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KNOWLEDGE REPRESENTATION BY CONNECTION MATRICES : A method for the on-board implementation of large EXPERT SYSTEMS

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ABSTRACT

Extremely large knowledge sources and efficient knowledge access characterizing future real-life AI applications represent crucial requirements for on-board AI systems due to obvious computer time and storage constraints on spacecraft.
In this paper a type of knowledge representation and corresponding reasoning mechanism is proposed which is particularly suited for the efficient processing of such large knowledge bases in expert systems.

1. INTRODUCTION

Many of today's AI systems are still experimental prototypes aiming at feasibility demonstrations. These systems normally have relatively limited knowledge bases, since research so far has had its focus more on the conceptual side of reasoning than on the treatment of large knowledge sources. However, it is becoming increasingly clear that for AI to display its full potential power not only the reasoning capacity of the human mind needs to be imitated, but also the fact that it has enormous knowledge sources at its disposal and is able to draw on this knowledge with extreme efficiency. Given the computer time and space constraints on spacecraft, this aspect becomes particularly crucial for on-board applications of AI and might necessitate, to a certain degree, a re-assessment of today's state of the art which has been mainly dictated by the endeavour to capture the reasoning aspect of intelligence only, regardless of the software overhead, high memory space demands, low performance, garbage collection problems etc. this often entailed.
In this paper a type of knowledge representation and corresponding reasoning mechanism is thus outlined, which is particularly suited for the processing of large knowledge bases in expert systems, maintaining the usual functionality of expert systems at the same time.

2. CONNECTIVITY IN THE BRAIN

Looking at the brain as the great example for processing speed and compactness of knowledge storage one notices, among other features :

f_1) extremely high performance in classification processes, i.e. fast mapping of large data sets on discrete descriptors (such as optical or acoustical data on corresponding objects or words)

f_2) relatively low performance in inference processes, i.e. comparatively slow generation of (long) chains of logically connected elementary operations (such as in doing maths problems step by step, where each step is usually solved or instantiated by a classification process "learned by heart", such as performing the simple mapping 2x2 = 4)

f_3) extremely efficient prompting of associated information (often quite unsolicited)

f_4) tolerance to incomplete or locally erroneous information in the classification process, such as in the identification of partially obliterated images, correction of misspelt words etc.

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These features are supplemented by some knowledge about the brain's structure, such as :

s_1) incoming continuous data (e.g. optical or acoustical) is spatially discretisized prior to further processing by resonant excitation of dedicated sensor cells (e.g. in eyes or ears)

s_2) these sensor cells are connected by nerve fibres to neurons, which obviously act as logical gates to the discretisized data, being themselves interconnected by an intricate fibre structure

s_3) which also seems to allow for lateral inhibition, i.e. the weakening of the sensory input of neurons by neighbouring neurons with stronger sensory input, apparently supporting the generation of excitation maxima in the neuronal network.

An extremely simplified model inferred from these features could consist for example of a set $O = [o_1, \ldots, o_n]$ of "observation cells" o_j and a set $D = [d_1, \ldots, d_n]$ of "descriptor neurons" d_K connected by a "connective structure" composed of nerve fibres as shown in Figure 1.
The descriptor neurons represent particular objects, situations, diagnoses etc. characterized by sets of discrete features.
Each observation cell represents one of these features and is only excited if this feature is found in the data stream (such as a particular frequency in the case of incoming acoustic data).
The connective structure is such that fibres link each descriptor neuron to all observation cells characterizing it. Conversely, this means that each observation cell o_j is linked to all descriptor neurons which contain o_j as a feature.

After the "local" classification of incoming data by the excitation of discrete observation cells (structural feature s_1) this excitation is thus passed on via the nerve fibres (feature s_2) in such a way that each descriptor neuron, whose characteristic features are contained in the incoming data, receives some input. Maximum input obviously is received by the neuron representing the situation, object etc. generating the incoming data, and feature s_3 given above could be viewed as a clue to the fact that the "global" classification of the incoming data is indeed achieved by some comparison of the input intensity of the descriptor neurons.
This could, for example, be achieved by setting the threshhold controlling the "firing" of a neuron d_K so that it only fires if input has come from the full set of all the observation cells o_{kj} connected to it.

Given the functionality of the human nervous tissue, the local data classification, message transmission from observation cells to descriptor neurons and particularly the checking of the firing conditions of each neuron could be performed concurrently, thus leading to an extremely efficient classification process (feature f_1).

