Neuro-fuzzy Logic and Complex Sensorial Systems Used for the Planning of some Intelligent Vehicles Needed for the Transport of the Persons with Handicaps

Lecturer Ph.D. Valeriu LUPU
Ph.D.Stud.eng. Cătălin LUPU

"Ştefan cel Mare" University of Suceava
valeriul@seap.usv.ro, lupucata@yahoo.com

Abstract. This article presents efficient algorithms used for the planning of some intelligent vehicles that have the mission to transport persons with handicaps inside of a building (or in a room). The cars work in a varied land, with walls, chairs, domestic appliances, lockers, and other obstacles that it might meet in its way (this obstacles are present from the beginning in the studied land or they can appear in every moment) and whom it might avoid. The cars can leave all at one moment or individually. They can meet on their way, but they must avoid the collisions by communicating between them through the server. The machines are equipped with complex sensorial systems like video cameras, transducers, proximity sensors, neuro-fuzzy logic. Sequential rapid algorithms – like Strassen's and Winograd's – are used for the matrices multiplication (by using parallel calculus) and Dijkstra's algorithm for the calculus of the optimum road between two points by using parallel programming.

1 General Presentation of the Studied Problem

The detection of obstacles and objects that are in the work area of a intelligent machine was and always is a difficult problem that has never find for itself a real robust solution because of some perturbation factors as: light variations, color differences (tones) and other continuous transformations factors from the environment (Figure 1).
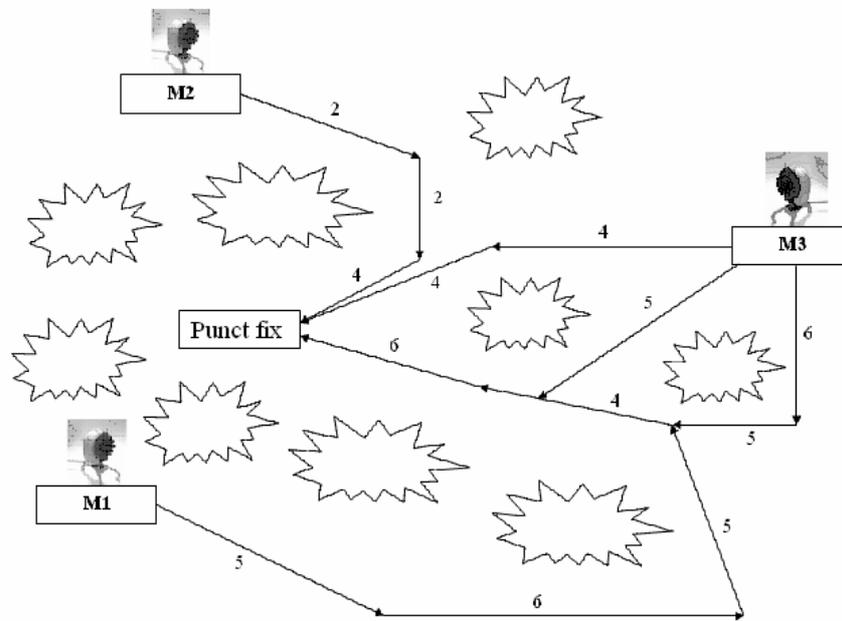
Figure 1

The analyzed land configuration

There exist an important number of applications, wherein it is required to recognize some plan forms. In these applications, but also in the case that the forms aren't anymore plans, the contour of the forms is an important descriptor from which we can leave in the process of similarity finding between the objects represented by the respective forms in the digital images. By leaving from the contour of the form, there exist many possibilities to describe the forms.

There were practically implemented descriptors of the following types:

- the chain code;

- polar signature;

- Fourier descriptors of the function of contour direction change;

- moments;

- the histogram of the intersection points with an array of randomly generated lines.

Actually there are developing pattern recognition systems using neuro-fuzzy logic.

The systems can work with images with a resolution of 256×256 or 512×512 pixels. Different forms arrays (including real forms) can be chosen, but also obstacles, as: chairs, tables, walls, domestic appliances, doors, etc.

Digital images are filtered for the noises reduction, contours extraction with techniques based on methods of gray level gradient. After that, methods for thinning and / or contour continuation are applied for obtaining in final a closed contour with a unitary thickness.

The filters weights, thresholds for the contour extractors and o the parameters implied were determined off-line, by repeated experiments until the finding of the best results.

