Hybrid Intelligent Systems

Lecture 7

Concept of hybrid intelligent system (HIS). Taxonomy of HIS

Paradigms in Logical (classic) Intelligent Systems and Neural Systems

- Classic logics
- Rules
- Frames
- Semantic networks
- Fuzzy logics
- Space of decisions
- Semantics spaces
- and e.s.

- Multi-layers perceptrons
- Kohonen's maps
- Hopfield's model
- ART
- RBF-nets
- Spikes Neural Nets
- and e.s.

Comparison of Expert Systems, Fuzzy Systems, Neural Networks and Genetic Algorithms

	ES	*FS*	*NN*	*GA*
Knowledge representation	rather good	good	bad	rather bad
Uncertainty tolerance	rather good	good	good	good
Imprecision tolerance	bad	good	good	good
Adaptability	bad	rather bad	good	good
Learning ability	bad	bad	good	good
Explanation ability	good	good	bad	rather bad
Knowledge discovery and data mining	bad	rather bad	good	rather good
Maintainability	bad	rather good	good	rather good

* The terms used for grading are:

- bad, - rather bad, - rather good and - good

Hybrid Approach is needed because

- In Logical IS -
- formalization of knowledge is needed
- learning is difficult
- parallel processing is difficult
- low tolerance and reliability
- In Neural Nets -
- verbalization is difficult
- verification and proving are difficult
- repeat of processes is unable

Architectures of Hybrid Intelligent Systems: mixture of models

- Combination of different knowledge models of knowledge engineering
- Combination of knowledge models and neural networks
- Combination of neural networks and genetic algorithms

By Medsker (1996)

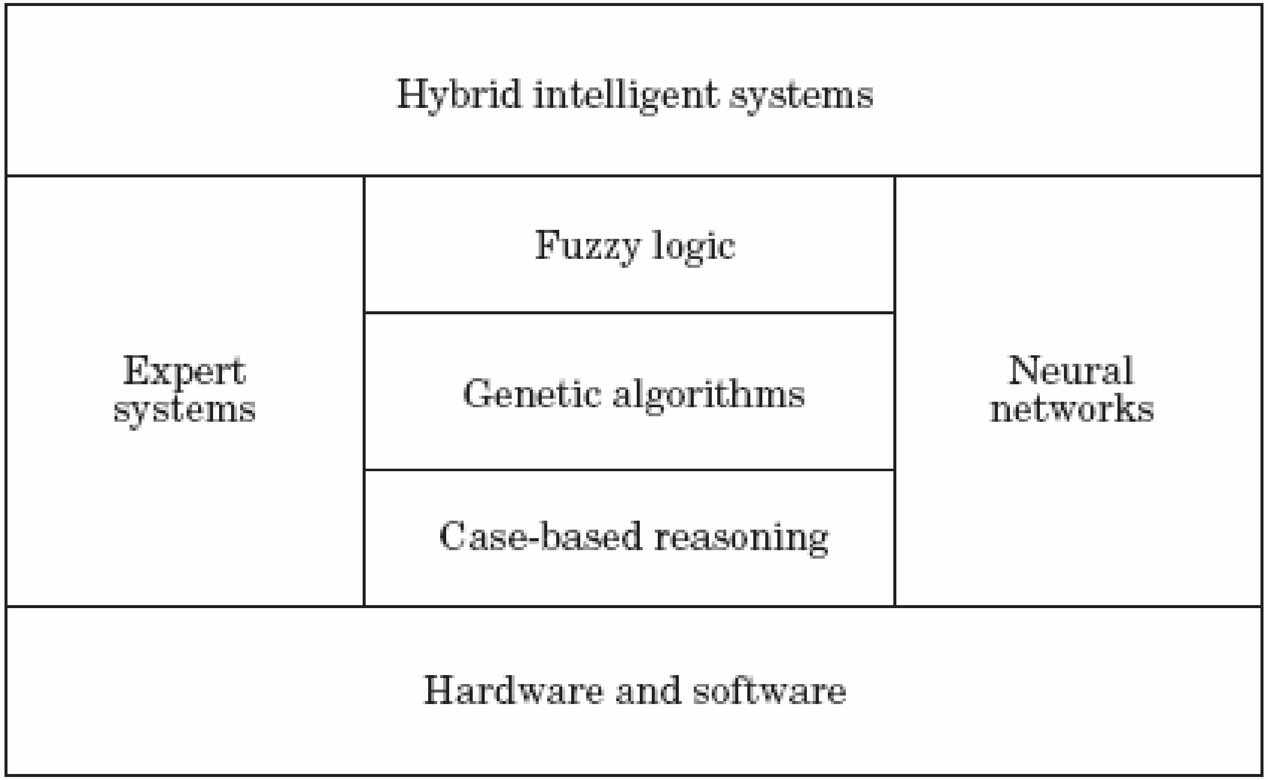


Figure 1. Intelligent technologies being used in hybrid intelligent systems.

By Medsker (2)

