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The Design of a Heuristically Learning System

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Abstract

The architecture of a system which is capable of heuristically learning based on a combination of artificial neural network - fuzzy logic control principles is proposed.

The proposed architecture will be simulated in an artificial environment created on the LCCS supercomputer to investigate the physical limitations and possibilities to implement a real device having sustained autonomous capability.

1. INTRODUCTION

In recent years, more and more researchers are developing biologically inspired "intelligent" systems. Among these, artificial neural networks and fuzzy logic based systems are very promising. Artificial neural networks may be viewed as attemptingto model the physiology of brain (or nervous system), fuzzy logic based systems attempt to model the psychology of human decision making mechanisms. Not to mention, although these derivatives of biological systems cover just a tiny subset of functions of real life counterparts. Nevertheless, they are capable of performing very interesting and important engineering tasks. Therefore these paradigms should be seen as useful abstractions of their biological origins.

Probably the most powerful and promising point about these systems is that, from the engineering point of view, artificial neural networks and fuzzy logic based systems process the inexact information and process it inexactly. artificial neural networks are capable of making generalizations or associations by looking at the noisy, ill defined, ambiguous information without precise rules. On the other hand, fuzzy logic based systems can estimate functions and control systems with partial descriptions of system behaviour. [Kosko, 90]

Artificial neural networks have very useful features: The processing in the network is highly parallel. So, processing time of the data is independent of the complexity of the performed function and amount of the stored information in the network. Second advantage, neural nets are highly fault-tolerant, since the processing elements are identical and information is not stored in a particular location, loss of some processing elements does not cause a significant performance degradation. [Churchland,90]

But, artificial neural networks suffer from very important drawback: "Training" them can be costly, time consuming and there is no guarantee that eventually they will learn something useful. Interestingly, their behaviour is very human in this respect !

Fuzzy Logic based systems are very powerful in capturing the human decision processing in mathematical terms and modeling in the circumstances of incomplete and vague information.

On the other hand, the difficulty about fuzzy logic based systems, once the fuzzy rules are determined, they are fixed in most implementations. Long term changes in the environment could make some rules not necessary any more and it would be necessary to introduce new rules.

To overcome the drawbacks of the both systems, a combined system having a fuzzy rule based **Behaviour Generation Unit** and an artificial neural network based **Decision Unit** is proposed. It is expected that by having a **Behaviour Generation Unit**, the general behaviour expected from the system to fulfill a task can be expressed in mathematical form and so can be modelled. In other words, human decision processes to perform the specified task could be encapsulated in the system. Then, during the life cycle of the system, Decision Unit can modify the behaviour of the system by learning from the past successes/failures. At the same time, could adapt to the long term changes in the environment. It does this by changing the significance of the individual rules contributing to the overall response.

A further improvement, the system could remove the rules that do not contribute to the overall response due to the long term changes in the environmental circumstances and could replace them with the new ones.

In short, it is hoped that a system can be implemented by combining the strong features of the two paradigms to alleviate their individual weaknesses. The visualized system will be "born" with knowledge (accumulated by human experience) to satisfy a specific task and will be let to sharpen its performance.

The general block diagram of the proposed system is shown in figure 1.

