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Analysis of the Stage

Karol Jaworowski
Institute of Computer Science, Jagiellonian University,
Prof. Stanisława Łojasiewicza 6, 30-348 Kraków, Poland
e-mail: *karol.jaworowski@gmail.com*

Abstract. The primary objective of this paper is to design a method of detecting road edges without using complex algorithms to identify and analyze images. Instead, neural networks are used, which allows to enhance and facilitate this process. The paper describes a program that recognizes the road in a picture with the use of a neural network trained on 500 samples. The samples contain original photos and images with a selected road. In the course of the research two solutions arose. The first solution is to use a single Perceptron to recognize the road. The second solution is to classify the photos using a Kohonen network and establish a separate network for each class.

Keywords: neural network, image recognition.

1. Introduction

Artificial vision systems are extremely useful in our life. They could help drivers by controlling traffic lights. Physicians could use them to detect diseases and they can also be used in the manufacturing process in a factory. One application of artificial vision systems, which may prove especially useful, is detecting the road in front of a car. Not only can it improve the comfort of driving, but also increase safety of the road users. This is a very interesting question because if a computer is able to identify the road and the location of the vehicle on the road it will be able to drive by itself. And certainly it would be helpful in keeping the vehicle on the proper lane. This paper presents a solution for the road edge detection problem, which uses neural networks. Using this wonderful tool – i.e. neural networks – was dictated by the desire to build a system that does not use complex algorithms to identify an image but is equally effective or better. One of the main objectives while creating this system was its ability to easily adapt to various road conditions. The neural networks used have been trained on 500 samples. The samples contain the original photos and images of a selected road. In the course of the research two solutions arose. The first solution is to use a single Perceptron to recognize the road. The second solution is to classify the photos using a Kohonen network and establish a separate network for each class. The second chapter of this paper describes a theoretical approach to the problem. A description of a solution is presented in the third, main chapter. Conclusions drawn while studying the said problem and suggestions for further development of the system are included in the last chapter.

2. Image recognition

By an image we will understand a two-dimensional illustration. The task of the image recognition process is to assign a test object to a grade. This assignment is based on a sequence, for which the correct classification is known and this immediately brings aforementioned neural networks to mind. In order to define image recognition properly, we must first define the equivalence relationship K, known also as a classification. This relationship ($K \subset DxD$) is defined on a set of recognized objects (D) and splits it into a collection of equivalence classes D^i that correspond to individual images. The number of classes generated by K is equal to L and I is a collection of indexes of these classes, therefore we can write:

$$D = \bigcup D^i, \tag{1}$$

$$\forall_{\mu,\nu\in I,\mu\neq\nu} D^\mu \cap D^\nu = \emptyset, \tag{2}$$

$$\forall_{d^\mu,d^\nu\in D} \langle d^\mu, d^\nu\rangle \in K \Rightarrow \exists_{i\in I}(d^\mu \in D^i) \wedge (d^\nu \in D^i). \tag{3}$$

It follows the representation:

$$A\colon D \to I, \tag{4}$$

$$\forall_{d\in D}\exists_{i\in I} A(d) = i \equiv d \in D^i. \tag{5}$$

The recognition algorithm should perform the following mapping: $\hat{A}\colon D \to I \cup \{i_0\}$, where i_0 means lack of response. It is the submission of three other mappings: $\hat{A} = F \circ C \circ B$.

$$B\colon D \to X \text{ – selection of features}, \tag{6}$$

$$C\colon X \to R^L \text{ – belonging function}, \tag{7}$$

$$F\colon R^L \to I \cup \{i_0\} \text{ – decision-making}. \tag{8}$$

Mapping B measures the characteristics of the test objects and turns them into items of the space features. The elements of this space are n-element vectors $\underline{x} = \langle x_1, x_2, ..., x_n \rangle \in X$, where $X \in \mathbb{R}^n$. Then the algorithm goes to the process of determining an object's $d \in D$ measure of similarity to classes D_i, where $i \in I$. On the basis of the $\underline{x}$ vector L functions of belonging are calculated and then the value of C mapping that is an object's measure of belonging to one of the classes is calculated D_i, $C^i(\hat{x}), i = 1, 2, ..., L$. Since there is L classes, so we can write R^L. The final stage of the image recognition is to decide to which class to assign the test object. The most common method is the general rule:

$$\forall_{\hat{x}\in X}[[F(C^1(\hat{x}), C^2(\hat{x}), ..., C^L(\hat{x})) = i] \equiv \forall_{\eta\in I,\eta\neq i}[C^\eta(\hat{x}) < C^i(\hat{x})]]. \tag{9}$$

The object is included in the class for which the value of belonging was the highest.