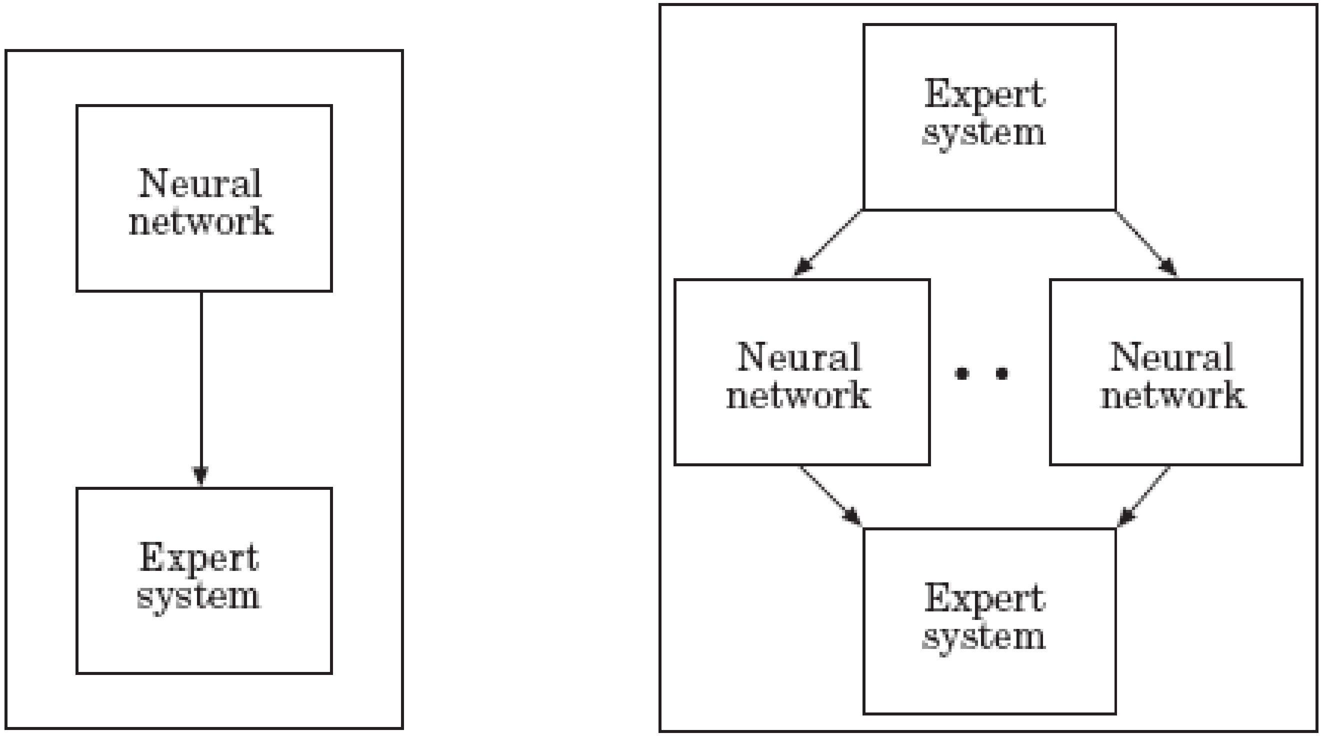


Figure 6. Simple structures for hybrid neural network and expert systems

What is Hybrid Intelligent Systems? (Wikipedia)

hybrid intelligent system denotes a software system which employs, in parallel, a combination of AI models, methods and techniques from such artificial intelligence subfields as:

- Neuro-fuzzy programming
- Fuzzy expert systems
- Connectionist expert systems
- Evolutionary neural networks
- Genetic-Fuzzy-Neural Systems
- Genetic fuzzy systems (Michigan, Pitsburg, Incremental)
- Rough fuzzy and fuzzy Rough systems, also known as rough fuzzy hybridization
- Temporal difference genetic algorithm reinforcement (TDGAR) learning
- Genetic algorithm fuzzy reinforcement learning (GAFRL)

with symbolic reasoning methods, using

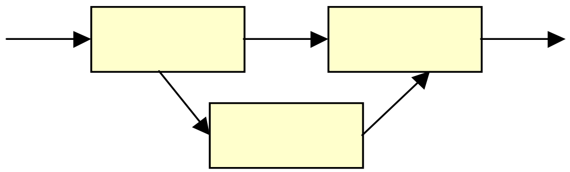
- Symbolic and knowledge/rule-based programming

References on HIS

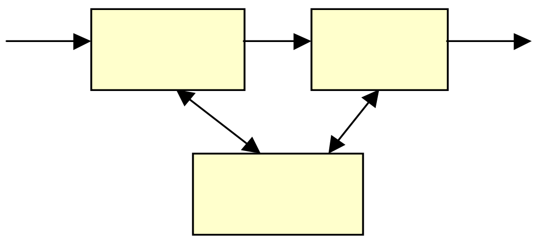
- International Journal of Hybrid Intelligent Systems http://ijhis.hybridsystem.com/
- http://www.iospress.nl/html/14485869.php
- International Conference on Hybrid Intelligent Systems http://his.hybridsystem.com/
- HIS'01: http://www.softcomputing.net/his01/
- HIS'02: http://tamarugo.cec.uchile.cl/~his02/
- HIS'03: http://www.softcomputing.net/his03/
- HIS'04: http://www.cs.nmt.edu/~his04
- HIS'05: http://www.ica.ele.puc-rio.br/his05
- Lectures on Robotics and Intelligent Systems
- HIS'06 http://his-ncei06.kedri.info/
- HIS'07 September 17-19, 2007, Kaiserslautern, Germany, http://www.eit.uni-kl.de/koenig/HIS07_Web/his07main.html

Classification of architectures of Hybrid Intelligent Systems

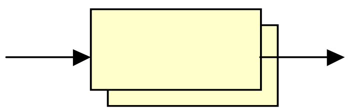
Funobashi M., Moeda A., Morooka Y., Mori K. Fuzzy and Neural Hybrid Expert Systems: Sinergetic AI. - AI in Japan, IEEE, 1995, august. - Pp. 33-40.



