Fourth International Conference on knowledge-Based Intelligent Engineering Systems & Allied Technologies, 30th Aug-1st Sept 2000, Brighton,UK

Neural Explicit and Implicit Knowledge Representation

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Abstract: *A unified approach for integrating explicit and implicit knowledge in connectionist knowledge-based systems is proposed. The explicit knowledge is represented by discrete fuzzy rules, which are directly mapped into an equivalent Multi Purpose Neural Network based on MAPI neuron. Some methods based upon interactive fuzzy operators are presented in order to extract fuzzy rules from trained neural networks. Architecture for a neural knowledge-based system is proposed as a combination of modules based on data learning and fuzzy rules mapping. The combination of explicit and implicit knowledge modules is viewed as an iterative process in knowledge acquisition and refinement.*

Introduction

The different types of information processed by both, human and AI expert systems have explicit and implicit representation. The MAPI neuron [13] could be a useful tool to add another level of programmability in qualitative reasoning. The combinations of generalized fuzzy computation, the expanded MAPI model and specific neural architecture, are used as a fuzzy-connectionist processing tool for knowledge representation, and qualitative reasoning.

This paper is focused on strictly neural approach, describing principles of connectionist knowledge processing. In second section, the formal neuron MAPI [13] is used to develop Multi Purpose Neural Networks (MPNN) to represent explicit knowledge. Interactive fuzzy operators are presented in the third section in order to extract implicit represented knowledge. In the fourth section it is proposed a global architecture of a connectionist expert system. The paper is ending with an integrated neuro-symbolic approach as conclusion.

The aim of the paper is to emphasize the theoretical aspects viewing explicit and implicit knowledge representation and processing in order to develop a neural intelligent system shell. Neural modules are integrated in a homogenous manner and give reasons to propose an extended classification of integrated neuro-symbolic systems [3].

Mapping explicit knowledge in neural networks

The capabilities of MPNN to perform fuzzy computing [13] are used to implement Discrete Fuzzy Rule Systems [2]. The neural reasoning engine is accorded to multiple premises fuzzy rules using fuzzy connectives. The extended version of Modus Ponens [14] is:

$$\text{(1) if } X_1 \text{ is } A_1 \wedge \ldots \wedge X_j \text{ is } A_j \text{ then } Y \text{ is } B$$
$$\underline{(X_1 \text{ is } A'_1) \wedge \ldots \wedge (X_j \text{ is } A'_j)}$$
$$Y \text{ is } B'$$

The standard implementation of fuzzy sets connectives [9], [11], [12] involves triangular norms or co-norms:

$$\text{(2) } y = \underset{i=1}{\overset{j}{\textbf{T-conorm}}} [x_i \ \textbf{T-norm} \ w_i].$$

$$\text{(3) } y = \underset{i=1}{\overset{j}{\textbf{T-norm}}} [x_i \ \textbf{T-conorm} \ w_i].$$

where x_i and w_i are the inputs and the weights of the MAPI neuron implementing fuzzy operators. The neural implementation is an equivalent structure, which uses the method of combining rules first [2].

Let be considered a single rule with two antecedents described as:

(4) IF X is A AND Y is B THEN Z is C, where A, B, C are fuzzy sets having associated matching functions μ_A, μ_B, μ_C. Let the matching function $\mu_A(\xi)$ be described by a vector X of size Nx, so that:

(5) $x_i=\mu_A(\xi)$, if $\alpha_i<\xi\leq\alpha_{i+1}$, i=1,2,.., Nx-1. Thus, the fuzzy set A is:

(6) $A=[x_1 \ \cdots \ x_{Nx}]$. Similarly, fuzzy sets B and C are described in discrete forms as follows:

(7) $B=[y_1 \ \cdots \ y_{Ny}]$, $y_i=\mu_B(\psi)$, if $\beta_i<\psi\leq\beta_{i+1}$, i=1,2,..,Ny-1

(8) $C=[z_1 \ \cdots \ z_{Nz}]$, $z_i=\mu_C(\upsilon)$, if $\gamma_i<\upsilon\leq\gamma_{i+1}$, i=1,2,..,Nz-1.

