An Approach to Integrate the Knowledge Based Systems

[1]Neeta Verma, [2]Swapna Singh

Inderprastha Engineering College Ghaziabad U.P India

[1]neeta140@gmail.com
[2]singhswapna@yahoo.com

***Abstract*— This paper discusses the different approach to solve the complex problems in real-world by a great diversity of intelligent techniques including traditional hard computing techniques such as expert systems and soft computing techniques such as fuzzy logic, neural networks, and genetic algorithms. The paper has a discussion of possibility to integrate several technologies into one basic structure. Intelligent hybrid Systems are defined as models and computational programs based on more than one artificial Intelligence technology. The integration of different learning and adaptation techniques to overcome individual limitations and to achieve synergetic effects through the hybridisation. Most of these hybridization approaches, however, follow an adhoc design methodology, justified by success in certain application domains.**

***Keywords*—Machine learning, expert system, neural network, inductive reasoning, deductive reasoning, intuitive reasoning.**

I. INTRODUCTION

Intelligent Hybrid Systems are defined as models and computational programs based on more than one Artificial Intelligence technology. In Figure 1 the representation of a schematic view of the integration of some AI techniques that can be combined in hybrid architectures is shown. Different aspects of intelligent behaviour can be modelled. Machine Learning and Neural Networks model the intuitive and inductive reasoning; Evolutionary Systems model the adaptive behaviour; Fuzzy and traditional Expert Systems model deductive reasoning; and Case Based Reasoning combines deduction and experience. Hybridization of intelligent systems is a promising research field of modern. Computational, a complex environment can be described as a complex system. There are several features that define a complex system

(a)Uniqueness – usually complex systems are unique or number of similar systems is unweighted.

(b)Hardly predictable – complex systems are very hard to predict. It means that it is hard to calculate the next state of a complex system if the previous states are known.

To build a complete model of an environment (complex system) that corresponds to the listed features is either impossible or very expensive. In this case the intelligent system will have incomplete model of environment or will not have it at all. In complex environments usually it is impossible to describe the environment completely. This is caused by a huge space of possible states of environment (or even infinite), expanses or other intelligence concerned with the development of the next generation of intelligent systems

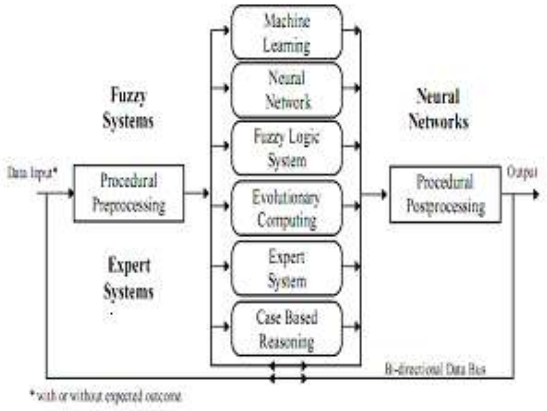

Fig 1. Copmonents of Hybrid System

II. DIFFERENT REASONING APPLIED FOR HYBRID APPROACH

A. Inductive Reasoning

Inductive reasoning works from observation (or observations) toward generalizations and theories. This is also called a "bottom-up" approach. Inductive reasoning starts from specific observations (or measurement if you are mathematician or more precisely statistician), look for patterns, regularities (or irregularities), formulate hypothesis that we could work with and finally ended up developing general theories or

drawing conclusion. In this approach, we observe a number of specific instances and from them infer a general principle or law. Inductive reasoning is open-ended and exploratory especially at the beginning.

B. Deductive reasoning

It is the process of reaching a conclusion that is guaranteed to follow, if the evidence provided is true and the reasoning used to reach the conclusion is correct. The conclusion also must be based only on the evidence previously provided; it cannot contain new information about the subject matter. Deductive methods involve beginning with a general concept or given rule and moving on to a more specific conclusion

C. Intuitive Reasoning

Intuitive reasoning has to do with the way something appears to be, how something "seems" or "looks", and is based on unverified guesses. While it may seem to be very rudimentary, it is very useful in giving a starting point from which induction or deduction can proceed. As compared with inductive, deductive reasoning is narrow in nature and is concerned with testing or confirming hypothesis.