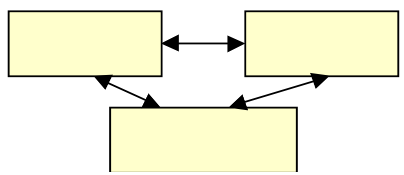
- Combination



- Integration



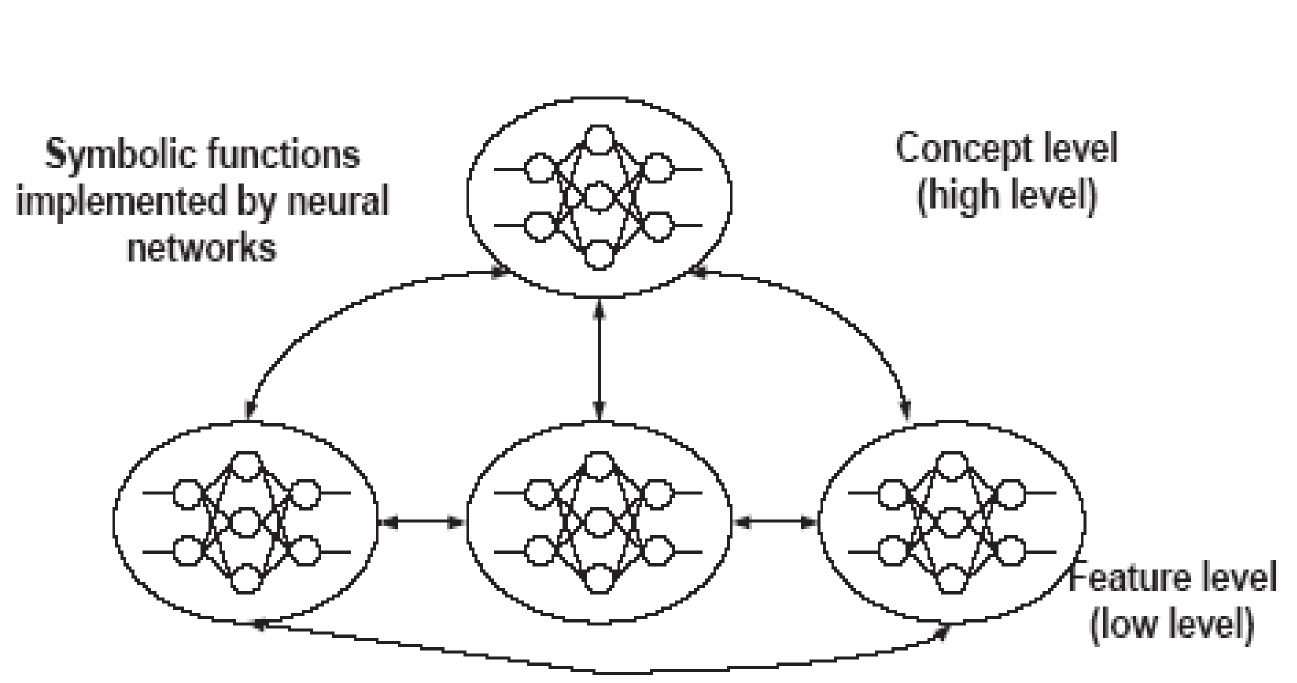
- Fusion



- Association

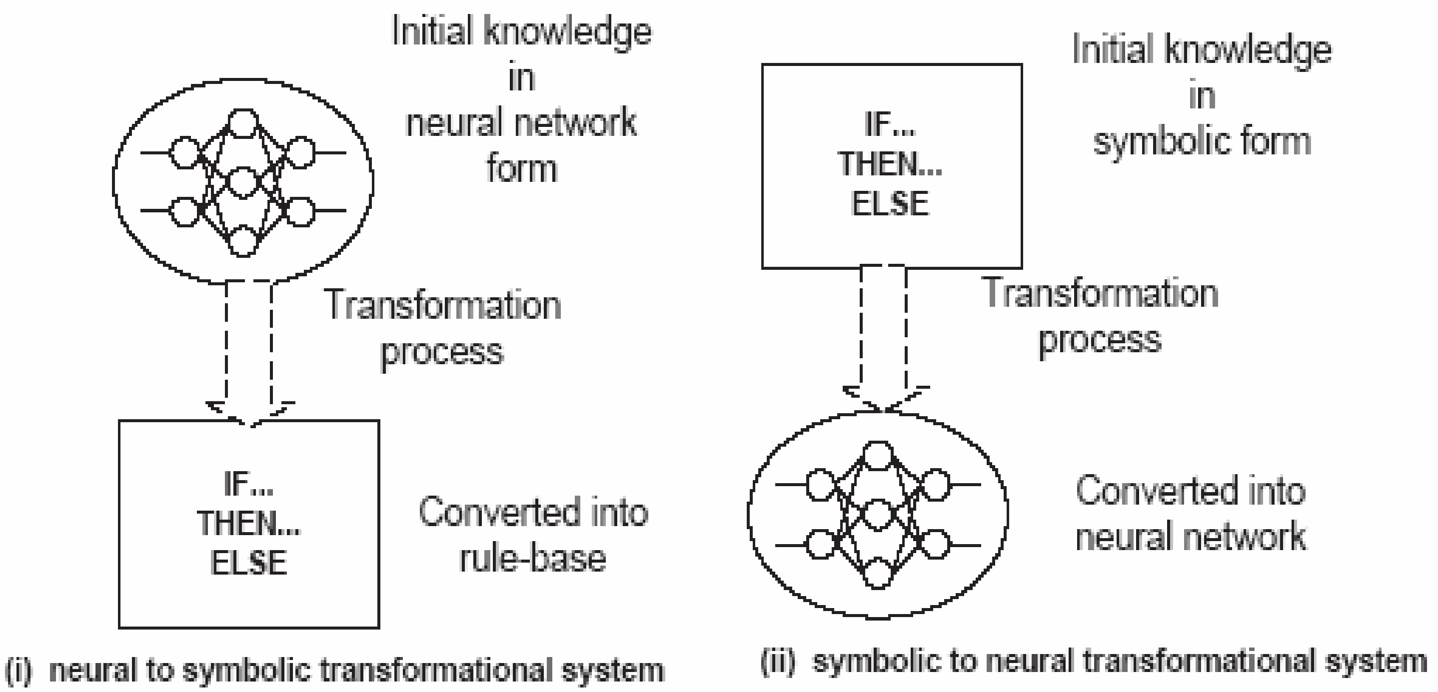
Other classification of architectures of Hybrid Intelligent Systems (2)

Kenneth McGarry, Stefan Wermter, John MacIntyre. Hybrid Neural Systems: From Simple Coupling to Fully Integrated Neural Networks. Neural Computing Surveys 2, 62-93, 1999, http ://www.icsi.berkeley.edu/~ jagota/NCS



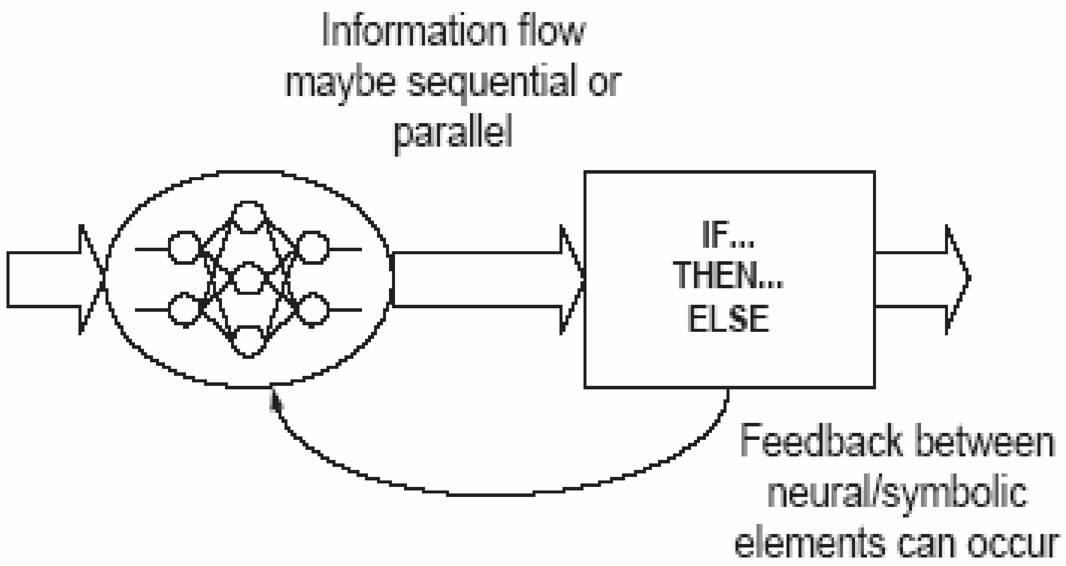
(a) Unified Hybrid Systems

Other classification of architectures of Hybrid Intelligent Systems (3)