The fuzzy relation:

(9) $R:A\times B\times C\rightarrow[0,1]$, having:

(10) $\mu_R(x,y,z)=(\mu_A(\xi)\wedge\mu_B(\psi))\Gamma\mu_C(\upsilon)$

defines the implication according to (1), where ^ is a conjunctive T-norm and Γ is an associative T-norm; so that given A', B':

(11) $C'=(A'\wedge B')^\circ R$, where ° is usually interpreted as max-Γ operator.

The implementation of an explicit multi-premises rule presented in (4) into an equivalent MPNN structure using MAPI neurons with fuzzy abilities is shown in fig. 1. The vectors are considered of size N_x, N_y, N_z, respectively. The MPNN in fig. 1 is equivalent with a DFRB described by (11) if: neurons N_i are used to convert the current values of entries X and Y to correspondent values $\mu_{A'}(\xi)$, $\mu_{B'}(\psi)$; weights between input and associative neurons are set to 1; associative neurons H_{ij} process $(x'_i \wedge y'_j)$ if the encoding function is the ^ T-norm; weights between associative and output neurons are: $w_{ijk}=(\mu_A(x_i)\wedge\mu_B(y_j))\Gamma\mu_C(z_k)$; setting neurons S_i, $i=0,..,N_x*N_y$, provide the synchronism $H_{11}<H_{Nx1}<H_{1Ny}<H_{NxNy}$ ("<" means *fires before*). In these conditions, $C'=(A'\wedge B')\circ R$. The generalization for a fuzzy rule with n antecedents is implemented in MPNN structure [5], [6], [7], [8], [13] by adjusting correspondent number of input neurons, a number of associative neurons verifying the constraint of $N_H=N_x*N_y*..*N_u$, and defining the adequate wiring between neurons in these two layers, and between neurons in associative and output layers.

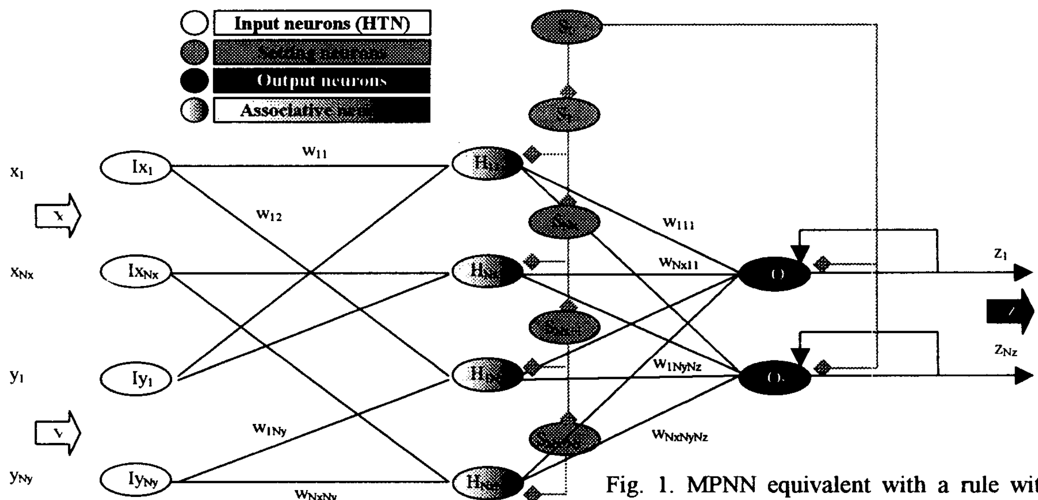

Fig. 1. MPNN equivalent with a rule with two premises

The defuzzification of the outputs follows the methods proposed in [12], [13], using a final controlling neuron. The method of defuzzification determines the programmable profile of the final neuron: center of gravidity is implemented by a MAPI averaging device, since procedures based on max and min values can be implemented with Max/ Min MAPI neurons.

Neural networks as equivalent fuzzy rule-based systems

The studies focused on the equivalence between ANN and FRBS [2] establish most of results through an approximation process, with the main disadvantage of exponential increase of needed number of rules or number of required neurons. Based on the theoretical results of [1], it is possible to build FRBS calculating the same function as the implicit knowledge representation using ANNs. In this case, the concept of f-duality applied on the three layered feedforward (with/without biases) neural network trained to represent a set of implicit data values supports the theoretical background to develop a new class of fuzzy connectives [1][5], with applications in the field of neuro-symbolic reasoning.