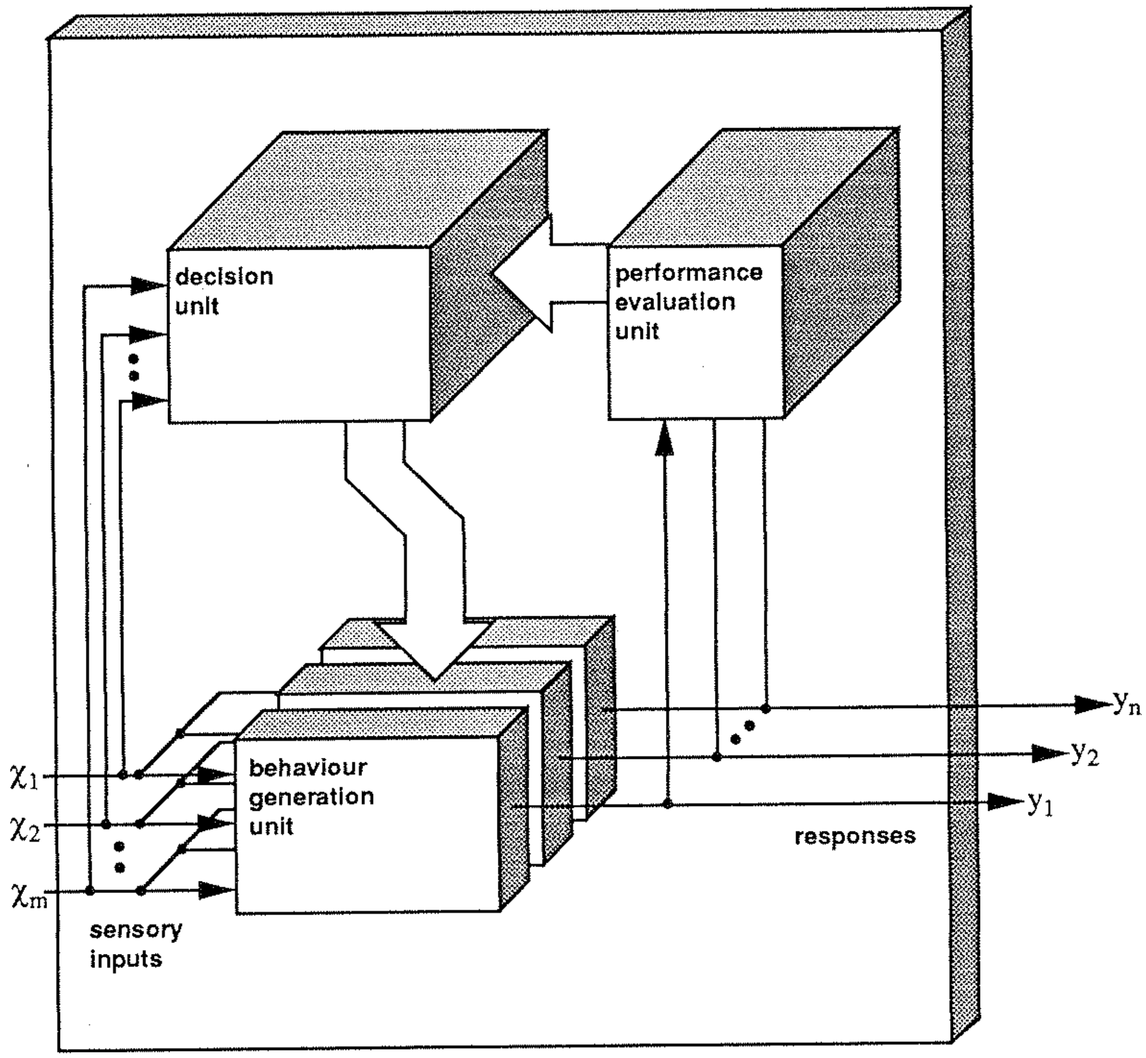

Figure 1: Block diagram of the Heuristically Learning System.

2. OPERATION OF THE SYSTEM

First, general operation principles of the system is described. Functional and structural details of the individual modules are depicted in later pages.

The system mainly has three modules: **Behaviour Generation Unit, Decision Unit** and **Performance Evaluation Unit.**

Input lines

$x_1, x_2, \ldots\ldots, x_m$

represent the stimuli from the outside world. The response of the system is represented by the output lines

$$y_1, y_2, \ldots\ldots, y_k$$

Behaviour of the system as a response to a particular pattern of input stimuli is encapsulated in **Behaviour Generation Unit.** i.e. when system comes to life, it already "knows" how to perform a certain task under certain circumstances. Here, the strength of fuzzy logic based control principles are employed to determine the overall behaviour of the system.

When input patterns begin appear on the input lines $x_1, x_2, \ldots\ldots, x_m$, system starts generating responses to achieve its task. During the initial stages of work, **Decision Unit** is ineffective. Upon the first sequence of responses, first, **Performance Evaluation Unit** starts operating and measures the difference between actual performance and desired performance. Second, generated information is used to "train" the **Decision Unit** to make associations and "remember" some successful generalized response patterns against the various sets of input patterns. It is hoped that when the system senses an input pattern, it will dynamically "remember" its best performance based on its past experience and this "recalled" response pattern will be used to adjust the actual response at this moment.

