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Construction of an Interactive and Competitive Artificial Neural Network for the Solution of Path Planning Problems

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Abstract.
In this paper we present an artificial visual system for autonomously moving vehicles. In this system visual information, extracted from the vehicle's surroundings by means of motion detection and range estimation strategies, is mapped onto a retinotopically ordered neural map. The activity pattern elicited in this neural map is projected onto an interactive competitive neural network which plans the next step of the vehicle on its path towards a given target location. The system has been implemented and tested for a two-dimensional, i.e. flat, world using computer simulations, giving encouraging results.

1. Introduction

Every autonomous moving system needs to observe its environment in order to be able to carefully plan the direction of its next step towards a target location without colliding with obstacles on its path. There are several constraints to the problem of planning a path, like: a good solution should be energy efficient and not harmful for the environment nor for the system itself. In nature, this planning problem is successfully solved with the help of visual perception. Small creatures like flies e.g. can perform even the most complex manouvres without errors. This has convinced researchers to seek an artificial solution for this problem based on the same principles and mechanisms found in biological systems (Franceschini et al.,[1]). To gain an understanding of the biological solution, parts of the visual system of insects have been modelled based on behavioural experiments (Reichardt at al.[6]) as well as electro-physiological measurements (Masteboek et al.,[4]).

2. Network Architecture

In order to be able to solve a path planning problem, based on visual input, there are several tasks an artificial system has to perform. In our design, the first task is to extract all relevant information from visual input that is

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needed to transform the visually observed environment into a set of usable representations. The second task is to obtain from these representations a clever estimate of the ranges of observed obstacles in the environment and to map this information into a neural map. The third task is to use this neural map in deciding how to take the next step of the vehicle towards a given target location. How these tasks can be realized and implemented, will be described in detail in the following subsections. The network has to rely not only on its own visual input, but also on (task specific) information supplied by other processes. One example of this is that the system has to "know" what (and where) the target is. In our system the target is just a goal defined by a higher order cognitive process that needs not to have a direct visual origin.

2.1. Visual Input

For reasons of simplicity, we assume a two-dimensional world, in practice these are surroundings that are "flat". Under these conditions obstacles can be detected by so called "ring vision". The two eyes are defined as collections of light detecting elements regularly placed on a ring segment with fields of vision that overlap. Each element has a sensitivity profile that can be described with a Gaussian distribution with a half-width which equals the inter-detector angle. The eyes can be moved back and forth over a small angle during operation, in order to allow a scanning movement towards the body axis, which results in an increase of the range of visual motion detection (Franceschini et al.,[2]) when the eyes are making a translational movement at a constant speed due to vehicle movement.

2.2. Representations

The output of the light detecting elements form the static intensity represention at any time. An array of directionally sensitive elementary motion detectors (EMDs) based on the correlation model (Reichardt et al.[6], Mastebroek et al.[4]) is extracting parallax movement information of contours and other contrast features of obstacles from the intensity information coming from the eyes and thus generates a retinotopic movement representation. In order to get proper movement information for an entire object and not only from its edges or other features, the movement information should be expanded over the entire object area. In "natural" environments, object textures will supply movement information for an entire object. However, in artificial surroundings (like those in our computer simulations) an extra "fill-in" mechanism is required to close the information gap between the object boundaries. For reasons of simplicity, objects have been chosen to be "light", while de background is "dark", so objects are easily identified and movement information is easily expanded over neighbouring elements which detect similar static intensities.

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2.3. Building a Neural Map

To create a topographical neural representation of the environment, objects are mapped to a number of neurones that represent a circular area in space around the vehicle. A radial column of neurones in the map represents a circle segment in the direction of an optical axis of one of the eye segments, while a circular row of neurones represents a distance range as shown in figure 1. By representing the environment in this way the neural representation will not only be topograpical but also retinotopical.