Allowing for secondary, lower thresholds permits the firing of neurons having received input from less than all the observation cells linked to them, thus generating associations, i.e. situations or objects sharing features with the primary data source, in an equally efficient manner (feature f_3). Moreover, lower threshholds obviously could also be used for approximate classifications based on some maximum input evaluation in the case of incomplete or locally erroneous data (feature f_4).

Inference processes could be realized by supplementing the set O of observation cells by additional cells d'_K which are not excited by incoming data, but by the firing of descriptor cells, thus providing additional input to the next cycle of mapping observations on descriptors.
The fact that such inference cycles have to proceed in series could be one reason for the relatively low performance in inference processing, as mentioned in f_2.

3. CONNECTION MATRICES IN EXPERT SYSTEMS

In the terminology of expert systems, where one distinguishes between a knowledge base and an inference engine, the main feature of the brain model described in the previous chapter and illustrated in Figure 1, is the fact that its knowledge base is mainly embodied in the connective structure between observations and descriptors, the appropriate knowledge representation being given by "connection matrices"

$$M_{kj} = \begin{cases} 1 & \text{if observation } j \text{ is connected to the descriptor } k \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

As implied by the model described in Chapter 2, data processing using this knowledge representation requires a prior local classification in which slots representing observations o_j of individual features or symptoms such as "temperature higher than nominal value" or "valve V_1 is open" etc. are instantiated by values o_j between 0 and 1 describing the degree to which the local classification holds (in many cases a two-valued classification : o_j = 0 or 1, however, is sufficient) providing an input i_{kj} (O or o_j) to the kth descriptor via the connective structure M_{kj} :

$$i_{kj} = M_{kj} \cdot o_j \quad \text{for each } j. \tag{2}$$

These inputs are collected by accumulation functions F_k to provide an integrated input intensity :

$$I_k = F_k\,(i_{k_1}, \ldots, i_{k_n}), \tag{3}$$

a possible example of F_k being

$$F_k = \sum_j \alpha_{kj}\, i_{kj}, \qquad \alpha_{kj} = 1 \tag{4}$$

α_{kj} describing the "implication strength" of o_j with respect to d_k

The global classification is then performed by identifying the descriptors d_k for which I_k = 1 holds. If none can be found, as in the case of incomplete or erroneous information, this threshhold value I_o = 1 is reduced to yield approximate classifications as described in chapter 2. (Details of the treatment of uncertainty on which this reasoning mechanism is based can be found e.g., in Ref. 1).

The ability to ask the user for missing data in case of incomplete information which is displayed by many expert systems, can be achieved by simply looking up the observations o_j connected to the approximate classifications d_k via M_{kj} and asking for them. This method can also be used to accelerate the classification process by first generating approximate classifications based on just a few randomly picked observations $o_j \neq 0$ and then automatically collecting the remaining evidence for just those classifications, a process which might be called "attention focussing on clues".
Knowledge processing can be further accelerated by parallel processing, dedicating a processor to each function F_k or at least to subsets of functions F_k.

Consecutive inferences are realized according to the method outlined in chapter 2.

4. ON-BOARD IMPLEMENTATIONS

The main functions of on-board AI systems will be failure diagnosis and recovery, MMI support (mainly by natural language understanding systems) and planning. AI systems for the first application fall into the category of typical expert systems, these being roughly characterized by their functionality as knowledge-based classification systems, as opposed to the somewhat different functionality of natural language understanding and planning systems, although they also encompass classification processes.

Thus connection matrices can be used particularly for the first type of application but also for the other two as far as classification is involved.

Obviously knowledge bases using this type of knowledge representation require much less computer storage and knowledge processing time (even more so if parallel processing is employed) than in the case of systems based on representations which imply symbolic knowledge representation, symbol matching techniques, symbol handling overhead, special implementation languages and garbage collection problems.
For example, whereas the realization of a connection matrix embodying the knowledge to classify, say, 400 sensor readings into 20.000 different malfunctions roughly requires 1 Mbyte of computer storage which is still quite feasible for on-board implementation, the realization of a corresponding rule-based system with tens of thousands of rules would pose a formidable problem concerning the required memory and processing time.

Moreover, a rule based system of this size could also pose a formidable problem as far as the development, verification, validation and maintenance of the knowledge-base is concerned, whereas the simple structure of connection matrices and the underlying reasoning processes greatly enhance the transparency of the system, the development of the knowledge base simply being effected by an enumeration of observations and states and an identification of their interconnections. Methods to automize this process on the basis of FMECA (Failure Mode Effect and Criticality Analysis) and system simulations are presently being investigated.