3. Solution

During the research into recognizing roads on photographs two systems have arisen. In both of them the engine used to identify the road is a two-layer neural network trained by means of the back-propagation method. The first system consists of a single network, which is used for every type of image. The second is a hybrid system in which two-layer Perceptrons (similar to the first system) and the Kohonen network work together.

Fig. 1. How the first system works

Fig. 1 illustrates how the first system works. At the input of the system a photo is loaded and processed, then the neural network locates the position of the road on the photo. On the output the system returns a binary picture of the road. During

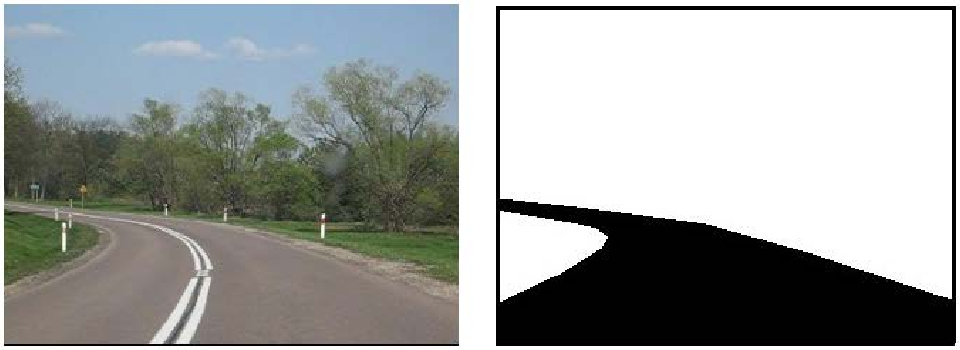


Fig. 2. Input and output images

the network training process 500 photos have been used. Output images had been created for them beforehand. Both images have a resolution of 320 x 240 pixels.

Input and output images are represented as lists of RGB values of individual pixels. It is calculated as follows:

$$\frac{valueR + valueG + valueB}{maxR + maxG + maxB},$$

where ($valueR + valueG + valueB$) – is the sum of R, G and B values for the pixel and ($maxR + maxG + maxB$) – is the sum of maximum R, G and B values. For example if the RGB value of a selected pixel equals (120, 90, 200), its value in the list equals $(120 + 90 + 200)/(256 + 256 + 256) = 0,56$. Pixels for a list are collected in accordance with the algorithm 1.

Algorithm 1

for (y=0; y¡yMax; y += 10) **do**

  for (x = 0; x ¡ xMax; x += 5) **do**
    list.Add(pixel(x,y));
  end for
end for

where x is a horizontal coordinate and y is a vertical coordinate. Point (0,0) is placed in the upper left corner as in Fig. 3.

A list of output points is created similarly, with the only difference being that the pixels are taken from black and white images. In this way two lists are created – input points and output points. Values from a list of entry points are in the range $(0, 1)$. Values from the list of output points are in the set $\{0, 1\}$, where 0 is a road and 1 is a field, which is not the road. In the first solution only one network is

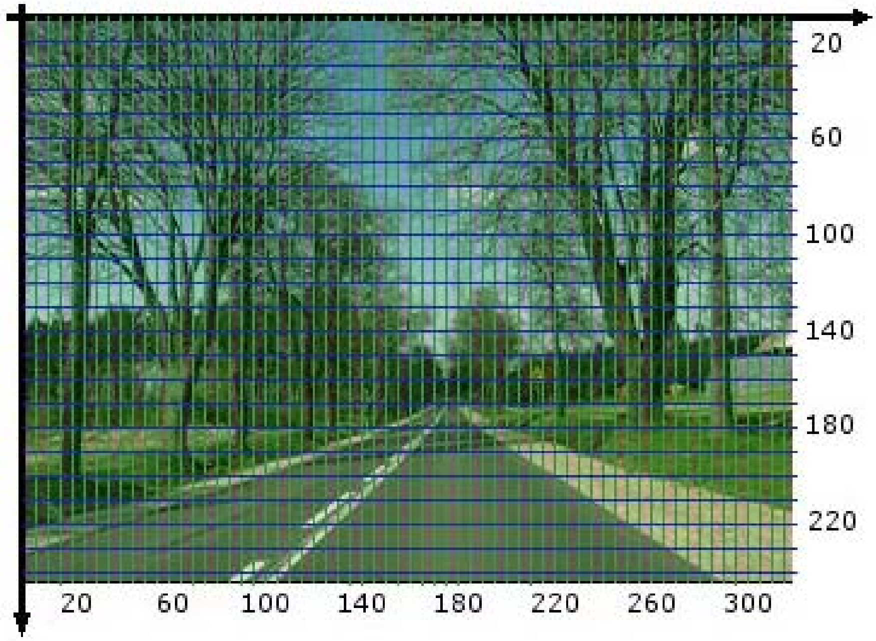


Fig. 3.

