictures for each class (different of those used for training). For comparison, we have considered a Self-organizing Map (SOM) [11]. From Fig. 3, one can remark a significant advantage of CSOM over SOM, using the same number of neurons (50) for both systems (for CSOM, the number of neurons/module remains constant and equal to 10).

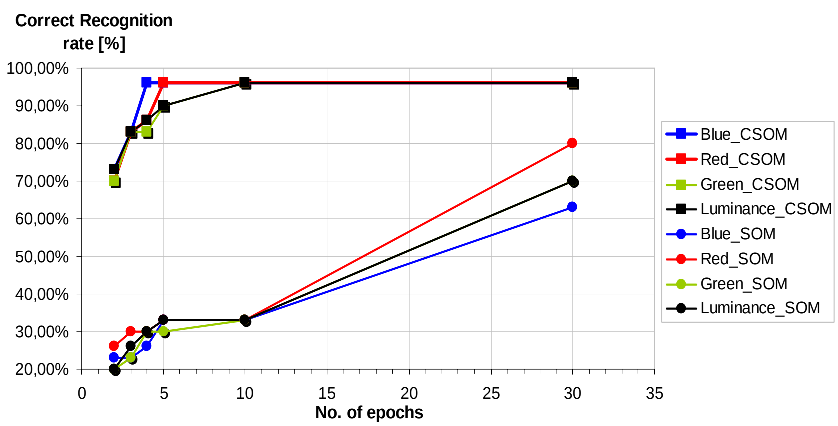

Figure 3. CSOM versus SOM correct road identification rate as a function of training epoch index (n=10 neurons/module).

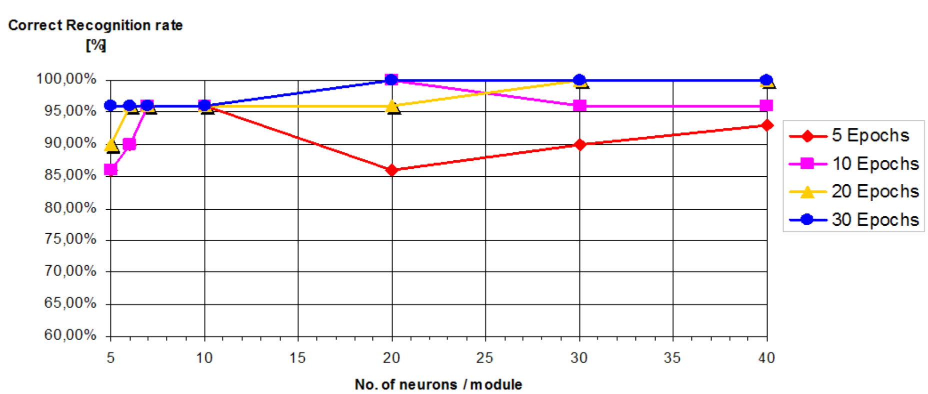

Figure 4. CSOM correct road identification rate as a function of the number of neurons/module.

In Fig. 4, the effect of the number of neurons/(CSOM module) on the road recognition rate is shown. Usually, the correct road identification performance increases, by increasing the number of neurons/module. The best results are obtained using 30 training epochs and a number of neurons/module greater than 20. One can also see the slight advantage of the blue image component.

3. CSOM FOR REAL TIME PATH DETECTION

We have used a small mobile robot ("police jeep" toy shown in Fig. 6) of sizes 30 cm (L) x 22 cm (W) x 19 cm (H). The artificial vision system (Fig. 5) has two modules: the on-board module and the stationary module. We have used a wireless TV camera mounted on the mobile robot whose video signal is transmitted through the 1.2 GHz channel to the computer. The second communication channel (40 MHz) transmits the direction commands from computer to the robot.

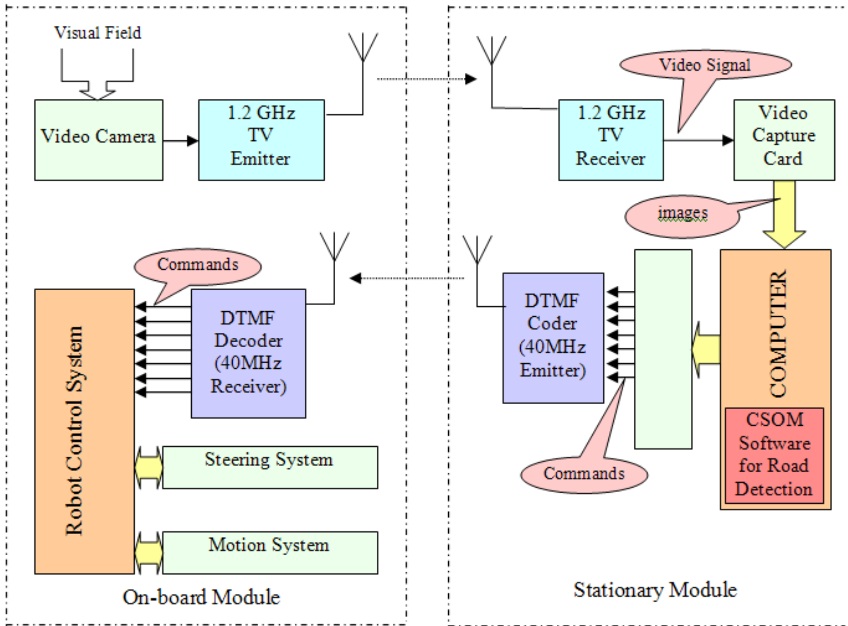

Figure 5. General block diagram of the artificial vision system for the automated guided mobile robot (on-board module, stationary module).

