A HYBRID INTELLIGENT MULTI-AGENT METHOD FOR MONITORING AND FAULTS DIAGNOSIS

Gang Yao and Tianhao Tang

Department of Electrical & Control Engineering, Shanghai Maritime University

1550 Pudong Road, Shanghai, 200135, P. R. China

thtang@cen.shmtu.edu.cn, shakesteel@hotmail.com

Keywords: Multi-agent system, Monitoring and diagnosis system, Data mining, Fuzzy neural networks.

Abstract: This paper presents a hybrid intelligent multi-agent method for monitoring and faults diagnosis. A new diagnosis process, combined with data mining and neural networks, are discussed as well as the functions and structure of agent which implements these algorithms. At last, some simulation results are shown to demonstrate the efficiency of the proposed system.

1 INTRODUCTION

The rapid development of modern industry calls for safer and more efficient control processes. Monitoring and faults diagnosis systems, specifically combined with artificial intelligent technologies, are implemented for state monitoring, trend predicting and fault diagnosis. Thereby, it is possible to improve the system efficiency and to guarantee the operation safety in the control process (Edgar 2000).

A general overview about distributed artificial intelligence in industry was given in (Parunak 1994). This paper reviewed the industrial needs for distributed artificial intelligence, and gave special attention to the needs arising from systems for manufacturing, scheduling and control. Since then more and more researches and contributions have been done in this field.

However, the complexity of the monitoring and diagnosis system is growing with the increasing complexity of industrial plants. To keep the monitoring and diagnosis system effective, it is essential to encapsulate different tasks and to define strict interfaces between plant components and between components of the monitoring and diagnosis system, although it is quite difficult. To guarantee flexibility -- changing needs in case of an industrial application, the monitoring and diagnosis system has to be configurable and expandable without the need of modifying any line of code (Luder 2001). The diagnostic knowledge about an industrial process is available on different parties (process specialists, component manufacturers, etc.). A modern monitoring and diagnostic system should be able to integrate the diagnostic knowledge from all available sources, even if different diagnostic mechanisms are applied. To achieve an overall diagnosis of a control process, several diagnostic tasks have to be performed in parallel. This requires new strategies to handle diagnostic conflicts that might occur between different diagnostic results.

Multi-agent system (MAS), about which rapid progress has been made, is an important research branch in distributed artificial intelligence (DAI) parallelized with distributed problem solving (DPS). Possessing modularity, adaptability and other attractive characteristics, MAS drew much attention in recent years and is adopted by many researches in monitoring and diagnosis system.

This paper presents a hybrid intelligent mutli-agent method for monitoring and faults diagnosis, which separates fault diagnosis process into several steps excuted by different types of agents. The macroscopical architecture of the MAS system and microcosmic structure of an agent are designed in section 2. Then, the intelligent monitoring and fault diagnosis process is presented in section 3. At last, the simulation experiment, applying the proposed method in marine engine room, is carried out in section 4.

2 SYSTEM ARCHITECTURE

2.1 Architecture of Proposed System

The framework of hybrid intelligent multi-agent method, with hierarchical and federal organized software agents that are responsible for different tasks, is presented in figure 1.

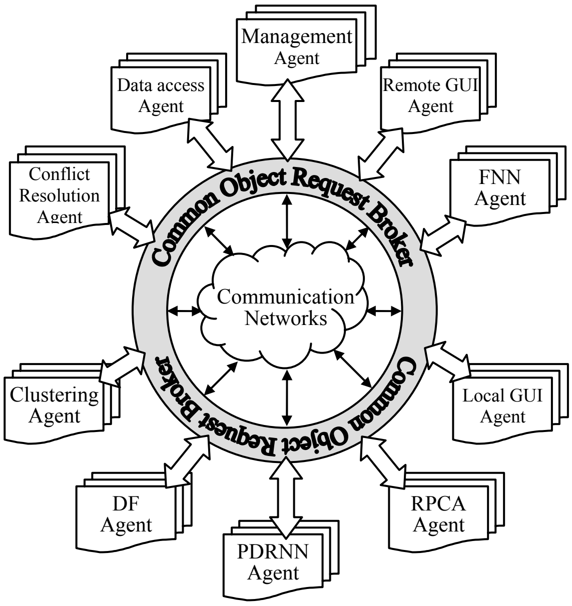

Figure 1: Architecture of MAS-based monitoring and diagnosis system.