Because the difficultness of the contour detection problems there are suggested many techniques for the obtaining of a solution. These techniques go from a simple spatial filtering and the application of a threshold based in flesh-tones, and arrive to complex models based on the probability of Gaussian distribution and Eigen spaces.

The advantage of using the illumination with infrared-domain radiations versus the classical techniques presented above is a well-known reflex of the objects that must take into account.

The used components of this system are (Figure 2):

- a Philips 740k web-cam;

- 8 infrared big power leds;

- 2 resistors of 330 ohms;

- a 8 V power supply;

- a laptop with a USB interface.

Figure 2
Image acquisition system

In order to prepare the web-cam, a disc will be removed from the front of the lens, which has the scope of preventing the saturation of a image with natural light and to deny the enter of infrared radiation (IR filter). The leds were arranged in a circle around the webcam's objective. They will be alimented from the 8V supply source through the two 330 ohms resistors that have the role to limit the current to

100mA. The closer from the axes the leds are, the bigger the quantity of reflected infrared radiation will be.

2. The Contour Function

The contour of a figure can be described by a function. This description presents some advantages beside other methods, as:

- diminution of the quantity of data: usually, only a few coefficients of the approximation of the contour function are necessary for a enough precisely characterization;

- a convenient characterization of the form's contour;

- an intuitive characterization of many more properties of the form.

For any form (Figure 3), it will be used the following function:

f(k) = Euclidian distance (O, A(k))

where O is the centre of gravity of the form, and A(k) is a point on the contour.
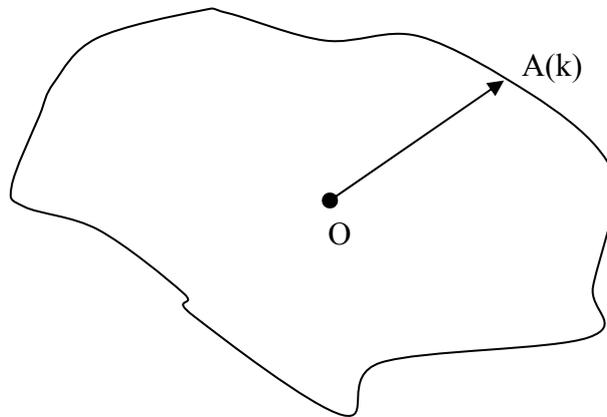
Figure 3
Example of a figure for which the contour function is computed

Let L be the length of the contour and O a starting point; in this case the function f(k) is defined on [0, L] in the continuous case. The analysis of the contour that will be presented hereinafter requires that the function f(k) to be defined on the interval [0, 2π] and – as follows – the function f(k) will be normalized.

Let $t = 2\pi k / L$; it will be defined $f^*(t) = f(t \cdot L / 2\pi)$, $0 \leq t \leq 2\pi$. Hereinafter, for the notation simplification, through f it will be represented the normalized function f^*.

In the discrete case there are N points on the contour and also a discrete contour function:

$f(k_i)$ = Euclidian distance (O, k_i), where $i = \overline{0, N-1}$.

Because a closed contour can be considered as being periodic, the contour function itself is periodic.

2.1 Fourier Analysis on the Contour Function

Let $f(x)$ be a periodic and continue function on $[0, 2\pi]$. The function $f(x)$ can be approximated with a Fourier series like:

$$f(x) = \frac{a_0}{2} + \sum_{k=1}^{\infty} (a_k \cdot \cos(k \cdot x) + b_k \cdot \sin(k \cdot x))$$

where the Fourier coefficients are:

$$a_k = \frac{1}{\pi} \cdot \int_{-\pi}^{\pi} f(x) \cdot \cos(k \cdot x) dx$$

$$b_k = \frac{1}{\pi} \cdot \int_{-\pi}^{\pi} f(x) \cdot \sin(k \cdot x) dx$$

The Fourier series can be also described as:

$$f(x) = \frac{a_0}{2} + \sum_{k=1}^{\infty} A_k \cdot \sin(k \cdot x + \varphi_k),$$

$$A_k = \sqrt{a_k^2 + b_k^2}, \quad \varphi_k = \text{arctg}\left(\frac{a_k}{b_k}\right)$$