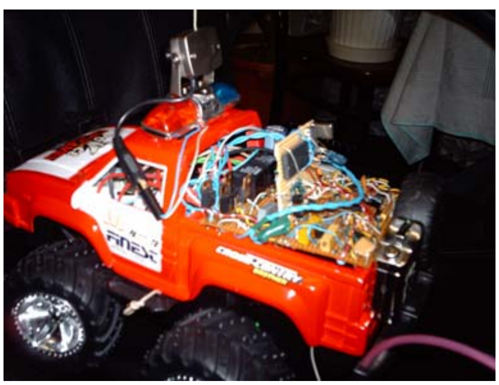

Figure 6. Mobile robot (jeep toy) including the on-board module.

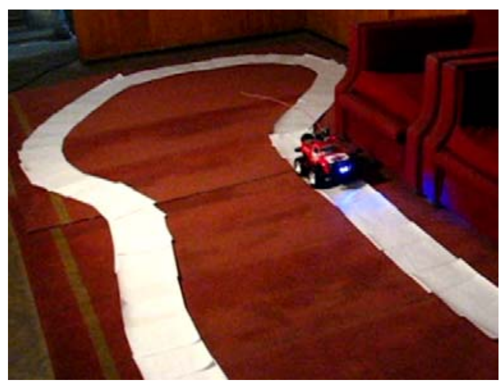

Figure 7. Autonomous driving area.

The software of the artificial vision system based on CSOM road detection has been implemented in Delphi 7.

In a preliminary phase, there have been performed the *acquisition and labeling* of the road picture set. A human trainer has driven the mobile robot to follow a specific path made by white sheets of paper on a red carpet (see Fig. 7). The computer software automatically stores the corresponding data (image & its direction label) sequence, obtaining the labeled road image set.

The *training of the CSOM modules* has been performed using five classes of labeled road image: *sharp left*, *wide left*, *straight ahead*, *wide right*, *sharp right*. Each neural module has been trained with the image subset corresponding to its class label.

The artificial vision system identifies in real time the correct direction as follows. The video signal captured by camera is transmitted through the 1.2 GHz channel to the computer, where the input path picture is stored. The CSOM software computes the minimum distance between the input picture vector and every neuron. The minimum distance neuron is the winner and the direction label of the module to which the winner belongs is assigned to the input image. This direction is coded and transmitted through the 40 MHz channel to the steering system of the mobile robot, so that it can follow the correct path.

REFERENCES

[1] D. A. Pomerleau, "Efficient training of artificial neural networks for autonomous navigation", *Neural Computation*, vol. 3, no. 1, 1991, pp. 88-97.

[2] D. A. Pomerleau, "Defence and civilian applications of the ALVINN robot driving system", *Proc. 1994 Government Microcircuit Applications Conference*, San Diego, CA, Nov. 1994, pp. 358-362.

[3] T. Jochem, D. A. Pomerleau, and C. Thorpe, "MANIAC: A next generation neurally based autonomous road follower", *Proc. Internat. Conf. on Intelligent Autonomous Systems*, February, 1993.

[4] M. Rosenblum, L.S. Davis, "An improved radial basis function network for visual autonomous road following, *IEEE Trans. Neural Networks*, vol. 5, 1996, pp. 1111-1120.

[5] V. E. Neagoe, M. Valcu, and B. Sabac, "A neural approach for detection of road direction in autonomous navigation", in *Computational Intelligence (Theory and Applications, ed. B. Reusch), Proc. Internat. Conf., 6th Fuzzy Days Dortmund*, Germany, May 1999, Springer, Berlin, pp. 324-341.

[6] M. Lützeler and S. Baten, "Road recognition for a tracked vehicle", *Proc. SPIE Conf. on Enhanced and Synthetic Vision*, AeroSense 2000, Orlando, FL, USA, April 24-28, 2000.

[7] Y. He, H. Wang, B. Zhang, "Color-based road detection in urban traffic scenes", *IEEE Trans. on Intelligent Transport. Syst.*, vol. 5, no. 4, Dec. 2004, pp. 309-318.

[8] H. Dahlkamp, A. Kaehler, D. Stavens, S. Thrun, and G. Bradski, "Self-supervised monocular road detection", *Proc. Robotics: Science and Systems*, Aug. 16-19, 2006, Philadelphia, USA.

[9] V. E. Neagoe and A. Ropot, "Concurrent self-organizing maps for pattern classification", *Proc. First IEEE Internat. Conf. on Cognitive Informatics, ICCI 2002*, Aug. 19-20, 2002, Calgary, Canada, pp. 304-312.

[10] V. E. Neagoe and A. Ropot, "Concurrent self-organizing maps - a powerful artificial neural tool for biometric technology", *Proc. World Automation Congress WAC'04*, Seville, vol. 3, 2004, IEEE Catalog 04EX832C.

[11] T. Kohonen, *Self-Organizing Maps*, Springer, Berlin, 2001.

[12] M. Bishop, *Pattern Recognition and Machine Learning*, Springer, New York, 2006.