As shown in figure 1, many agents with different capabilities are connected together by accessing common object request broker (CORBA) functionalities and through communication networks to form a multi-agent society. In this society, each individual has a special 'survival skill' that can work autonomously and independently. For example, when this MAS is connected to a control system, the data access agent, who has the skill of accessing database, it can get signals periodically and automatically from given sensors and store them into a record set with the intelligence of maintenance the integrity of database.

On the other hand, like human beings, agents in the figure trend to seek cooperation to fulfil more difficult task if they believe that better rewards will gain by cooperation or the job assigned to the agents is impossible to achieve with their own capability. A cooperation coalition will form successfully if following precondition is met

$$v(A_1)+ v(A_2) \leq v(A_1+A_2), (A_1 \cap A_2=\phi) \qquad (1)$$

Where $v(A_1)$ is the benefit gained by coalition A_1 after A_1 accomplished a job.

Management agent is the one who take charge of negotiation within the formation of a cooperation coalition. When a task is received, management agent decomposes the task into sub-jobs or steps if necessary, and then adopts contract net protocol to distribute them to appropriate agents to form a cooperation coalition. Other agents decide whether to respond to the bidding or not according to the job been doing, priority and rewards. After the mission is accomplished, the cooperation coalition will dismiss automatically.

This MAS approach will bring us following advantages: Modularity and scalability, instead of adding new capabilities to a system, agents can be added and deleted without breaking or interrupting the process; Adaptability, agents have the ability to reconfigure themselves to accommodate new changes and faults; Concurrency, agents are capable of reasoning and performing tasks in parallel, which in turn provides more flexibility and speeds up computation; Dynamics, agents can dynamically collaborate to share their resources and solve problems and finally, Reliability, MAS are more fault-tolerant and robust than traditional AI systems.

2.2 Architecture of an Intelligent Agent

At agent level, all the agents in proposed method have the same hybrid behaviour architecture, where the agents are capable of reactive and deliberative behaviours. In general, the agents should be neither totally deliberative nor totally reactive. If they are only reactive, they cannot reason about their actions and will not be able to achieve any sophisticated behaviour; if they are just deliberative they may never be able to act in time. The proposed architecture is based on horizontal layering where all layers are connected to the perception and actuation of the agents with the environment. Figure 2 shows the proposed agent architecture in monitoring and diagnosis system.

In figure 2, an agent can collect information from two channels: the perception module, which apperceives from the ambient and to check the influence of last action, and the communication module, which receives message from other agents. All the perception information is distinguished as 'urgent' or 'not urgent' based on the signal type, priority, security policy and experience in order to trigger corresponding response mechanism.

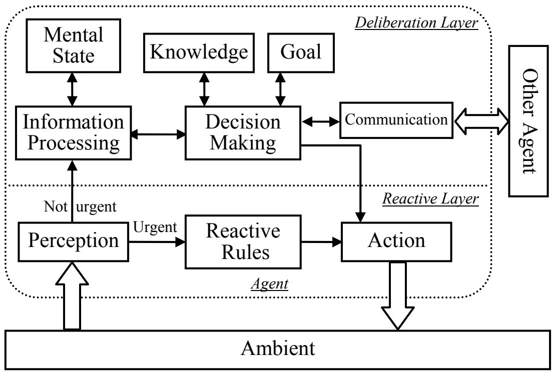

Figure 2: Architecture of an agent.

If an urgent message is received, the reactive layer will be triggered, and the agent will execute according to the most similar rule in rules library without thinking. The reactive rules library could be modified in accordance with the experience automatically.

If the message is not urgent, the agent will 'think' for a while about how to respond. In this period, agent uses its special ability to process this information and then make decision with the consideration of mental state, knowledge and its goal. After the agent's action is executed, if the action really works, the agent will record this action as a paradigm into reactive rules library and update the mental state, knowledge base if necessary.