5. CONCLUSIONS

On the basis of an assessment of some of the features of the human brain which seem to pertain to its extremely efficient utilization of very large knowlege sources a type of knowledge representation and corresponding inference mechanism for expert systems has been presented which is particularly suited for the processing of large knowledge bases at comparatively low storage and computer time requirements.

Whereas expert systems of this type are conceptually similar to systems involving the treatment of uncertainty, they are representationally different in that the effort in describing the connectivity between observations and descriptors has been reduced to a minimum by replacing symbolic descriptions by simple elements of connection matrices thus eliminating high storage and computer time demands typical of systems characterized by symbolic knowledge representation, symbol matching techniques, symbol management overhead, special implementation languages and garbage collection problems.

6. REFERENCES

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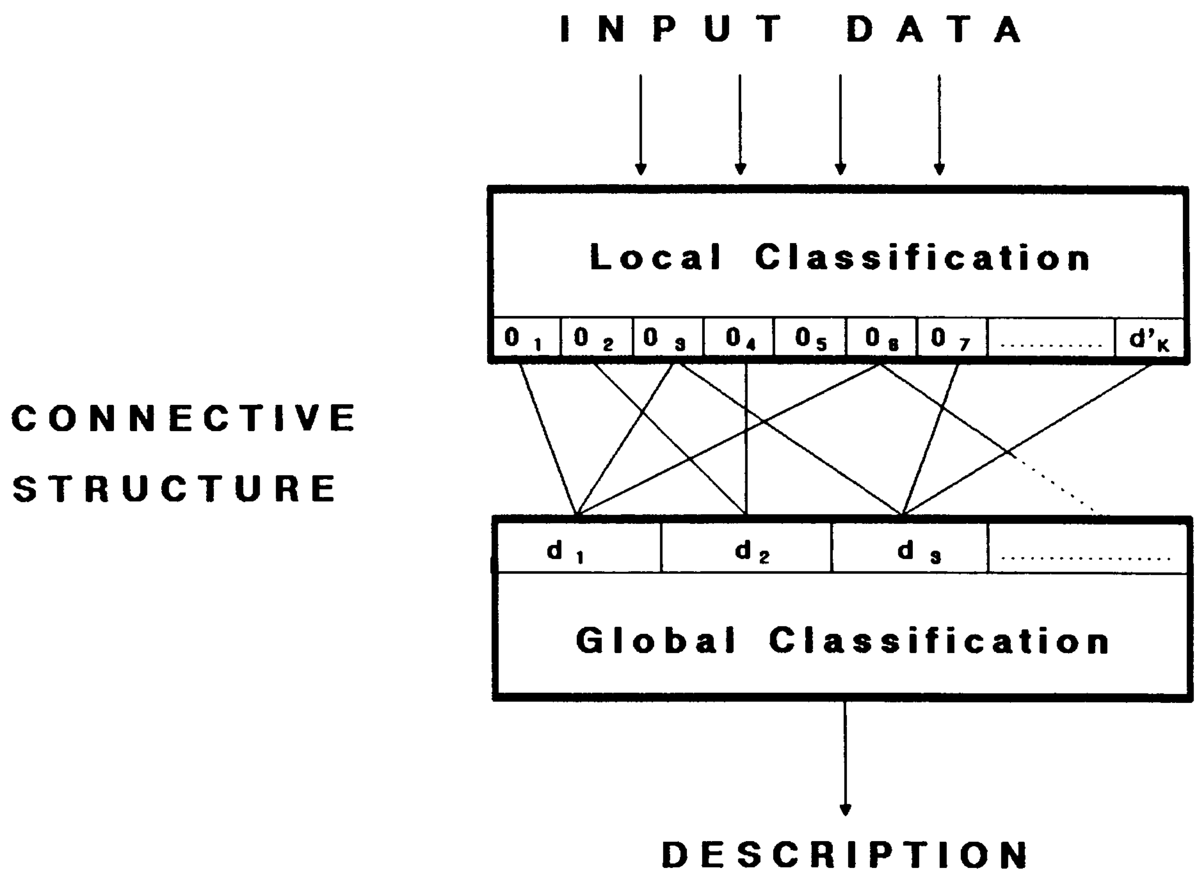

Figure 1 : Model for expert systems based on connection matrices