It can be expected that, due to the long term changes in the environment, some input pattern combinations will appear less frequently and, will ultimately never reoccur, so, some rules in the **Behaviour Generation Unit** will become ineffective. In this case, replacing these rules with the new ones can be an interesting study.

In the following sections, individual units are described.

2.1. BEHAVIOUR GENERATION UNIT

Behaviour Generation Unit is a classical fuzzy control system [Zadeh, 88] having only slight modifications. Figure 2 depicts the general structure of the Behaviour Generation Unit.

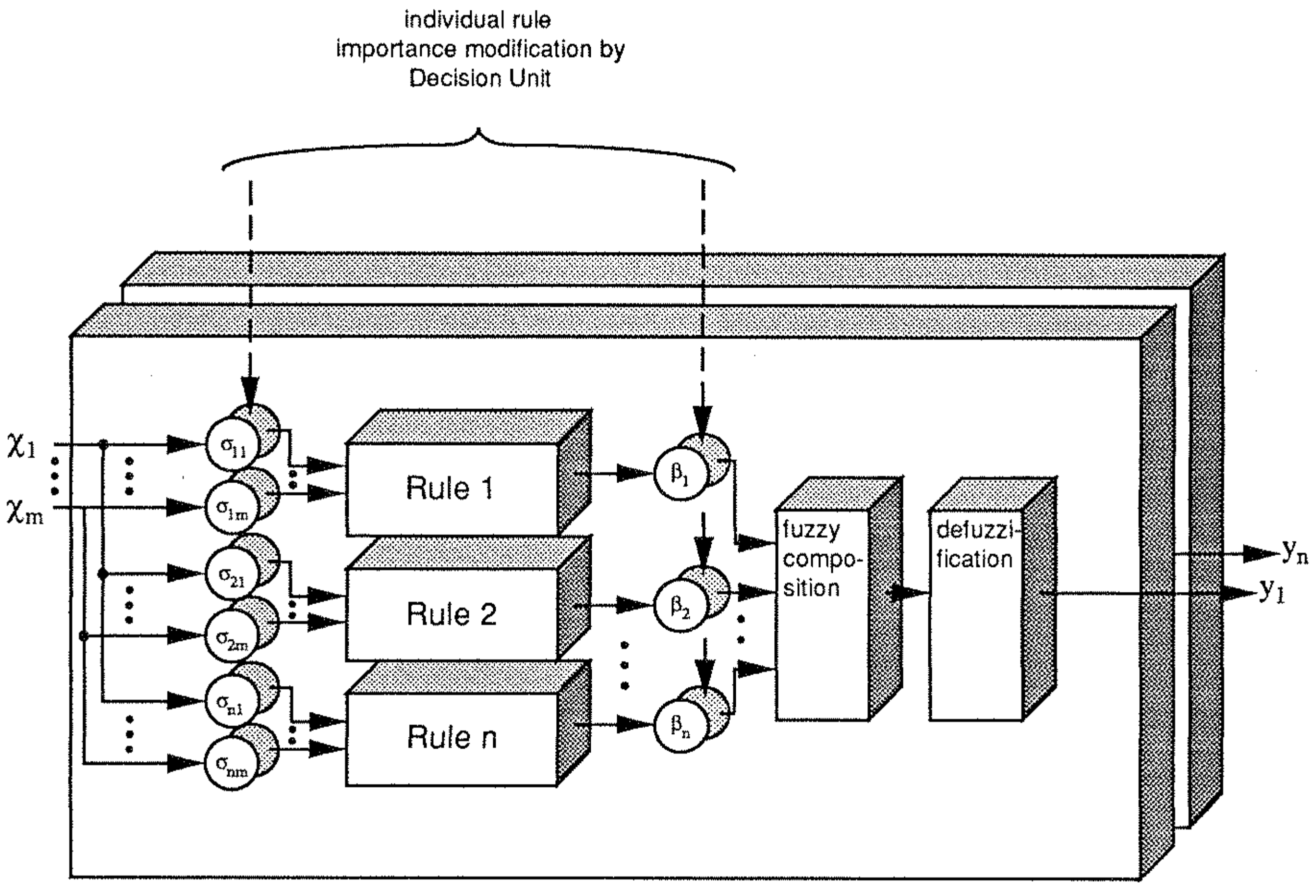

Figure 2: Overall structure of the **Behaviour Generation Unit.**

Operation of the unit can be summarized as below:

First, to determine the desired response, linguistic variables, possible linguistic values of these linguistic variables represented by fuzzy set membership functions and fuzzy control rules that operate on these rules determined to model the behaviour.