D. Case Based Reasoning

Case-based reasoning (CBR) is defined as the process of solving new problems based on the solutions of similar past problems. It has been argued that case-based reasoning is not only a powerful method for computer reasoning, but also a pervasive behaviour in everyday human problem solving; or, that all reasoning is based on past cases personally experienced. In comparison to rule based systems (see expert system) which are useful where only one or a few solutions to a problem are possible, case based systems are useful in solving complex problems with many alternative solutions.

III. Components of Hybrid Intelligence System

1.Machine Learning and Neural Networks model the intuitive and inductive reasoning .
2.Evolutionary Systems model the adaptive behaviour .
3.Fuzzy and traditional expert Systems model the deductive reasoning .
4,Case Based Reasoning combine deduction and experience .These modules interact during the solving process or prepare the data to future processing by other module.

The input data in a hybrid system may be provided for some procedural pre-processing method and then passed to the system modules .These modules interact during the solving process or prepare the data to future processing by other module. The result can be sent to another procedural processing to prepare the system output. Depending upon the problem complexity, this output may be entrance to another hybrid system.

IV. Classification of Hybrid Intelligent Systems

There are several architectures for integrating neural and symbolic models shown in fig 2..

A. Stand Alone

No integration or communication between the modules. They are implemented independently. Stand-alone architectures are composed by independent modules without any integration between the parts . This can be used in comparison of different diagnosis in computer repair. Although these models are not an alternative to hybrid solutions, but they are a direct means of comparing solutions offered by both techniques for a same problem. Second, the implementation of a module after the other allows the validation of the first system.

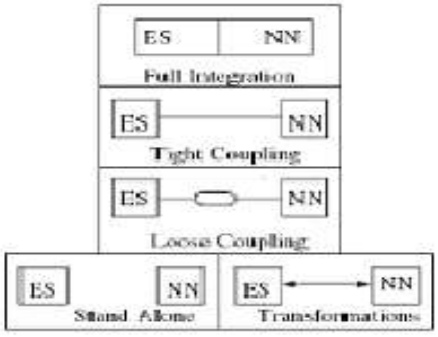

Fig 2. Different Hybrid intelligence systems

B. Transformational

Transformational models are similar to stand-alone architectures regarding the independence between the modules. In transformational models the system begins as one model (ES or NN) and ends up as the other .The limitations of transformational models include the absence of automated means of transforming one technique to the other and the difficulty in maintain both modules when new features are added to the solution. This is used in model marketing decision aid. An NN is built ti identify trends and relationships within the data and it used as basis to built an expert system to assist marketing researchers in allocating advertising.

C. Loosely Coupled

In these models expert system and neural network are independent and separate modules that communicate via data files. Both modules can be pre-post or co-processors in relation to the other. This is used for

forecasting of workforce utilization The NN predicts the workforce and ES allocates the task. They are easy to implement (each module can be developed separately in several shells available commercially) and maintain (due to the simple interface between the modules).On the other hand, this architecture is slower in the operation and may have redundancy in the independent developments of each module (identical data may be considered independently)

D. Tightly-Coupled

The next level of integration is the tight coupling model. The only difference is how the communication between the modules takes place. In these modules, NN and ES communicate through memory resident data structures. Tightly-coupled architectures are more adequate to embedded systems this Can be used as forecasting stock prices and consequent definition of appropriate strategy.

VI. FULLY INTEGRATED

The last level of integration is the fully-integrated architecture. NN and ES share data and knowledge representation and the communication between them is accomplished due to the dual nature (neuro-symbolic) of the structures .This can be used for object identification based on feature data received from sensors and environmental data.

