
A Self-organizing Associative Memory System for Control Applications

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ABSTRACT

The CMAC storage scheme has been used as a basis for a software implementation of an associative memory system AMS, which itself is a major part of the learning control loop LERNAS. A major disadvantage of this CMAC-concept is that the degree of local generalization (area of interpolation) is fixed. This paper deals with an algorithm for self-organizing variable generalization for the AMS, based on ideas of T. Kohonen.

1 INTRODUCTION

For several years research at the Department of Control Theory and Robotics at the Technical University of Darmstadt has been concerned with the design of a learning real-time control loop with neuron-like associative memories (LERNAS)

setpoints but is large during setpoint control. Therefore a self-organizing variable generalization, adapting itself to the amount of available data would be very advantageous. Up to now, when working with fixed generalization, finding the right parameters has meant to find the best compromise between performance and learning time required to generate a process model. This paper will show a possibility to introduce a self-organizing variable generalization capability into the existing AMS/CMAC algorithm.

2 THE AMS-CONCEPT

The associative memory system AMS is based on the "Cerebellar Model Articulation Controller CMAC" as presented by J.S. Albus. The information processing structure of AMS can be divided into three stages.

- 1.) Each component of a n -dimensional input vector (stimulus) activates a fixed number ρ of sensory cells, the receptive fields of which are overlapping. So $n \cdot \rho$ sensory cells become active.
- 2.) The active sensory cells are grouped to form ρ n -dimensional vectors. These vectors are mapped to ρ association cells. The merged receptive fields of the sensory cells described by one vector can be seen as a hypercube in the n -dimensional input space and therefore as the receptive field of the association cell. In normal applications the total number of available association cells is about $100 \cdot \rho$.
- 3.) The association cells are connected to the output cells by modifiable synaptic weights. The output cell computes the mean value of all weights that are connected to active association cells (active weights).

Figure 2 shows the basic principle of the associative memory system AMS.

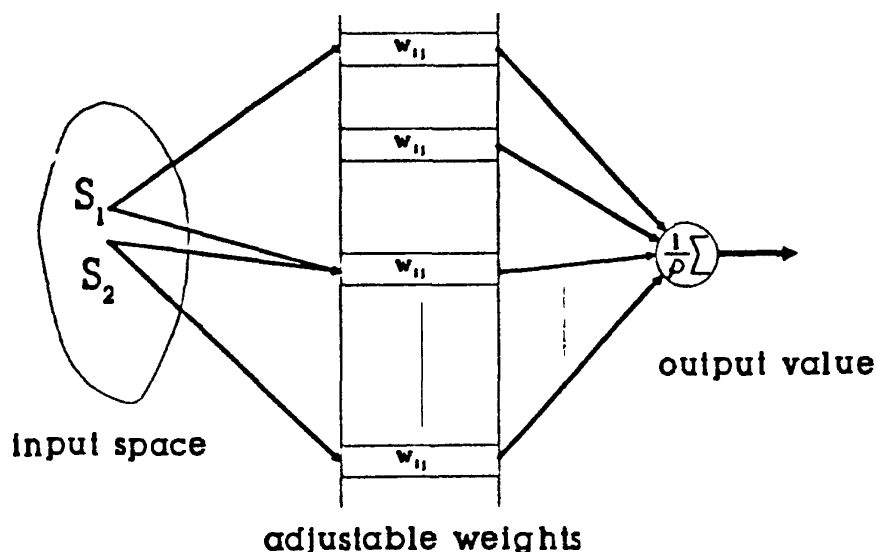


Figure 2: The basic mechanism of AMS

During training the generated output is compared with a desired output, the error is computed and equally distributed over all active weights. For the mapping of sensory cells to association cells a hash-coding mechanism is used.

3 THE SELF-ORGANIZING FEATURE MAP

An approach for explaining the self-organizing capabilities of the nervous system has been presented by T. Kohonen (Kohonen, 1988).

In his "self-organizing feature map" a network of laterally interconnected neurons can adapt itself according to the density of trained points in the input space. Presenting a n -dimensional input vector to the network causes every neuron to produce an output signal which is correlated with the similarity between the input vector and a "template vector" which may be stored in the synaptic weights of the neuron. Due to the "mexican-hat" coupling function between the neurons, the one with the maximum output activity will excite its nearest neighbours but will inhibit neurons farther away, therefore generating a localized response in the network. The active cells can now adapt their input weights in order to increase their similarity to the input vector. If we define the receptive field of a neuron by the number of input vectors for which the neurons activity is greater than

that of any other neuron in the net, this yields the effect that in areas with a high density of trained points the receptive fields become small whereas in areas with a low density of trained points the size of the receptive fields is large. As mentioned above this is a desired effect when working with a learning control loop.

4 SELF-ORGANIZING VARIABLE GENERALIZATION

Both of the approaches above have several advantages and disadvantages when using them for real-time control applications.