Every linguistic variable has a set of linguistic values and the linguistic values are modelled by the fuzzy sets. At a particular instant, a linguistic variable claims membership in one or more of these linguistic values attached with a "degree of confidence".

Furthermore, the instances of linguistic variables and the decisions arrived at by the individual rules are modified in real time by multiplying their current values by the coefficients

$\sigma_{11}, \sigma_{12}, \ldots., \sigma_{1m}$

$\sigma_{21}, \sigma_{22}, \ldots., \sigma_{2m}$

.

.

$\sigma_{n1}, \sigma_{n2}, \ldots., \sigma_{nm}$

and

$\beta_1, \beta_2, \ldots., \beta_n,$

are determined by the **Decision Unit.**

The rules are in the form

$\mathbf{R}^1$: if (x'_{11} is A^1_1) and (x'_{12} is A^1_2) and ... and (x'_{1m} is A^1_m) then response is $\mathbf{C_1}$.

$\mathbf{R}^2$: if (x'_{21} is A^2_1) and (x'_{22} is A^2_2) and ... and (x'_{2m} is A^2_m) then response is $\mathbf{C_2}$.

.

.

$\mathbf{R}^n$: if (x'_{n1} is A^n_1) and (x'_{n2} is A^n_2) and ... and (x'_{nm} is A^n_m) then response is $\mathbf{C_n}$.

where

$\mathbf{R}^i$ is the i^{th} rule,

$x'_{i1} = \sigma_{i1}x_1,\ x'_{i2} = \sigma_{i2}x_2,\ \ldots..,\ x'_{im} = \sigma_{im}x_m$,

the sensory inputs $x_1, x_2, \ldots.., x_m$ are linguistic variables,

$\mathbf{A}^i_j$'s are linguistic values that linguistic variables in the rule $\mathbf{R}^i$ can claim membership and,

$\mathbf{C}^i$ is the response recommended by the rule $\mathbf{R}^i$.

For any given sensory input vector $(x_1, x_2, \ldots.., x_m)$, the rules $\mathbf{R}^i$'s, individually determine their responses and responses have confidence values, W^i's attached. Each of these confidence values can be calculated as

$$W^i = \mu_{A_1^i}(x'_{i1}) \wedge \mu_{A_2^i}(x'_{i2}) \wedge \ldots \wedge \mu_{A_m^i}(x'_{im})$$

where $\mu_{A_j^i}(x'_{ij})$ is the grade of membership of a particular value of linguistic variable x'_{ij}

$$\min(\, A_j^i(x'_{ij}) \mid j = 1,2, \ldots, m \,)$$

To find the overall response of the system to the sensory inputs $x_1, x_2, \ldots, x_m$, first, in the fuzzy composition stage, the membership function

$$\mu_{C_i}(y)$$

of the particular linguistic value for the output linguistic variable suggested by each rule is scaled by the output importance modification factor β_i and confidence value W^i of the rule;

$$\tilde{\mu}_{C_i}(y) = W^i \beta_i \mu_{C_i}(y)\,.$$

Second, in the defuzzification stage, the centroid of the areas of the scaled membership functions of the suggested linguistic values is calculated to find the "crisp" value of the response:

$$y = \frac{\sum_i \int \tilde{\mu}_{C_i}(y)\; y\, dy}{\sum_i \int \tilde{\mu}_{C_i}(y)\; dy}\,.$$

Every individual rule produces a response having a confidence degree attached to. Furthermore, the coefficients $\beta_1, \ldots, \beta_n$ which are determined by the **Decision Unit** modify the effect of the individual response to the overall response to reflect the belief of the system at that moment. The resulting combination of the individual responses can be seen as the result of a weighted vote.