(b) Transformational Hybrid Systems

Other classification of architectures of Hybrid Intelligent Systems (4)



(c) **Modular Hybrid Systems**

Unified HIS

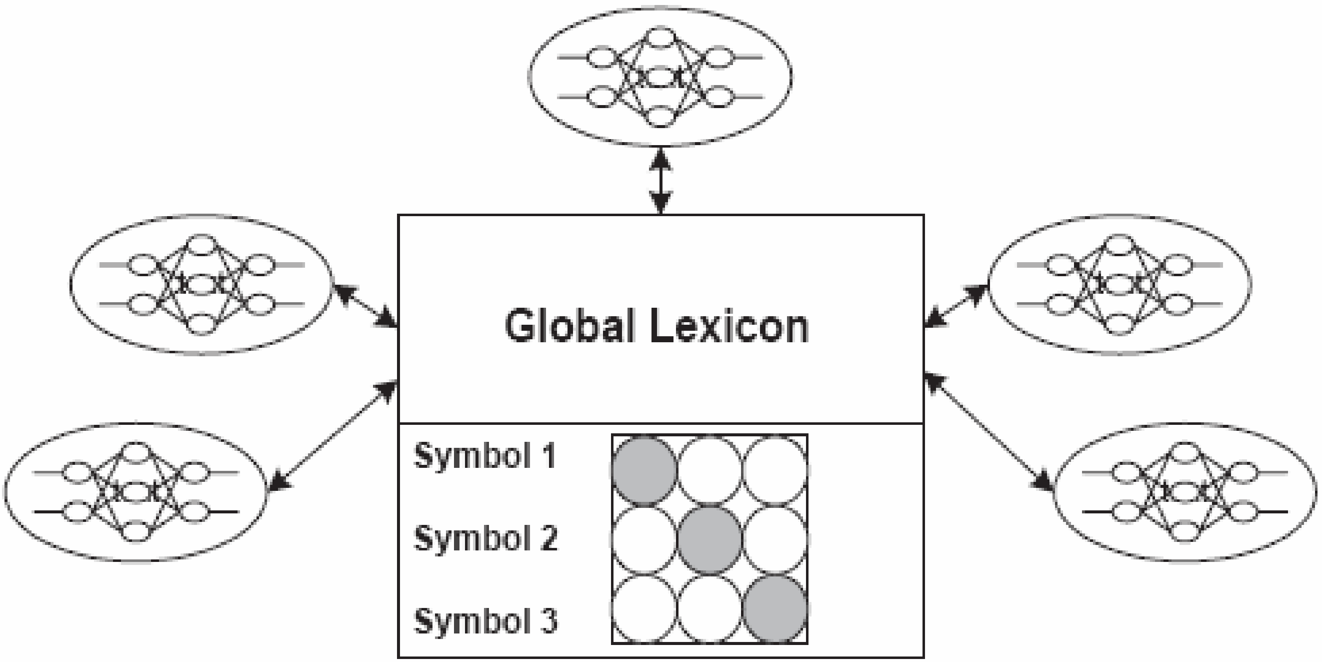
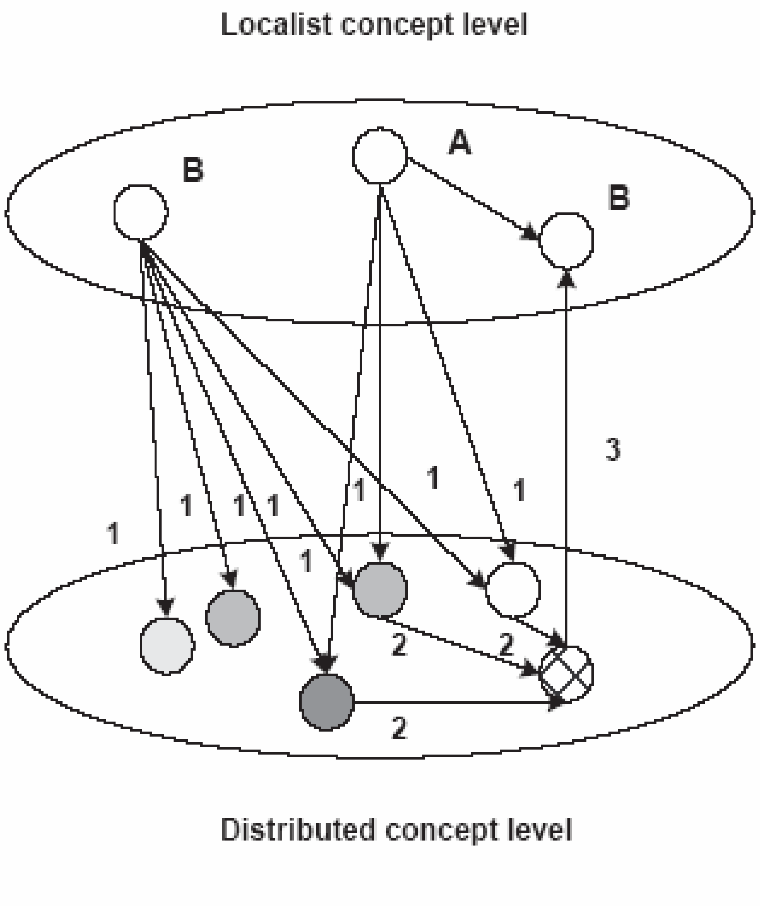