V. STAGES OF HYBRID INTELLIGENT SYSTEMS

There are six stages in the construction of hybrid intelligent systems:

a) Problem analysis
b) Property matching
c) Hybrid category selection
d) Implementation
e) Validation
f) Maintenance

Most current hybrid intelligent systems are built either from scratch or following this development process. This is based on object-oriented techniques current hybrid intelligent systems are built either from scratch or following this development process. Hybrid intelligent systems are very important for complex problem solving and decision making. At the same time, they are difficult to build. Many hybrid intelligent systems used in different application fields appeared in the past years. A typical development cycle in the implementation of these hybrid intelligent systems is shown in Fig. 3. This is based on object-oriented techniques.

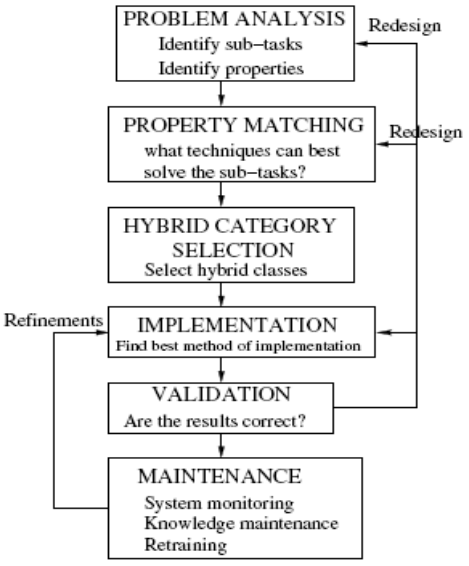

Fig 3. Stages of hybrid intelligence system

VI. APPLICATIONS OF HYBRID SYSTEMS

The hybrid neuro -symbolic systems have several applications, some in commercial environments. These include systems that require fault tolerance, generalization, implicit and explicit reasoning, incremental learning and flexible architectures. The neuro-symbolic systems in several areas of engineering, medical and company diagnostic are used. Hybrid systems are a current trend in Artificial Intelligence. Particularly regarding neuro-symbolic systems, one can expect the dissemination in several areas, especially with the development of hybrid shells that integrating different AI technologies under the same environment. Nevertheless, the commercial application of hybrid systems in large scale depends on research in several topics, including the study of unified architectures rather than hybrid solutions and the development of formal knowledge representation models for neural networks. The increasing number of publications in this area reveals that several researchers are working in hybrid systems and one can expect solutions to these and other open issues.

VII. CONCLUSIONS

This paper discusses the approach for stimulus to investigations into hybrid intelligent systems. The awareness in the research and development communities that combined approaches will be necessary if the remaining tough problems are in artificial intelligence. The integration of different learning and adaptation techniques to overcome individual limitations and to achieve synergetic effects through the hybridisation are to be solved. The successes in integrating of expert systems and neural networks, and the advances in

theoretical research on hybrid systems, point to similar opportunities for when other intelligent technologies are included in the mix. From knowledge of their strengths and weaknesses, we can construct hybrid systems to mitigate the limitations and take advantage of the opportunities to produce systems that are more powerful than those that could be built with single technologies.

ACKNOWLEDGMENT

We would like to thank to our Director for providing the full cooperation, support and for helpful comments on an earlier draft of this paper.

REFERENCES

[1] A.Nikitenko, J.Grundspenkis "The kernel of hybrid intelligent system based on inductive, deductive and case based reasoning" KDS2001 conference proceedings, St. Petersburg 2001.
[2] P.S.Rosenblum "Improving Accuracy by Combining Rule-based and Case based Reasoning" 1996.
[3] Bradley J. Rhodes "Margin Notes Building a Contextually Aware Associative Memory", The Proceedings of the International Conference on Intelligent User Interfaces (IUI '00), New Orleans, LA, January 9-12, 2000.
[4] M. Pickering "The Soft Option" 1999.A.R.Golding.
[5] J.R. Quinlan "Comparing Connectionist and Symbolic Learning Methods" Basser Department of Computer Science University of Sydney, 1990.
[6] J.R. Quinlan "Improved Use of Continuous Attributes in C4.5" Journal of Artificial Intelligence Research 1996.