To express these ideas in a relevant example and give some insight about the operation of the Behaviour Generation Unit, assume a linguistic variable FRONTAL_DISTANCE_FROM_THE_OBSTACLE. The frontal distance can be LONG, SHORT etc. It means that this linguistic variable can claim membership from the set of linguistic values { LONG, SHORT } and these values are individually expressed as fuzzy sets. Every instance of linguistic variable FRONTAL_DISTANCE_FROM_THE_OBSTACLE has a degree of membership to these linguistic values. The degree of membership to the fuzzy sets is defined by membership functions. An example membership function plot for LONG and SHORT is in figure 3.

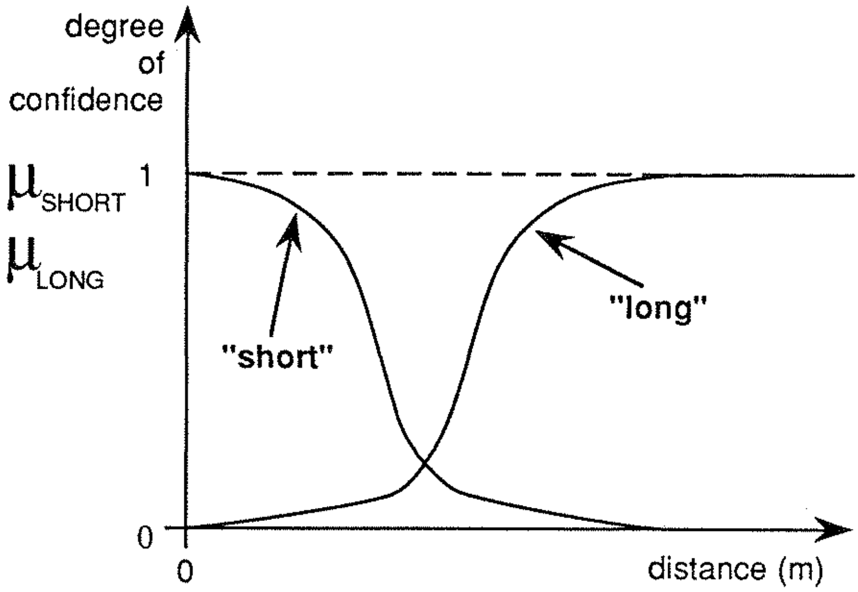

Figure 3: Fuzzy linguistic values "LONG" and "SHORT".

Once the linguistic values LONG, SHORT defined as fuzzy sets, based on the desired precision, by using the linguistic hedges and fuzzy operations, more linguistic values can be derived. Some representatives of these hedges can be

{ VERY, NOT, EXTREMELY }.

To define VERY one can use CON() fuzzy "concentration" operator, which is

$$\mathrm{CON}(A) = \{ a(x) * a(x) / x \mid x \quad U \}.$$

where a(x) is the membership value of x in fuzzy set A.
Therefore VERY SHORT, VERY LONG, EXTREMELY LONG could be described in terms of SHORT and LONG.

Figure 4 describes all of these fuzzy sets.