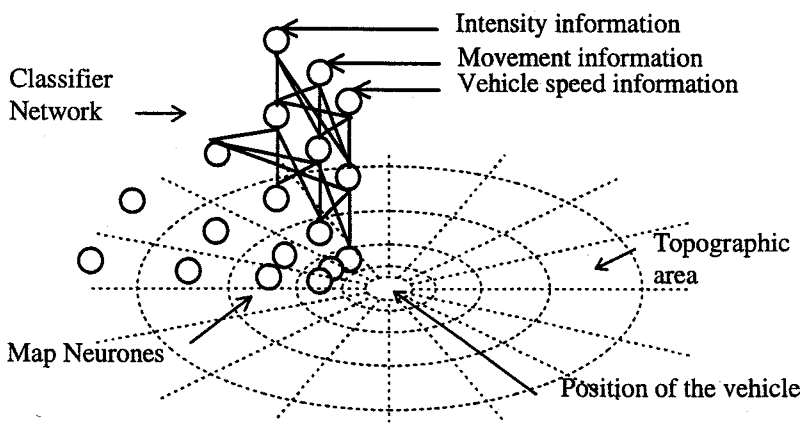

Figure 1: In the neural map each neuron represents an area in the system's environment. Movement and static visual information are combined in a set of backpropagation networks to classify in which area on the map objects are present. This results in a map with activated neurones in the areas where obstacles are detected. Note that not all neurones and connections are shown for reasons of clarity.

The movement representation obtained from the EMD array (and subsequent filling layer) together with the static intensity representation from every eye segment and the translational speed of the system serve as an input for a set of backpropagation (BP) networks, one BP network for each segment. Each BP network estimates the distance at which an object is present and classifies these distance on a scale from "very close" to "very far". The activations on the outputs of one BP network correspond to the activations in one column of the earlier described neural map. The map that is formed in this way has a frame of reference that is fixed to the system which means that the pre-processing of the visual information described so far has to be repeated after each step of the vehicle in order to update the neural map of the changed surrounding. In order to be able to anticipate these changes continuously, the range classification has to be performed at a high speed, this is the reason that BP networks are used for this task.

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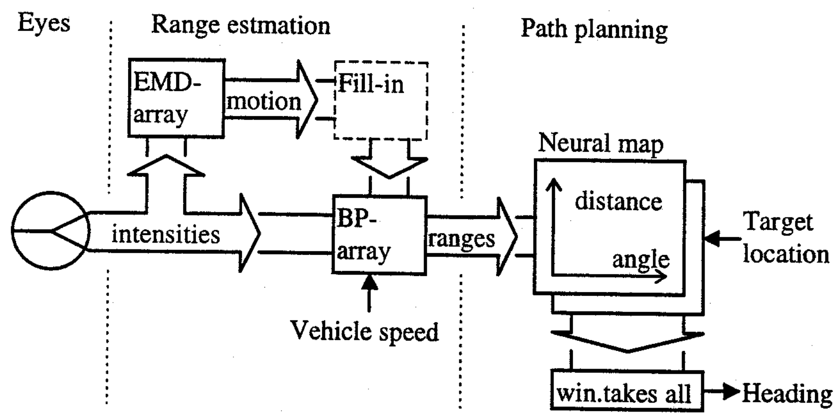

Figure 2: A sketch of the total artificial visual system. First the eye picks up light from its environment, then an EMD array extracts the parallax movement of features in the image, the movement is expanded for an entire object (optional, see text) and finally an array of BP networks estimates the ranges of the objects and maps them onto a solving interactive and competitive neural network.

2.4. Path Planning and Heading Decision

For solving the path planning problem, a method similar to the so-called distance-transform or the wave-propagation method is used (Glasius et al.[3]) This method uses a topographical neural map in which through lateral interactions the activation of a target position spreads through the network except at the object locations. The target is then found by performing a "gradient ascent" or "hill climbing" algorithm. For the network presented here, there are two of these relaxation layers. In the first relaxation layer, only the neuron corresponding to the area in which the target is located, is set to a constant activation. The activity of all other neurones is given by:

$$y_i(t+dt) = \alpha \left[\frac{\sum_j w_{ij} y_j(t)}{\sum_j w_{ij}} \right] \tag{1}$$

$$w_{ij} = \begin{cases} 1 & j \in \text{Neighbours of } i \\ 1 & j = i \\ 0 & \text{otherwise} \end{cases}$$