used to recognize the road. This is a two-layer Perceptron, in which the first layer (input) has 400 neurons, while the second one contains 1536 neurons. The number of neurons in the second layer is also the number of examined pixels. To train the network the following functions have been used:

- input layer – radial basis transfer function, $y = e^{-n^2}$,
- output layer – log sigmoid transfer function, $y = \frac{1}{1+e^{-n}}$.

The network has been trained with the back-propagation algorithm using 500 examples. The network's learning coefficient was 0.9.

Due to the fact that the activation function of the second layer is continuous, the network may return values from 0 to 1. In order to specify which values, returned by the network, should be classified as a road, a special parameter has been used in the system. It operates on the principle that all values smaller than this parameter are treated as a road, while all values greater than that are treated as a field that is not the road. The tests proved that the best parameter for this system equals 0.4. Therefore, all values returned by the network, which are lower than 0.4 are regarded as a road and greater values are not. The estimation error is a result of incorrectly detected pixels divided by all tested pixels, where incorrectly detected pixels are pixels, which the network incorrectly classified as the road and pixels, which should have been classified as a road but they were not. In Fig. 4 black points make up a correctly-detected road, the green ones are the pixels which are the road but the network has not identified them as a road and the red pixels are incorrectly classified as a road.

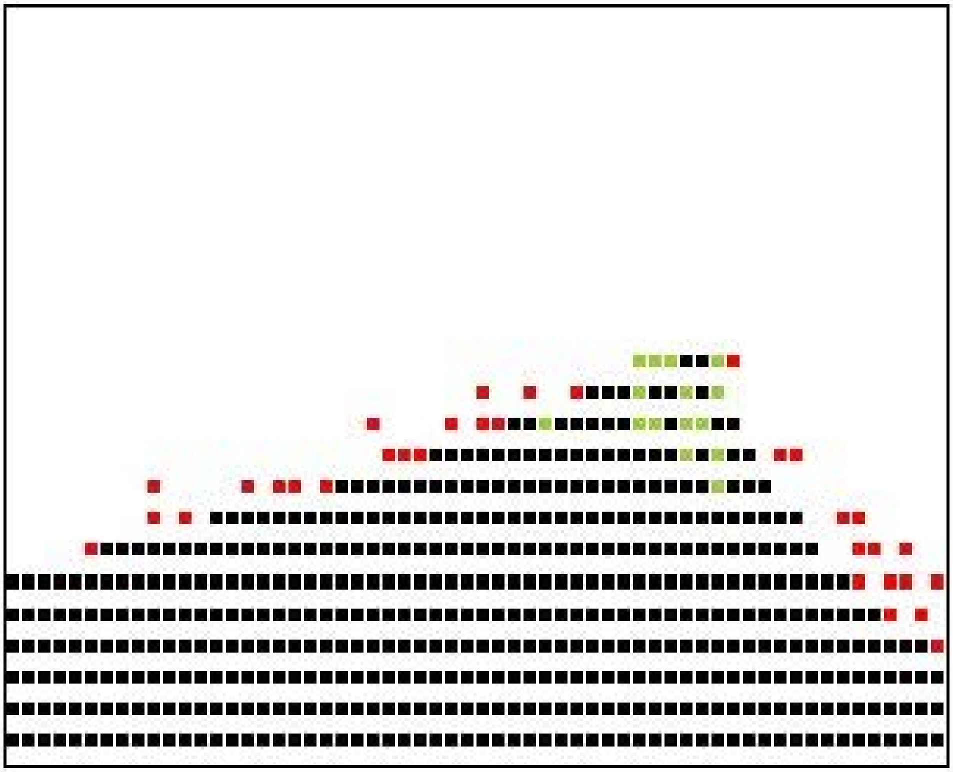


Fig. 4. Black points – correctly detected road, green points – not detected road, red points – incorrectly detected road

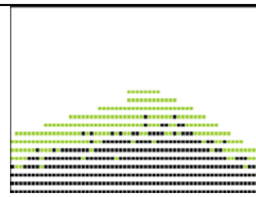
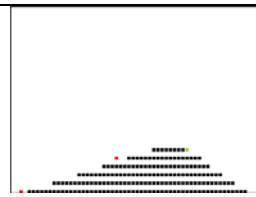
The error in Fig. 4 equals 3,125%, it is the sum of red and green pixels (33 + 15) divided by the number of tested pixels (1536) multiplied by 100.