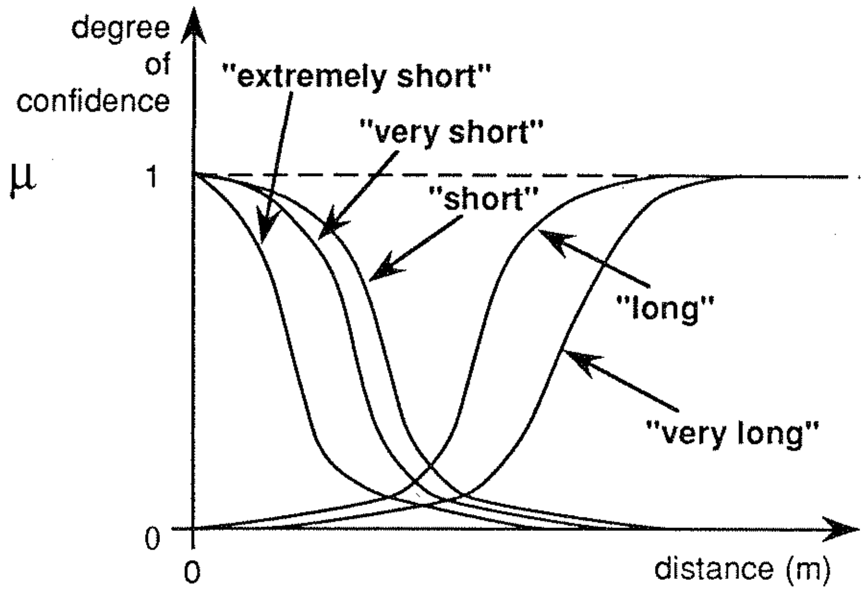

Figure 4: New fuzzy linguistic values generated with hedges "VERY" and "EXTREMELY".

So, if the system represents an autonomous vehicle, one of the rules could be :

if FRONTAL_DISTANCE_FROM_THE_OBSTACLE is
EXTREMELY SHORT
then SPEED is NEGATIVE MODERATELY and
STEERING_ANGLE is RIGHT GREATLY.

Normally, there are a large number of rules describe the behaviour of the system. Individual rules try to shape the response by assuming that they are acting alone and fuzzy control attaches a degree of confidence to the individual response, which is evaluated from the membership functions and as a result, every rule effects the actual overall response with this degree of confidence.

To further illustrate the system operation, assume an autonomous vehicle and a fictituous terrain cluttered with some obstacles (figure 5).

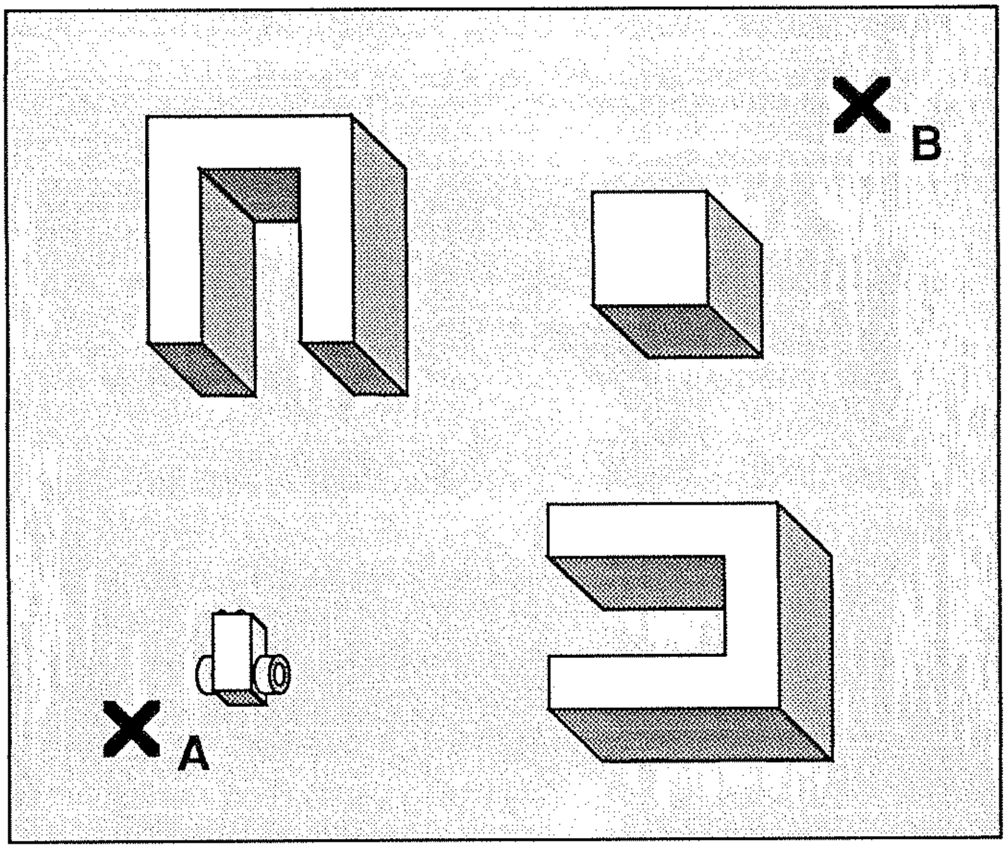

Figure 5: Heuristically Learning Device is on a fictituous terrain.