Let us consider the operation + in $\mathbb{R}$ and the sigmoid function atan: $f_{\text{atansig}}(x)=\frac{1}{\pi}\text{atan}(x)+\frac{1}{2}$ (fig. 2.), bijective application from $\mathbb{R}$ to (0,1).

Lemma: The $f_{atansig}$-dual of + is •, defined as:

$$(12)\; a\bullet b=\frac{1}{\pi}\left(\frac{\pi}{2}+\text{atan}\frac{\sin(\pi(a+b-1))}{\cos(\pi(a-0.5))\cos(\pi(b-0.5))}\right)$$

(proved in [5]).

Definition: The operator defined in previous lemma will be called the *interactive*$_{atan}$-OR operator (i_{atan}-OR, fig. 3.).

Based on the properties of i_{atan}-OR [5] and the theorem proving the equivalence between a feedforward neural network and a fuzzy additive system described in [1] by:

$$(13)\; R_{jk}\text{: IF } \sum_{i=1}^{n} x_i w_{ij} + \tau_j \text{ is } A_{jk} \text{ THEN } z_k=\beta_{jk},$$

the fuzzy rule "x_i is A^i_{jk}" must be interpreted "x_i is greater than approximately $r/w_{ij}-\tau_j$" (if $w_{ij}>0$), or "x_i is lower than approximately $-(r/w_{ij}-\tau_j)$" (if $w_{ij}<0$), where r is a positive real number obtained from an α-cut.

Since the concept of f-duality is general, it could be used to produce other interactive operators: *i*-OR [1], i_{tanh}-OR [5] (fig. 4.), or some conjunctive forms such as *i*-AND [5] (fig.5.). The main applications of these operators are both, a method for knowledge acquisition [1], and a method to refine and motivate the neural inferences [5].

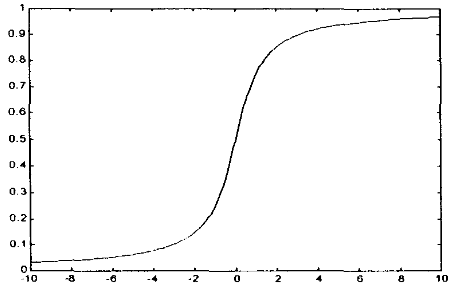

Fig. 2. Sigmoid activation function $f_{atansig}(x) = \frac{1}{\pi}\text{atan}(x) + \frac{1}{2}$.

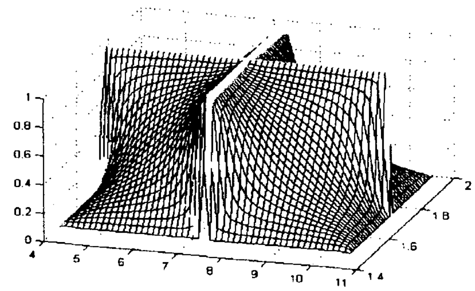

Fig. 3. $Interactive_{atan}$-OR operator (in a portfolio application context).

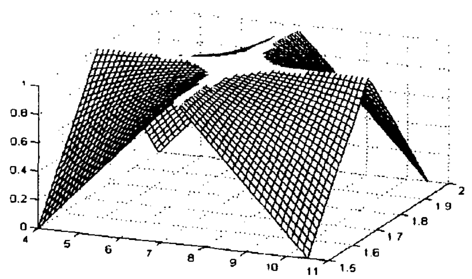

Fig. 4. $Interactive_{tanh}$-OR operator (in a portfolio application context).

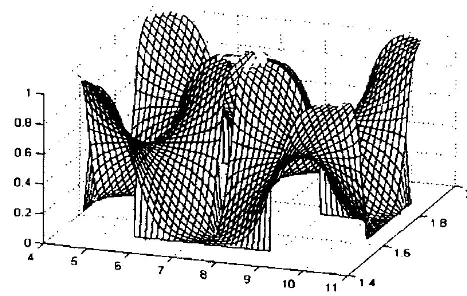

Fig. 5. *Interactive*-AND operator (in a portfolio application context).

Neural explicit and implicit knowledge-based systems

Symbolic processing is considered as a traditional way in Artificial Intelligence; unlike symbolic models, learning plays a central role in connectionist structures. A combination of both approaches is already the subject of research in hybrid systems [10]. Viewing connectionist models as a powerful tool to process knowledge, it is straightforward to try to build connectionist intelligent systems, mainly applied to perceptual tasks, where discovering explicit rules does not seem either natural, or direct.