In the discrete case, the above relations become:

$$f(x_r) = a_0 + \sum_{n=1}^{(N+1)/2} (a_n \cdot \cos(x_r \cdot n) + b_n \cdot \sin(x_r \cdot n))$$

where

$$x_r = \frac{2\pi r}{N}, \quad r = \overline{0, N-1}$$

$$a_n = \frac{2}{N} \sum_{r=0}^{N-1} f(x_r) \cdot \cos(x_r \cdot n)$$

$$b_n = \frac{2}{N} \sum_{r=0}^{N-1} f(x_r) \cdot \sin(x_r \cdot n)$$

$$A_k = \sqrt{a_k^2 + b_k^2}$$

$$a_0 = \frac{1}{N} \sum_{r=0}^{N-1} f(x_r)$$

2.2 Neural Network Used for the Determination of Contour Function for the Forms that Exists in the Webcam's Aperture

2.2.1 KNN Classifier based on the Identification of the Most Closer k Neighbours, in the Characteristics' Space, without the Implication of Prototypes

It will be fallowed the following steps:

1. for every form it will be determined the contour function f.

2. it will be calculated the a_k, b_k and A_k coefficients for $k = \overline{0,14}$

3. the 15 A_k coefficients will represent the input for a neural network (multilayer perceptron), with three layers, which was preliminarily learned;

or

3'. having created a database, for every form i existing a number of records represented as $(A_0^i, A_1^i, ..., A_{14}^i)$, it will be calculated the distances between the form which must be recognized and it will be applied the rule of the most closer k neighbours (the K-NN algorithm).

It will be used the Euclidian distance between two points in the R^{15} space.

2.2.2 The Use of RBF Neural Networks for the Classification

Why RBF neural networks were used instead of multilayer perceptron? Both kinds of neural networks are universal approximators of continous multidimensional

functions. The differences between the two architectures are, essentially, the followings:

1. A RBF network has, in its base form, a single hidden layer;
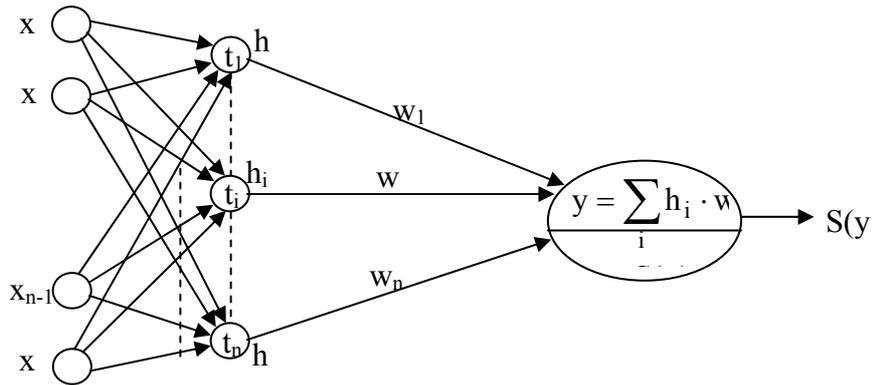
Figure 4

Topology of a radial neural network

where,

x – input vector (i = 1, n)

t – weights vector

h_i – output of the neuron i, where

$$h_i(x) = e^{-\frac{\|x-t_i\|^2}{2\sigma^2}},$$

where

σ - dispersion of the neuron output curve;

h_i – a radial n-dimension function.

The only output neuron of the network has the activation $y = \sum_i h_i \cdot w_i$, where

w_i represents the weight of the connection of hidden neuron i with the output neuron.

The vectors t_1, t_2, …, t_n represent the centers of radial functions. The training of the radial neural network implies two steps:

(i) establish of the value for the center-vector t_i and for the dispersion σ_i for every hidden neuron i;

(ii) determination of the weights by a training method. The training can be iterative or non-iterative.

It can be taken into account and RBF architectures, in which it exist a number of m outputs. In this case m=15. In this case, if the matrix W of the weights is singular, the weights can be determined by using an iterative method.

Let d_j be the desired output of the neuron j from the output layer and y_j the real output of this neuron. The weight w_{ij} of the connection between the hidden neuron i and the neuron j is updated by using an error minimization algorithm. By using a gradient method, the actualization rule obtained is:

$w_{ij} (k+1) = w_{ij} + c \cdot x_i \cdot (d_j - y_j)$,

were c is the training rate.