In the AMS algorithm one does not have to care for predefining a network and the coupling functions or coupling matrices among the elements of the network. Association and weight cells are generated when they are needed during training and can be addressed very quickly to produce a memory response. One of the disadvantages is the fixed generalization once the parameters of a memory unit have been chosen.

Unlike AMS, the feature map allows the adaption of the network according to the input data. This advantage has to be paid for by extensive search for the best matching neuron in the network and therefore the response time of the network may be too large for real-time control when working with big networks.

These problems can be overcome when allowing that the mapping of sensory cells to association cells in AMS is no longer fixed but can be changed during training.

To accomplish this a template vector \underline{t} is introduced for every association cell. This vector \underline{t} serves as an indicator for the stimuli by which the association cell has been accessed previously. During an associative recall for a stimulus \underline{s}_0 a preliminary set of ρ association cells is activated by the hash coding mechanism. Due to the self-organizing process during training the template vectors do not need to correspond to the input vector \underline{s}_0 . For the search for the

best matching cell the template vector \underline{t}_0 of the accessed association cell is compared to the stimulus and a difference vector is calculated.

$$\underline{\delta}_i = \underline{t}_i - \underline{s}_0 \quad i = 0, \dots, n_s \quad (1)$$

n_s number of searching steps

This vector can now be used to compute a virtual stimulus which compensates the mapping errors of the hash-coding mechanism.

$$\underline{s}_{i+1} = \underline{s}_i - \underline{\delta}_i \quad i = 0, \dots, n_s \quad (2)$$

The best matching cell is found for

$$j = \min_i \|\underline{\delta}_i\| \quad i = 0, \dots, n_s \quad (3)$$

and can be addressed by the virtual stimulus \underline{s}_j when using the hash coding mechanism. This search mechanism ensures that the best matching cell is found even if self organization is in effect.

During training the template vectors of the association cells are updated by

$$\underline{t}(k+1) = \alpha(k,d) \cdot (\underline{s}(k) - \underline{t}(k)) + \underline{t}(k) \quad (4)$$

d lateral distance of neurons in the network

where $\underline{t}(k)$ denotes the value of the template vector at time k and $\underline{s}(k)$ denotes the stimulus. $\alpha(k,d)$ is a monotonic decreasing function of time and the lateral distance between neurons in the network.

5 SIMULATION RESULTS

Figure 3 and 4 show some simulation results of the presented algorithm for the case of a two dimensional stimulus vector.

Figure 3 shows the expected positions in input space of the untrained template vectors (x denotes untrained association cells).

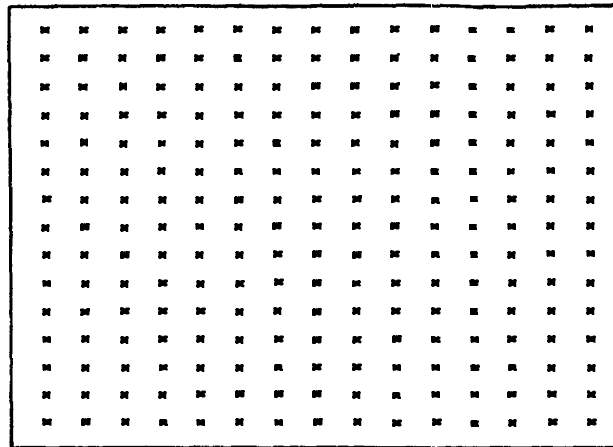


Figure 3: Untrained Network

Figure 4 shows the network after 2000 training steps with stimuli of gaussian distribution in input space. The position of the template vectors of trained cells has shifted into the direction of the better trained areas, so that more association cells are used to represent this area than before. Therefore the stored information will be more exact in this area.

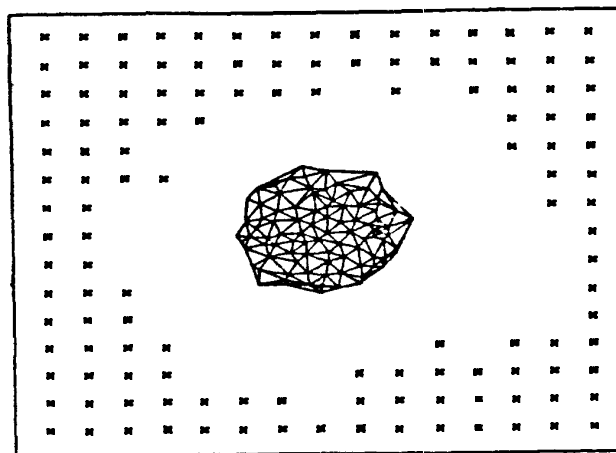


Figure 4: Network after 2000 training steps

6 CONCLUSION

The new algorithm presented above introduces the capability to adapt the storage mechanisms of a CMAC-type associative memory according to the arriving stimuli. This will result in various degrees of generalization depending on the number of trained points in a given area. It therefore will make it unnecessary to choose a generalization factor as a compromise between several constraints when representing nonlinear functions by storing them in this type of associative memory. Some results on tests will be presented together with a comparison on respective results for the original AMS.

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