The aim of the vehicle is to travel from point A to point B. The vehicle is able to measure the frontal distance from an obstacle straight ahead and measure distances between the both sides of the vehicle and lateral obstacles.

A human observer, by looking at the U-shaped obstacles, can devis a fuzzy rule that

> if LEFT_SIDE_DISTANCE_FROM_THE_OBSTACLE is
> VERY SHORT and
> RIGHT_SIDE_DISTANCE_FROM_THE_OBSTACLE is
> VERY SHORT
>
> then
> SPEED is NEGATIVE MINIMUM.

So that, the vehicle does not lose time by entering in the fjords of the U-shaped obstacles in this environment. After some time, say, if the U-shaped obstacles erode into conical obstacles in this fictituous terrain, this rule is no longer required. Here the

Decision Unit gradually reduces the effect of this rule by changing its "importance multiplication factor". Finally, this rule can be removed from the rule base.

2.2. DECISION UNIT

Decision Unit is basically an "Adaptive Bidirectional Associative Memory" [Wasserman, 89][Kosko, 88]. Among the several different structures of Artificial Neural Network interconnections Bidirectional Associative Memory paradigm is selected because of the similarity of some real neuron populations in the brain. Here is an interesting observation:

> "In the brain, axons projecting from one neuronal population to another are often matched by axons returning from their target population. These descending or recurrent projections allow the brain to modulate the character of its sensory processing. More important still, the existence of these feedback paths makes the brain a dynamical system whose continuing behaviour is both highly complex and to some degree independent of its peripheral stimuli." [Churchland, 90]

The authors believe that the recurrent structure of Adaptive Bidirectional Memory will suit the dynamics of Heuristically Learning System.

The overall structure of Decision Unit is depicted in figure 6.