In the second relaxation layer neurones, corresponding to object locations are inhibited to a certain percentage of their "unfixed" activation, i.e. the activation generated by the corresponding neurones in the first layer. This is easily done since the topography of the maps are chosen to be identical. By inhibiting the object areas to a certain percentage, a less strict inhibition can be realized at larger distances, so the target attraction still makes the system

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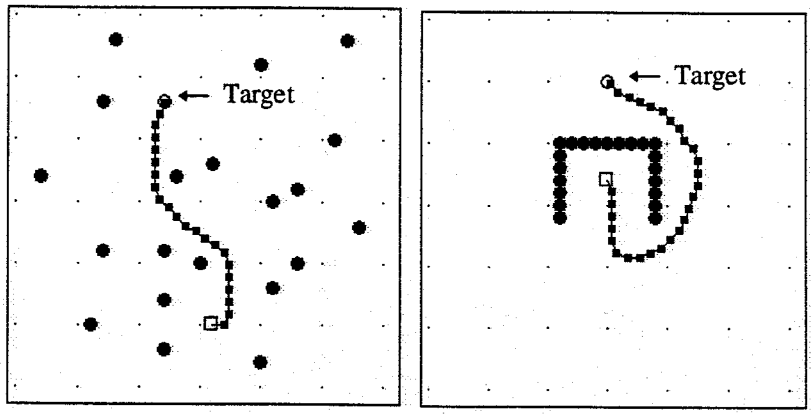

Figure 3: Some example solutions: Left: Moving through a "forest" of objects. Right: Escape from an U-shaped group of obstacles.

roughly move towards the target even if there seems to be no direct path. This enables the system to discover new openings, if any, when the spatial resolution increases at closer range. The relaxation layer with the obstacle inhibitions present can be used direcly to select a new heading towards the target location. The activiation of the row corresponding to the nearest ranges can be used to locate the heading of maximum activation and thus enables the network to perform the hill-climbing algorithm. Selecting the maximum activation is then easily performed by a competitive "winner takes all" layer.

3. Simulation Results

The discussed network has been developed and implemented using computer simulations. In figure 3. some typical results are shown.

The solutions were generated using a network that could move in only 15 directions and classified the ranges in only 8 classes. To obtain smooth trajectories a small enhancement was introduced: the weights of the connections from the elements in the inner row of the solving map to the heading decision "winner takes all" layer were given a gaussian distribution with a maximum at the forward side of the vehicle. A distribution like this is can be seen as giving the system a field of attention; this makes moving forward more preferable over very sharp turns (without excluding them). The concept of an attention field is also found in biological systems. To increase the capabilities of the system, objects near the "blind angle" in the rear of the visual field are extended by duplicating the information of the outer colunms into this region where no visual input is available. This made it possible for the network to generate solutions to escape from an U-shaped group of obstacles as shown in the right half of figure 3.

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4. Conclusions

The simulated network works in fairly cluttered environments. Due to the continuous planning of the path to follow, obstacles and targets are in principle not restricted to being at rest. Compared to a path solving system proposed in [3] the capabilities are more restricted: this system is not capable of solving problems requiring a representation of *all* obstacles in the system's environment, i.e. including the representation of completely occluded obstacles. The less strict inhibition of obstacle locations at larger distances partially makes up for this lack of knowledge. This, and the fact that the system relies on information from other (cognitive)processes, is one of the main reasons that this system will find its most promising applications as a low-level part of a larger system in a visually navigating robot. More complicated tasks, like solving a maze, requires a memory that stores currently invisible obstacles, so that they can be included in a global planning. The network presented here [5], should be used for simple subgoals, like "move from one end of the hallway to the other" without having to worry about any obstacles residing there, like pieces of furniture, doors being opened and people walking around. Improvements could include a speed control system based on principles in [2] and a way to memorize occluded obstacles to improve the path planning mechanism.

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