- Error of road recognition for pictures on which the network has been trained.

The highest estimation error of the road identification process was 14.9%, the lowest 0.19%, while the average error of road recognition in this solution was equal to 2.9%.The results of the system performance in case of the highest and the lowest error are presented in Tab. 1.

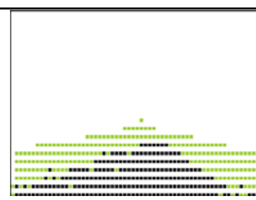
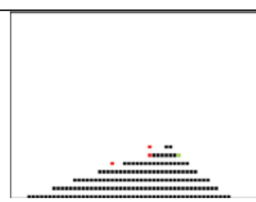
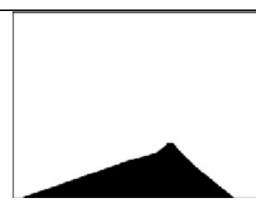
- Error of road recognition for pictures previously unknown to the network.

Tab. 1. Road recognition error for pictures on which the network has been trained

Original image	Detected road	Actual road	Error
			14,9%
			0,19%

The highest estimation error of the road identification process was 15.82%, the lowest 0.32%, while the average error of road recognition in this solution was equal to 3.28%. The results of system performance in the case of the highest and the lowest error are presented in Tab. 2.

Tab. 2. Road recognition error for pictures previously unknown to the network

Original image	Detected road	Actual road	Error
			15,82%
			0,32%

The second solution is a hybrid system, which uses a Kohonen network in addition to the Perceptron. How the second system works is illustrated in Fig. 5. Photos used for the research are not identical and sometimes they differ in many areas. It was observed that it is very easy to divide them into groups. An automatic classifier has been used in order to divide them quickly. The Kohonen network managed to perform this task very well.

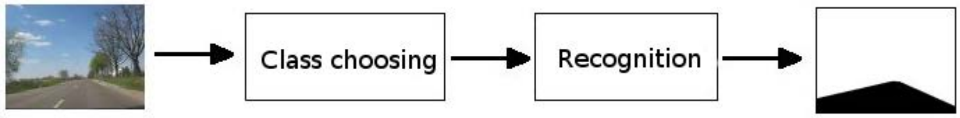


Fig. 5. How the second system works

The module selection class has arisen during the Kohonen network learning process. At its input 9-dimensional vectors representing the individual images were given. The coordinates of each of the vectors correspond to the average RGB values of the 9 areas in the image. These areas are shown in Fig. 6.

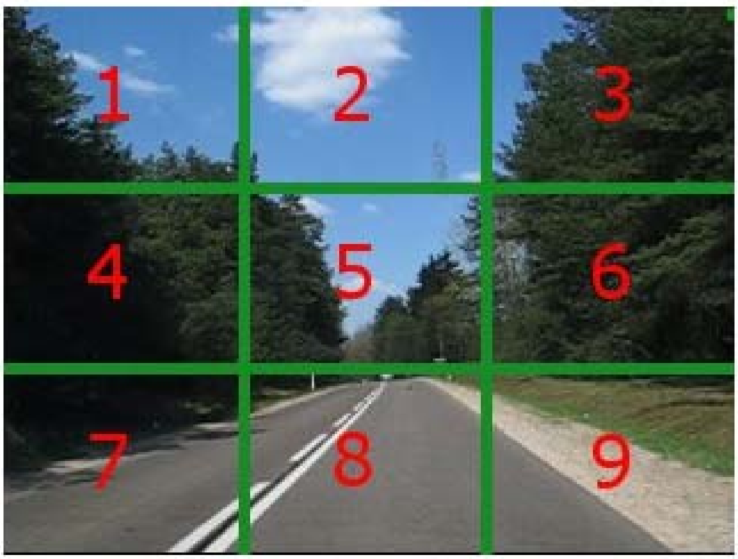


Fig. 6. 9 areas in the image

From each of the 9 areas the average values of colors have been taken according to formula 2.