Figure 2: Symbolic recirculation within a unified hybrid system

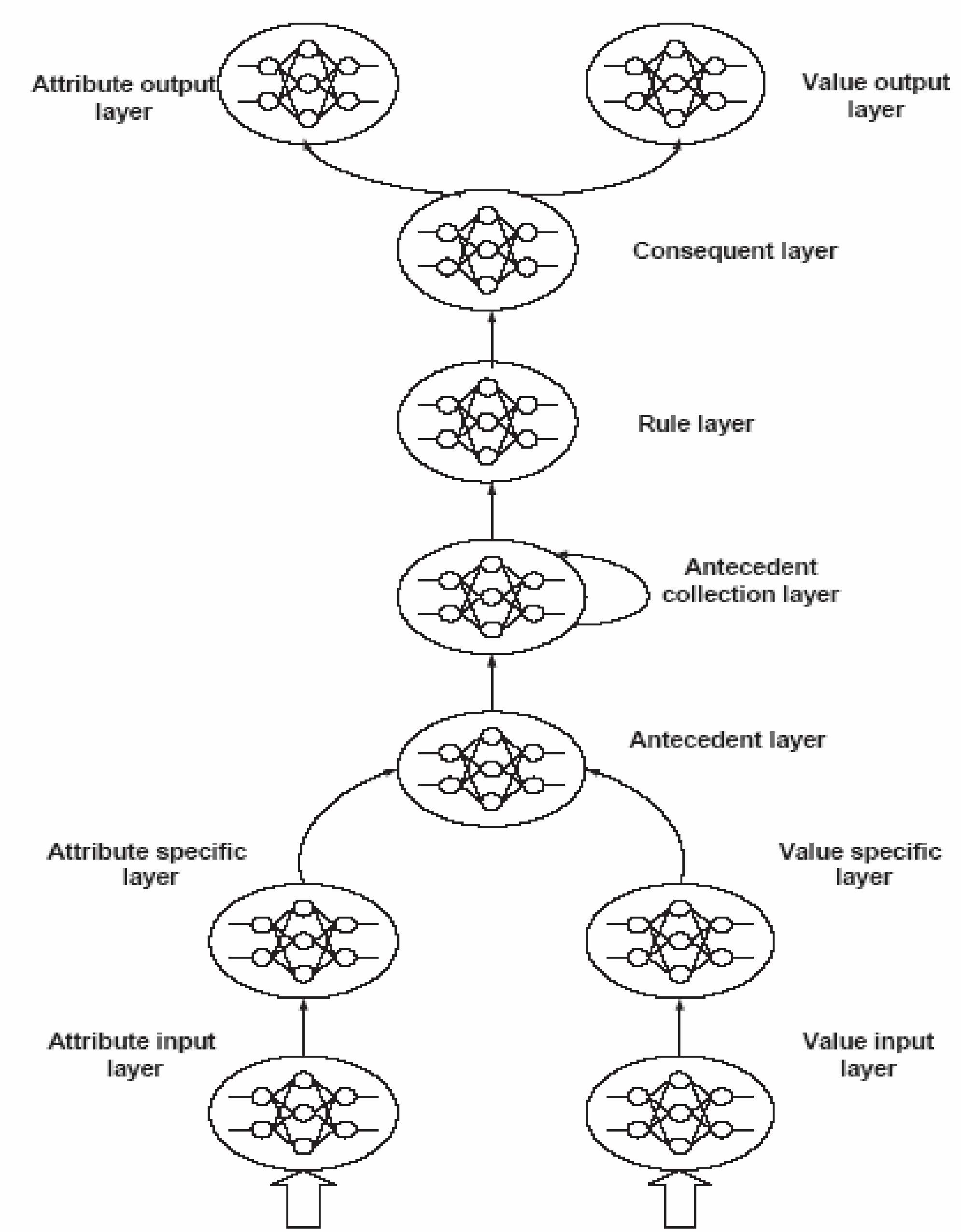
Unified HIS (2). CONSYDERR

CONSYDERR stands for CONnectionist System with Dual-representation for Evidential Robust Reasoning



Two-level neural network system that reasons subsymbolically using a distributed representation and symbolically using a localist representation. The architecture was designed to have two different levels in order to overcome the brittleness and uncertainty involved with knowledge based systems.
The bottom level consists of microfeatures, which are fine grain elements implemented by nodes that have linkages to the higher concept nodes in the top level.

Unified HIS (3). RUBICON



The RUBICON hybrid system incorporates both distributed and localist forms of neural network architecture. The integration of both types of architecture enables the representation of complex knowledge structures that are able to manipulate structured information. RUBICON was designed with the goals of reducing the knowledge acquisition bottleneck problem and of reducing the brittleness problem normally associated with expert systems. Currently, RUBICON does not manage real-valued inputs. This will be a major shortcoming for any industrial, scientific or technical task that deals with continuous real-world data.

Unified HIS (4). SC-NET

- The SC-NET is a hybrid network that operates upon attribute value pairs and has certain similarities to RUBICON. SC-NET is applied to the twin spirals problem and an industrial diagnosis problem.
- The main form of internal data structure within SC-NET is the cell. A cell is similar to a typical neuron in the sense that it is comprised of an activation function, a threshold function, and associated set of weight values for each connection.
- The output activation levels are constrained to take three values; 0 for false, 0.5 for unknown and 1 for true.
- A key feature of SC-NET is a dynamic cell growth algorithm that creates concept nodes when needed.