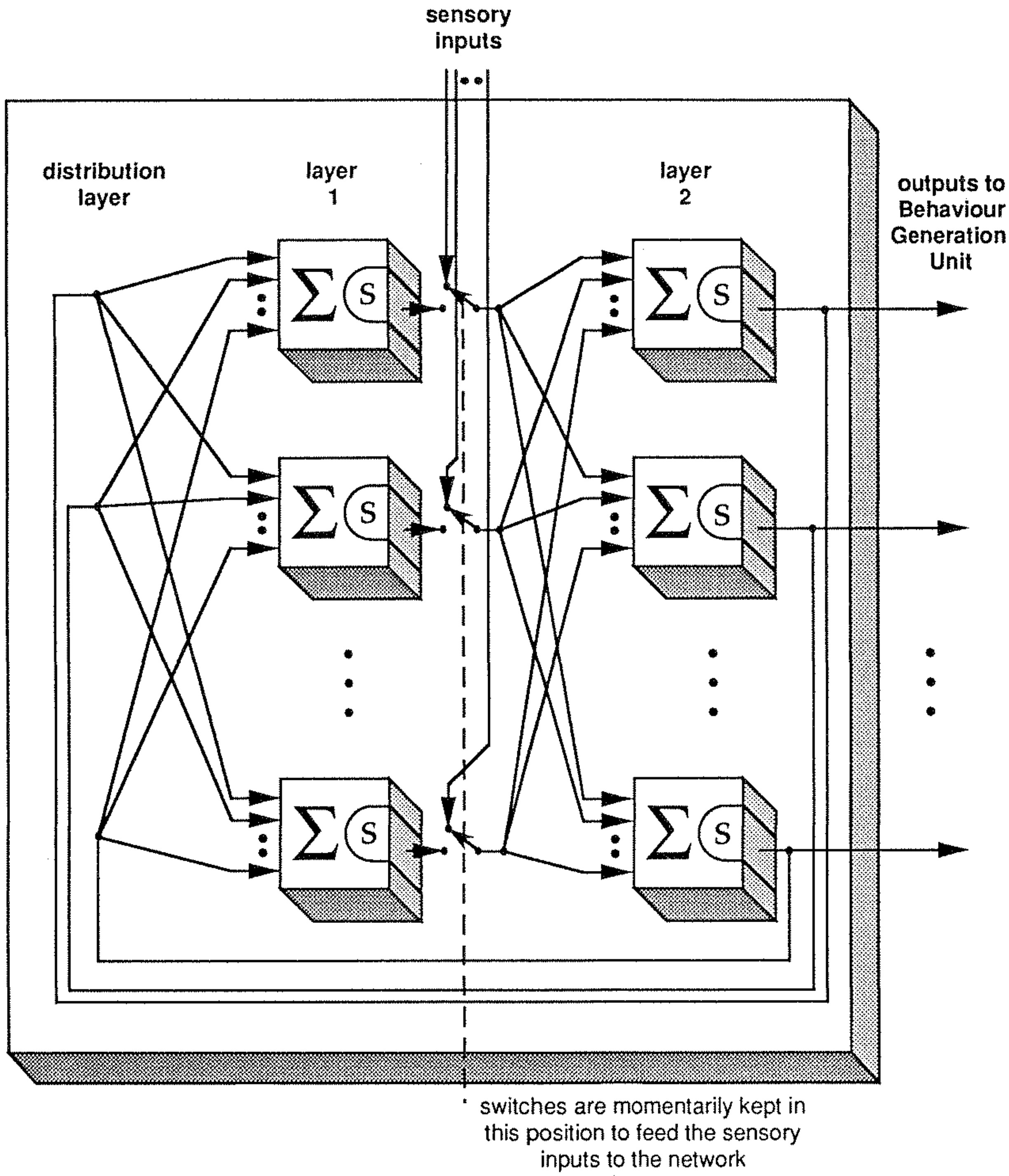

Figure 6: Overall structure of the **Decision Unit**.

The artificial neural network elements can be seen as nonlinear summing amplifiers. Inputs to the individual elements are first multiplied by the corresponding coefficients and their sum then is shaped by the sigmoid function.

The process can be summarized by this equation:

$$\text{OUTPUT} = \frac{1}{1 + \dfrac{1}{e^{\lambda \sum_i x_i w_i}}}$$

where

λ is a constant,

x_i 's are inputs to the artificial neural network element,

w_i's are corresponding weights.

2.3. PERFORMANCE EVALUATION UNIT

Associations in the Adaptive Bidirectional Associative Memory is updated during the operation. In other words, when an input pattern generates an output pattern on the output ports of the Decision Unit, this pattern is used to tune the actual response of the device. If similar patterns repeat, Performance Evaluation Unit updates the weights of the relevant processing elements such that, they become more effective. As`a result short-term memory associations seep into long-term memory.

To implement the Performance Evaluation Unit, different algorithms will be experimented with. The most classical one, Hebbian Learning Model, is given below.

In this scheme, the change in a weight is proportional to the product of the activation level of its source processing element and that of the destination processing element.

This process can be formulated as

$$\delta_{w_{ij}} = \eta \times out_i \times out_j$$

where,

δwij : the change in a specific weight connecting artificial neural network element i to the element j,

outi : the output of element i in layer 1 or 2,

η : learning rate coefficient ($0 < \eta < 1$).

3. THE PROJECT

In order to understand the performance and limitations of the proposed system, **Decision Unit** and **Behaviour Generation Unit** will be simulated first separately, then together by using the supercomputing facility of the Laboratory for Concurrent Computing Systems.

The project will focus initially on issues such as,

- Investigating the relationship between the number of Processing Elements in the **Decision Unit** and complexity of the environment,
- Investigating the relationship between the number of rules stored in the **Behaviour Generation Unit** and complexity of the environment,
- Dynamics of learning and shaping the responses,
- Stability issues.

If the simulations provide promising results, the research will focus on performance enhancement issues :

- Doing research on **Behaviour Generation Unit** realization on data-flow based hardware to employ the parallelism of data-flow architecture.

- Construction of an autonomous vehicle with its control based on this heuristically learning architecture.

The authors believe that this research will result in better understanding of structure and dynamics of adaptive neural-fuzzy systems and will result in some industrial applications having commercial potential.

4. REFERENCES

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