The function of the neighborhood was calculated as follows:

$$\sqrt{\sum_{i=1}^{9}({x_i}^2 - {y_i}^2)},$$

where x_i and y_i are coordinates of an input vector. The network's learning coefficient was 0.5. The vector representing the image shown in Fig. 7 has the following coordinates:

$$0{,}38 \times 0{,}654 \times 0{,}246 \times 0{,}088 \times 0{,}378 \times 0{,}151 \times 0{,}240 \times 0{,}411 \times 0{,}450.$$

Algorithm 2

```
for (y=0; y¡yMax; y+=10 ) do

   for ( x = 0; x¡xMax; x+=10 ) do
      colourValue += pixelRGBvalue( x, y );
   end for
end for
```

where xMax is a maximum value of X coordinate and yMax is a maximum value of Y coordinate. When the photo's resolution is 320 x 240, xMax is equal to 106 and yMax is equal to 80. PixelRGBvalue(x,y) normalized sum of red, green and blue pixel's value of x and y coordinates. ColourValue is a sum of normalized colour values of the tested pixels. The (0,0) point was set in the upper left corner of the image, like in Fig. 7.

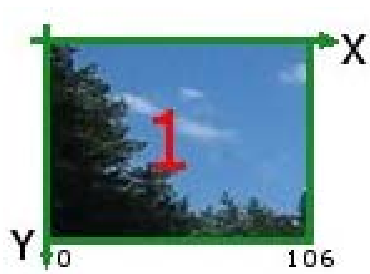


Fig. 7.

The second area on the picture is the brightest, so the second coordinate in the vector has the highest value (0.654). In turn, the forth area is the darkest, so the coordinate which represents this area has the lowest value (0.088). In this way, the processed images have been passed on the Kohonen network entry, which has divided them into classes and created a structure that allows to assign to other photos a class number. When the pictures were divided into classes, for each of them a separate neural network has been created.

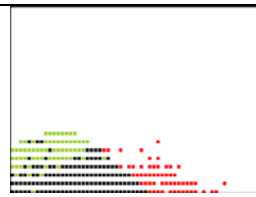
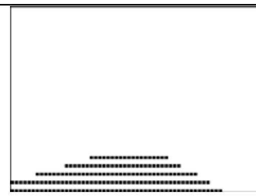
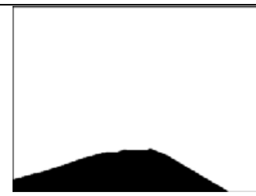
The images, which have been submitted to the process of recognition, were prepared in the same manner as in the first solution. According to the process of identification shown in Fig. 5, at the beginning a picture was assigned to one of the classes and then an appropriate Perceptron was used in order to recognize the road.

- Road recognition error for pictures on which the network has been trained.

The highest estimation error of the road identification process was 8,56%, the lowest 0%, while the average error of road recognition in this solution was equal to 0,44%.

The results of system performance in the case of the highest and the lowest error are presented in Tab. 3.

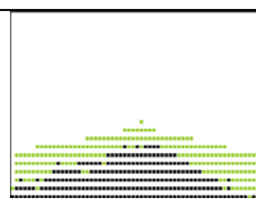
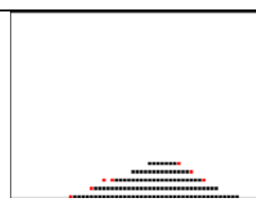
Tab. 3. Road recognition error for pictures on which the network has been trained

Original image	Detected road	Actual road	Error
			8,56%
			0%

- Road recognition error for pictures previously unknown to the network.

The highest estimation error of the road identification process was 14.51%, the lowest 0.52%, while the average error of road recognition in this solution was equal to 5%. The results of system performance in the case of the highest and the lowest error are presented in Tab. 4.

Tab. 4. Road recognition error for pictures previously unknown to the network

Original image	Detected road	Actual road	Error
			14,51%
			0,52%

4. Conclusions

Two systems of road edge detection based on neural networks have been described in this paper. The first uses one network to recognize the road on any kind of picture. This is a two-layer Perceptron which has been trained on 500 samples. At the input of the system a processed photo is served and the neural network locates the position of the road on it. On the output the system returns a binary picture of the road. It is a system that does not require a complex mathematical process to perform recognition, and that was the main reason for using it. The average estimation error equals 2.9%, for photos on which the network has been trained, and 3.28% for the photos, which were not used in the process of learning. The second solution is a hybrid system, built from the Kohonen network and several Perceptrons. The first module in the system – the Kohonen network – designates the appropriate Perceptron, which should be used in the recognition process. The average estimation error equals 0.4%, for photos on which the network has been trained, and 5% for photos, which were not used in the process of learning. In the future we plan to modify and improve the hybrid system, by increasing the amount of sample photos for each class, and change the grading method. This raises the idea of creating an autopilot, which would help the driver to keep a vehicle on its lane, or even replace the driver.

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