The connectionist integration of explicit knowledge and learning by example appears to be a natural solution of developing connectionist intelligent systems. The problem to be solved is the uniformity of integration: explicit and implicit rules should be represented in a neural manner. Architectures combining cooperating connectionist modules are proposed to solve integration of explicit and implicit knowledge. Since the discrete fuzzy inputs and outputs are considered common for all rules, it is identified a general strategy (described in [6]) used to combine:

- explicit knowledge modules EKM's (developed in a top-down manner, using the methods of mapping available explicit rules in neural structures, as described above) and
- implicit knowledge modules IKM's (responsible for unmanageable cases of implicit knowledge, achieved using learning by example paradigm).

The global architecture combines the explicit and implicit sub-modules using a gating network, which mediates [6] the competition (in the unsupervised version) or promote the collaboration (in the supervised version) of all involved expert networks (fig. 6.) as a network based on firing different (explicit and implicit) rules first. After training, different expert networks compute different functions mapping different regions of input space. The weights introduced to realize the global network are obtained using a hybrid-learning algorithm [4]. The number of output neurons of gating network is indicated by the number of expert networks, and the activations of the output neurons must be nonnegative and sum to one [4].

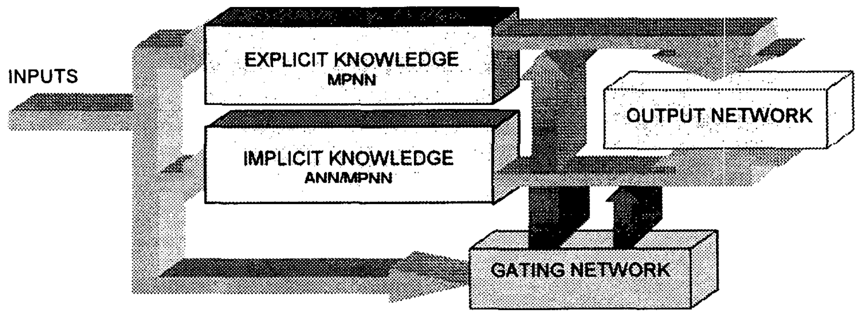

Fig. 6. Basic configuration of integrated network based on firing explicit and implicit rules first.

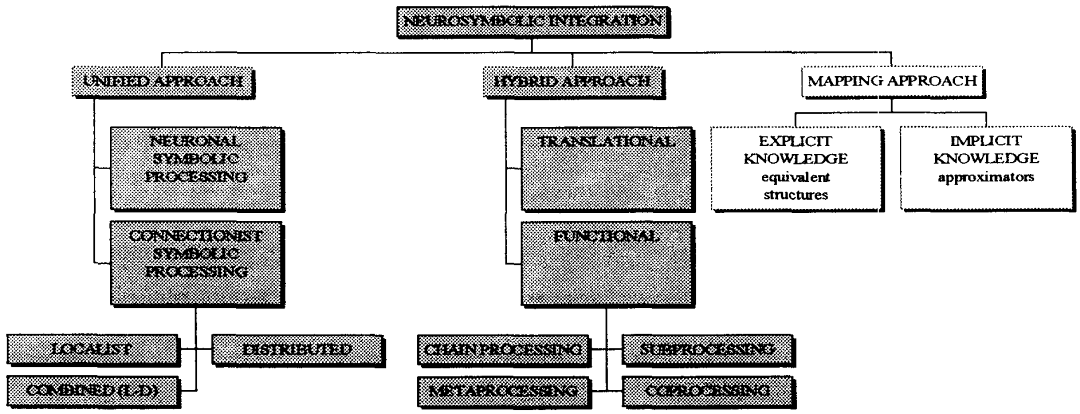

Fig. 7. An extended classification of neurosymbolic integration

Conclusions

Throughout its history, the field of AI has been arena of jousts between symbolicism and connectionism. Between these two radical stances, a number of paradigms have emerged at the interface of connectionist and symbolic AI, viewing the various approaches to neuro-symbolic processing.

Since the hierarchy proposed in [3] divided these strategies in unified and hybrid ones, this paper described purely connectionist tools, which exhibit qualitative capabilities. This review of connectionist tools used in a global architecture which process explicit and implicit knowledge proves the original proposal to extend the hierarchy with a third approach of homogenous knowledge processing and mapping (fig. 7).

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