(2) At a perceptron the calculus units have the same activation type (not linearly), no matter of the layer they belongs to. In the case of the RBF network, the hidden nodes, not linearly, have a completely different role in the output layer;

(3) The argument of the activation function of a hidden node on RBF network represents the distance (defined by the Euclidian norm) between the input vector and the center of that node. The hidden node of the perceptron calculates the scalar product between the input and the weight vector associated to that node.

(4) The multilayer perceptron achieves global approximations of the input-output correspondence, being capable to generalize in the input-space areas for which aren't available the input data;

The RBF networks build local approximations of the non-linear input-output function, having as a result a faster training and a most reduced sensibility towards the presenting of training data.

The RBF neural network for the determination of contour function is presented in the figure 5.
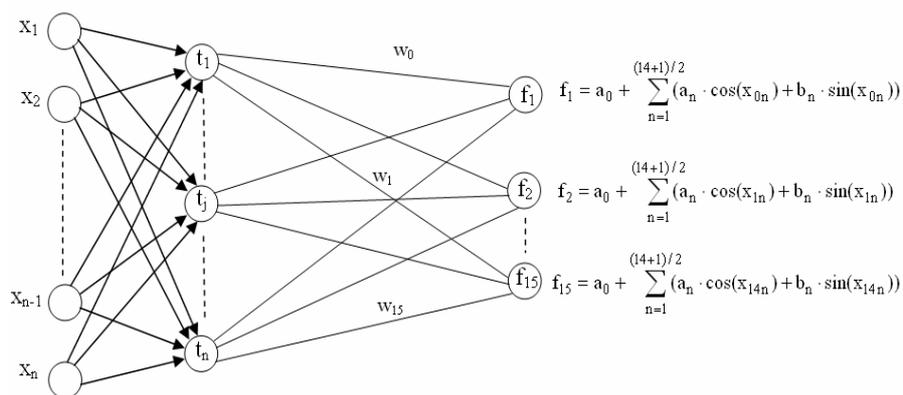
Figure 5
RBF neural network with m outputs

3   The Use of Artificial View for the Obstacles Detection

A difficult task of the intelligent vehicles consists in the finding of some obstacles with video cameras, with the scope of avoiding them. So it is imposed that optical axis of the camera to superpose over the axis of the machine command device (figure 6a). On the base of the coordinates of the obstacle A, B, C, D afferent to the current camera image (figure 6b) and the points A*, B*, C* şi D* of the desired image (figura 6c) it is determined the position changes (Δx_i, Δy_i) and orientation – respectively - $\Delta \theta_i$ for the images coincidence.

The variations of the coordinates Δx_i, Δy_i of the four points is applied at the inputs of a neural network (figure 7) for which the outputs are the variations of the orientation $\Delta \theta_i$.
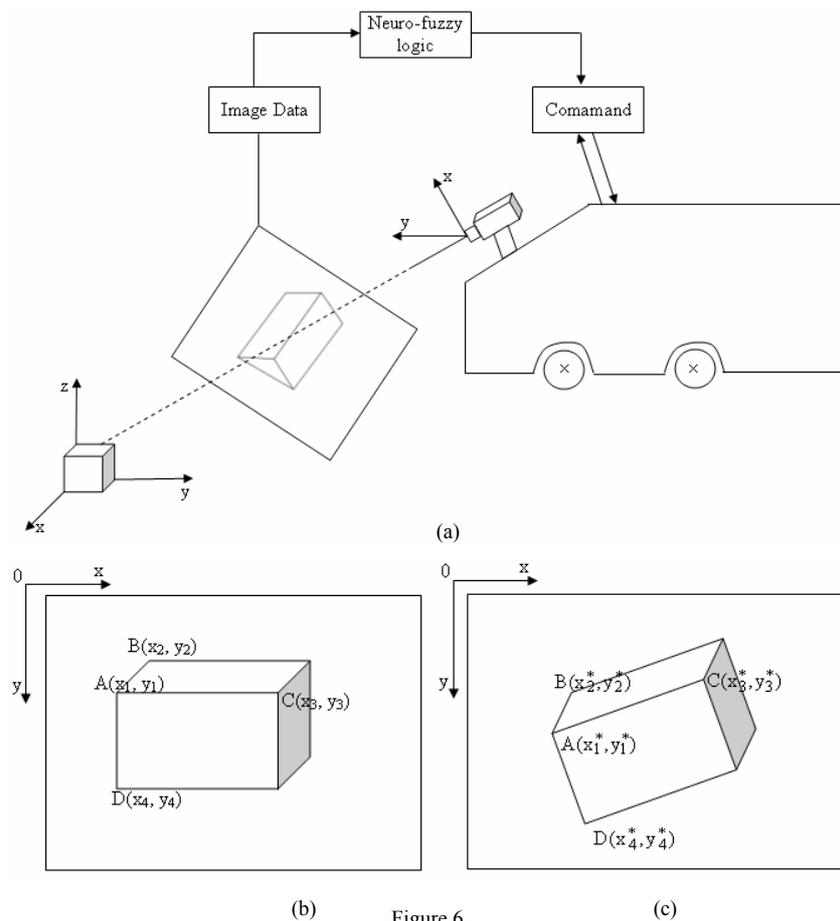
Figure 6
The use of a video camera for the objects detection