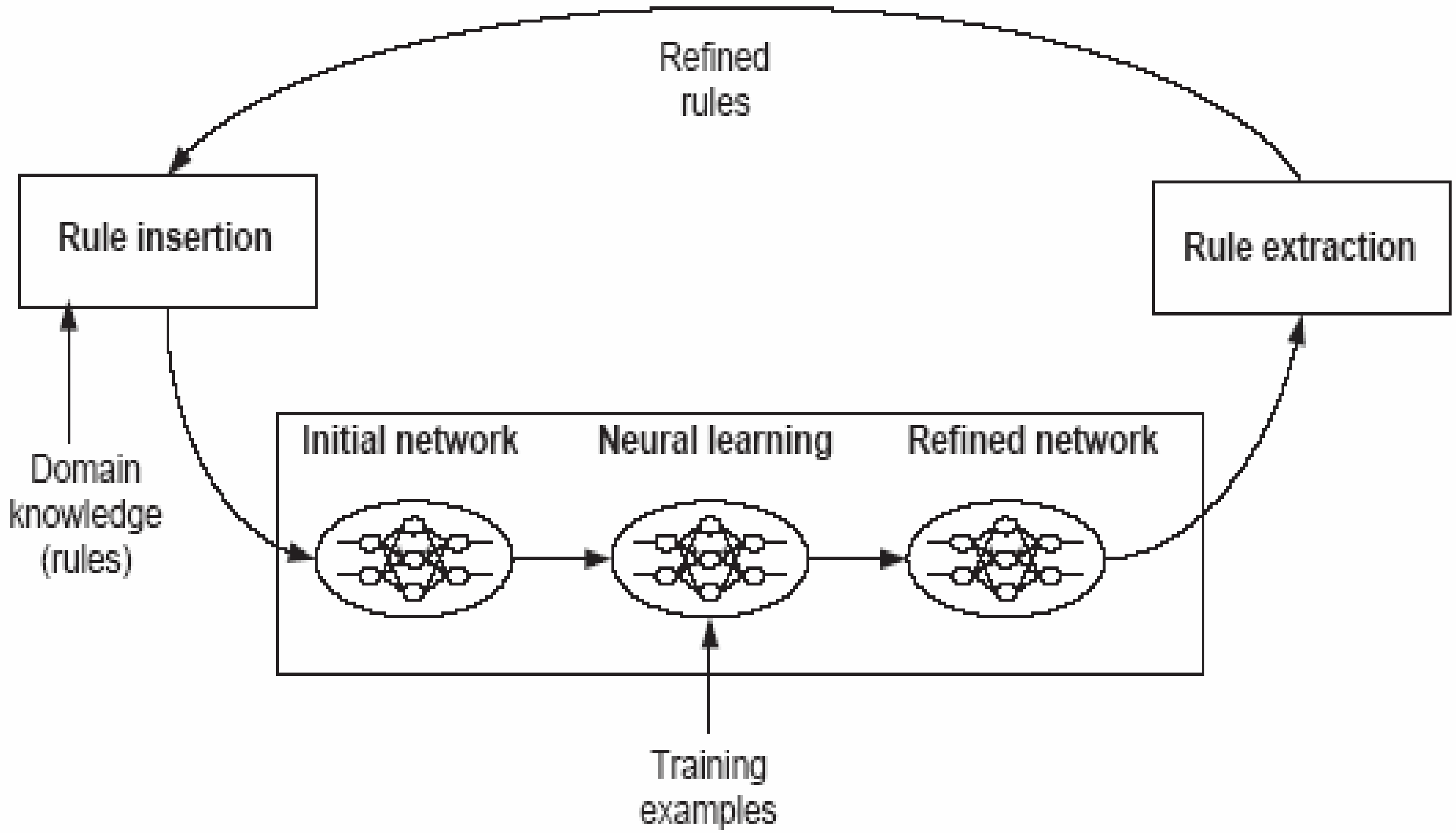
Transformational HIS

- The transformational models are able to convert an initial symbolic domain into a modified neural network architecture or vice-versa.
- The transfer process can be a complete compilation of all information from one form into another or it may create intermediate stages.
- The transformational process creates special opportunities for building hybrid systems that can operate between the two levels of neural/symbolic knowledge representation.
- An important capability of transformational hybrid systems is the possibility to build architectures that confer the benefits of both symbolic and neural processing in a single system.

Transformational HIS (2)

- The possibility of incremental learning, which means that the neural network need not be retrained with all previous training data in addition to newly, acquired data. New classes may also be included in addition to new training samples for existing classes.
- The inclusion of prior knowledge will have the effect of speeding up the learning process and will be useful in those situations where training examples are scarce. This is called the knowledge insertion, extraction and refinement stage in many systems.
- A more deterministic architecture is possible rather than the empirical process that must occur with multi-layer perceptron networks in order to discover a very good architecture, i.e. the number of layers, hidden units etc.
- The reasoning and classification operations are rendered more transparent, although some knowledge based neural network architectures (KBNN) require a further process of symbolic rule extraction.

Transformational HIS (3). Rule extraction process

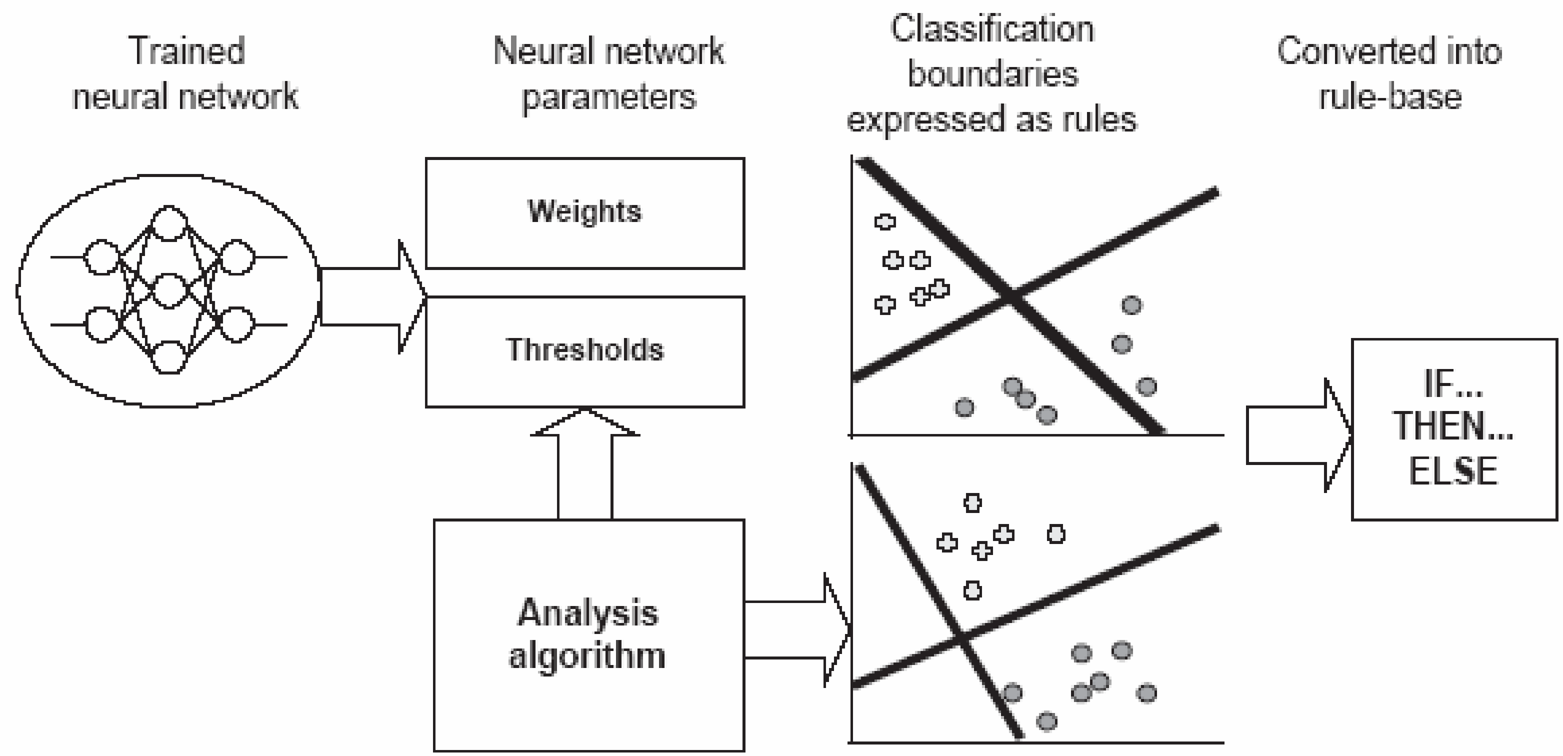


Transformational HIS (4). Rule extraction

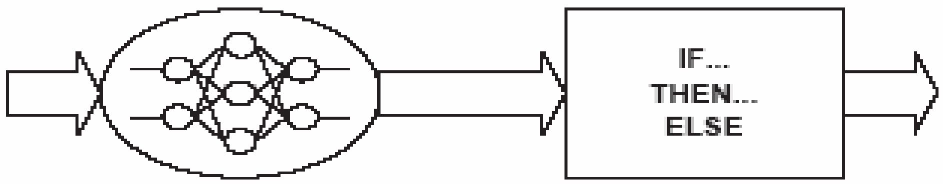
The benefits of extracting rules from neural networks are:

- Provision of an explanation facility by examining extracted rules for various input configurations.
- Deficiencies in the original training set may be identified, thus the generalization of the network maybe improved by the addition/enhancement of new classes.
- Analysis of previously unknown relationships in the data. This feature has a huge potential for data discovery/mining and possibilities may exist for scientific induction.
- Once having extracted rules from a neural network we have a rule base that has the potential to be inserted back into a new network with a similar problem domain. This is similar to the heuristics given to expert systems. Also like the heuristics the extracted/inserted rules may be refined, as more.

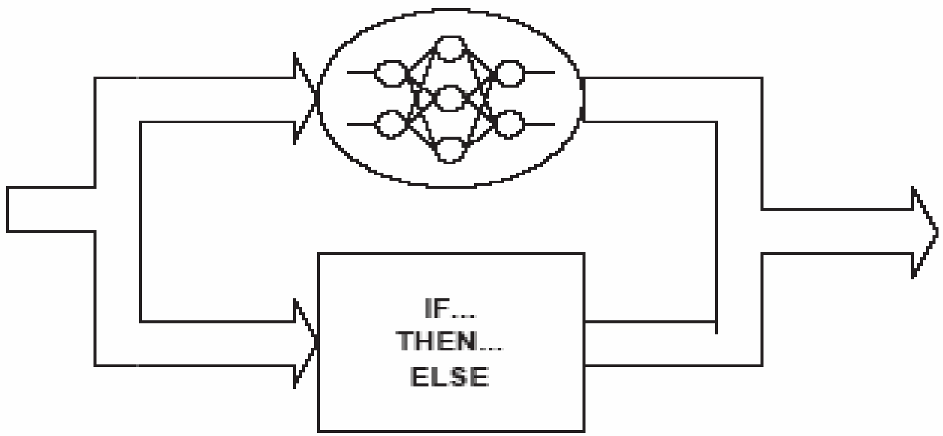
Transformational HIS (5).
Cyclic rule extraction, insertion and refinement



Modular HIS



(a) Sequential Processing

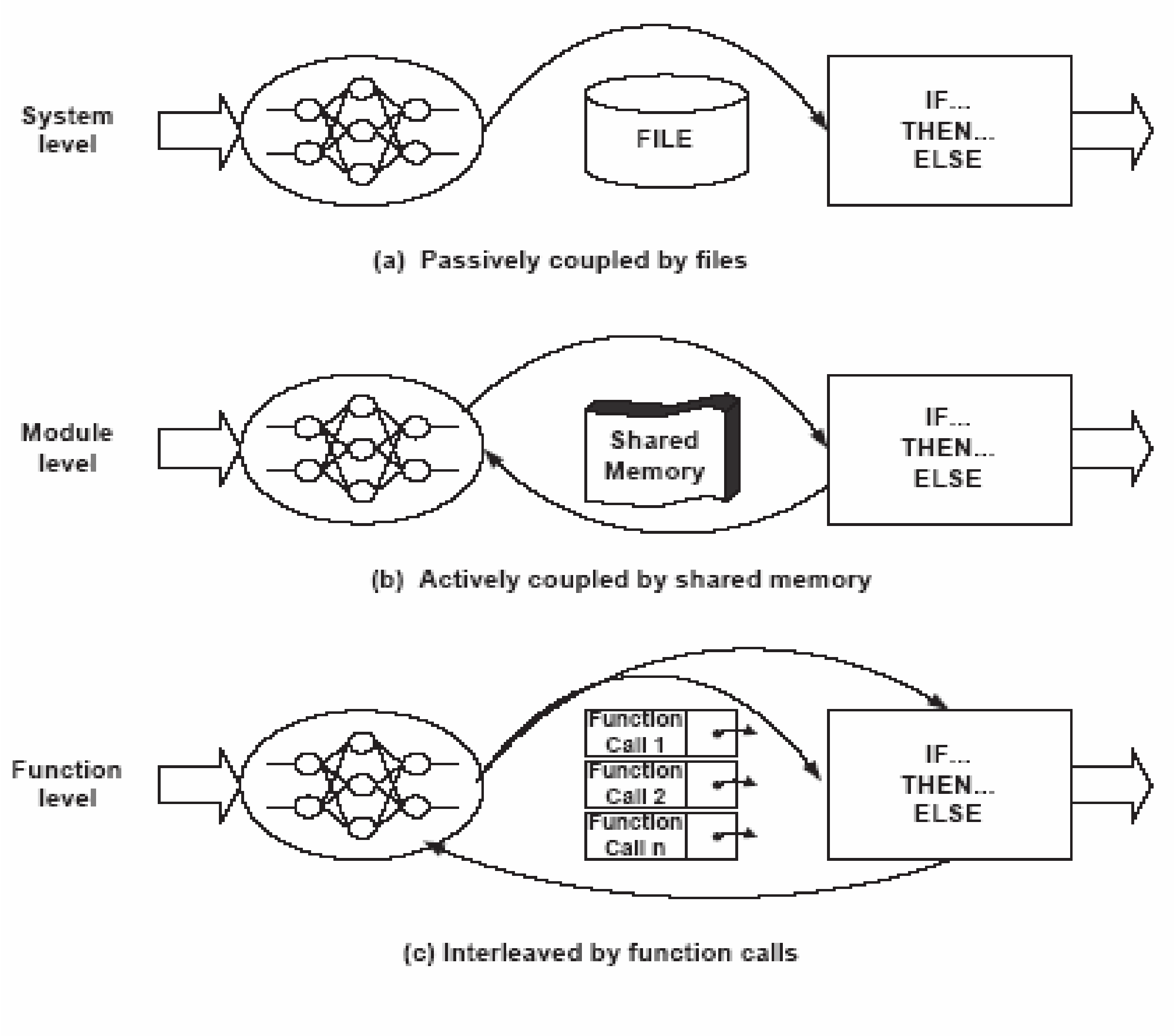


(b) Parallel Processing

Modular HIS (2)