The relations between the angular changes and those of coordinates can be obtained through the training by the neural network at the coincidence of the object images.
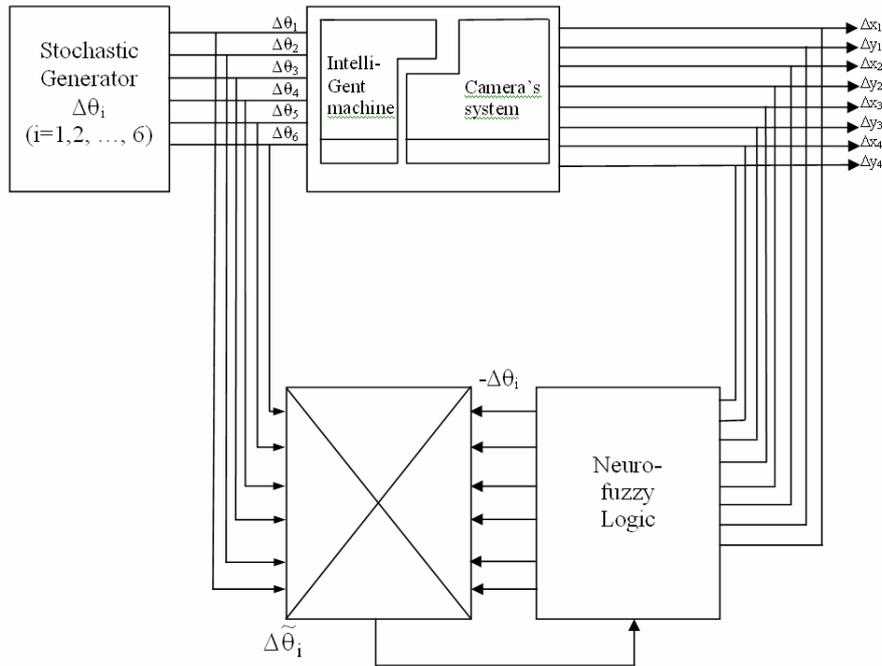
Figure 7
Use of neuro-fuzzy logic for the detection of obstacles based on artificial vision

Conclusions

In this article it was presented the fulfillment of an application with intelligent machines used for the transport of the persons with handicap inside a room, without any attendant. There were used RBF neural networks and neuro-fuzzy logic. The following perspectives for the research in this domain are possible:

- transport of the luggage inside the airports without any crew;

- transport of dangerous wastes without any crew;

- transport of the containers in the ports;

- detection and extinction of fires using complex sensorial systems, etc.

Bibliography

[1]   Y. Arrouye et al. Manuel du Meganode, version 2.1. Technical Report RT79, LMC-IMAG, 1992

[2]   P. Bjorstad, F. Manne, T. Sorevik, and M. Vajtersic. Efficient Matrix Multiplication on SIMD Computers. SIAM J. Matrix Anal. Appl., 13(1):386-401, 1992

[3]   B. Dumitrescu, J. L. Roch, and D. Trystram, Fast Matrix Multiplication Algorithms on MIMD Architectures. Technical Report RT87, LMC-IMAG, 1992

[4]   J. L. Roch and D. Trystram, Parallel Winograd Matrix Multiplication. In W. Jossen and E.Milgrom, editors, Parallel Computing: From Theory to Sound Practice, pages 578-581, IOS Press 1992

[5]   V. Starssen. Gaussian eliminination is not optimal. Numer. Math., 13:354-356, 1999