- Sequential configuration: The main feature of this configuration is the serial processing of data as it is passed from one module to the next. One module acts as a preprocessor of data extracting the required features into a form suitable for the next module. A neural network could act as a preprocessor for a rule-based system by converting signal level information into a form more suitable for symbolic level decision making. It is also the case that a rule-based module can preprocess data for a neural network by identifying the relevant parameters for the appropriate input units.
- Parallel configuration: In this configuration a neural network and rule-based system operate in parallel on some common data. The reason for this approach is to compare the classifications obtained for greater confidence and reliability. Another possibility for parallel operation is where the neural network and rule-based elements operate on different data but combine their results for an overall classification. Parallel configurations have the capability to use feedback of information from the output of one module into the input of another enabling a more sophisticated degree of control to be implemented. Time/sequence dependent information may be used to alter the operation of the system.

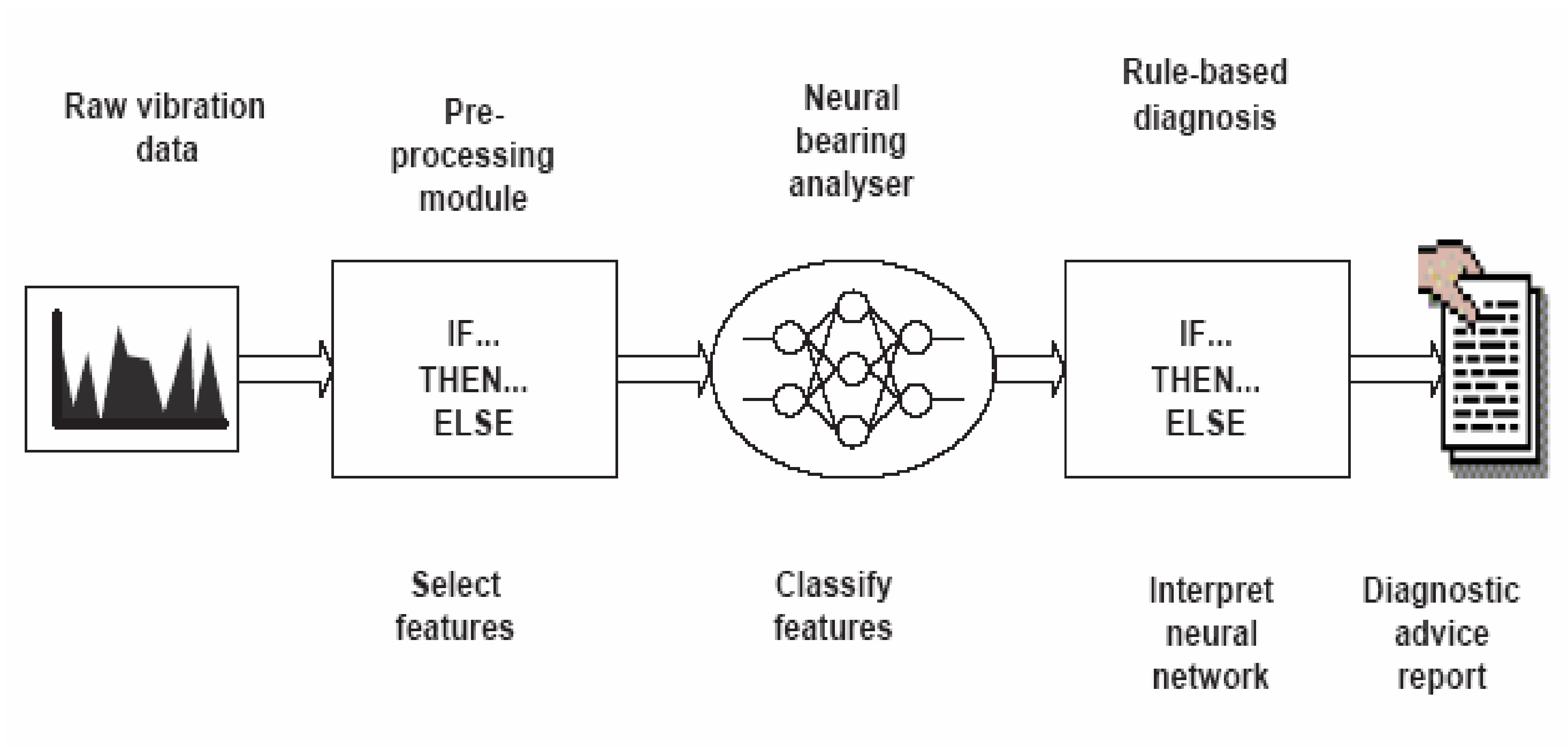
Modular HIS (3)



Modular HIS (4)

- Passively coupled: The simplest method of integration is called passively coupled because of the almost autonomous existence of the neural and rule-based components. The method of communication is usually by a data file shared by the components. After the first module finishes its computation it deposits the results in a file to be read by the second module. Passive coupling does not require any sophisticated handshaking control to synchronize the modules since the flow of communications is normally uni-directional and all the data is usually deposited in a single action. A typical configuration would involve a neural network processing an input data stream and saving the output unit activations as vectors/arrays stored in a file.
- Actively coupled: Actively coupled systems are more complex than passively coupled models since communication is by means of shared memory/data structures and so greater effort must be taken to ensure module synchronization. Inter-module communication by shared data structures enables faster runtime performance and allows more sophisticated messages to be passed. Communications can be bi-directional enabling feedback to occur between the modules, which allows a module to alter its operation based on its effect on another module. The use of feedback enables the behavior of a system to be dynamically alterable which in certain hybrid system applications such as speech understanding and industrial process control is necessarily based on changing external conditions.

Vibration diagnostic hybrid system



Vibration diagnostic hybrid system (2)

The diagnostic hybrid system is designed to detect and report bearing faults in heavy rotating machinery such as large motors and fans. The diagnostic information is based upon vibration data gathered from sensors connected to the various items of plant under observation. A great deal of preprocessing must be carried out since the raw vibration data has a high dimensionality and only a small fraction can be used to train the neural networks.

The preprocessing module reduces the dimensionality of the raw input spectra by selecting the most important parameters, which are easily calculated using heuristics. The transformed data is then passed onto the neural network module, which is designed to detect a number of bearing faults. A neural network is required for this task since several faults exhibit the same symptoms. The output of the neural network is interpreted by a rule-based diagnosis module which provides details of the faults and is also able to provide trend analysis.