When the agent finds the job got from the message is too difficult to accomplish, three options are available: (1) if the agent know who can help it, it will ask for help directly to that agent; (2) if the agent has no idea who is the right agent, it will contact the management agent to try to organize a cooperation coalition; (3) if no one responds its request, abandoning the goal is its last choice.

The special capability mentioned above is the agent's 'survival skill' encapsulated in information processing module (IPM). Different method in IPM determines different type of agent. As shown in figure 1, ten kinds of agent are designed in this system:

(1) Local and remote GUI agent: local and remote graphical user interfaces (GUI) are used by the operator users to display monitoring and diagnosis results, initiate diagnostic processes, give a phonic or flaring alarm, and receive user's instructions locally and extendedly.

(2) Management agent: management agent is used to decompose task and start organizing cooperation as mentioned in section 2.1.

(3) Conflict resolution agent: a conflict resolution mechanism is required to investigate whether the diagnostic results, as reported by different diagnostic agents, are contradicting or completing each other. The diagnostic agents do not communicate with each other to merge their knowledge, but do report their diagnosis to a conflict resolution agent. For this purpose, the history credit evaluation of a diagnosis agent is important. Beyond this, knowledge of relations among the components and among the possible failures which may be related within the components, need to be well known (H.Worn 2002).

(4) Directory facilitator agent: the directory facilitator (DF) agent is responsible for communication and agent management. It can provide the naming service, represent the authority in the platform and also provide Yellow Pages service by means of which an agent can find other agents providing the services he requires in order to achieve his goals. All the capabilities of the registered monitoring and diagnostic agents and the available CORBA functionalities are managed by the facilitator agents.

(5) Data access agent: what data access agent can do has discussed as an example in section 1.

(6) Clustering agent, Relative Principal Component Analysis (RPCA) agent, Parallel Diagonal Recurrent Neuron Network (PDRNN) agent and Fuzzy Neural Network (FNN) agent: these agents are dealing with monitoring and diagnosis process which will be discussed in next section.

3 INTELLIGENT MONITORING AND DIAGNOSIS PROCESS

Faults diagnosis for complex control system is the process of mining valuable omen variables from mass data collected by sensors and mapping omen variables to faults modes. Thereby data mining plays an important role in diagnosis. In this paper, a new hybrid intelligent monitoring and diagnosis method is proposed in figure 3. This method divided the process of data mining and fault mode mapping into several independently data fusion modules, which are implemented by agents:

(1) Database: database is made up with two main storage areas, which correspond to history and online data access respectively. History data are used for intelligent data mining, executed by collaborated agents, and real time data are collected by the data access agent from sensors.

(2) Pre-processing module based on clustering methods: This module is executed by clustering agent. Data selection and data mining usually do not need all the data, some data object and propriety has no contribution to the modelling, on the contrast they will greatly reduce the efficiency of data mining, even will lead to the variation of data mining result. In this case, it is very necessary to select data effectively. Pre-processing module based on clustering methods can select the preventative points as feature data and filter some fake data.

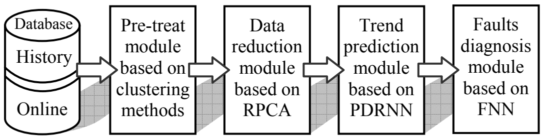

Figure 3: Data mining based intelligent information fusion method.

(3) Data reduction module based on RPCA: Data reduction will figure out the essential data set to shrink the scope, which is the further step of reduction based on data selection. Data reduction also is called as data enriching, the process of which is transferring the original data set to the more compact data set without losing any semantics. Herein Relative Principal Component Analysis Algorithm (RPCA) is adopted and encapsulated in the IPM of RPCA agent, which can avoid the parameters having bigger absolute values or variation values to play the great role when getting main element, which is the shortage of PCA method. For RPCA, more representative main element can be got from the data array made up with evenly distributed system variables series. This module is majorly used to reduce data dimension and extract system feature (Tianhao Tang 2005).

(4) Trend prediction module based on neural network: Prediction mode can predict some phenomena or data value. Parallel Diagonal Recurrent Neuron Network (PDRNN), which is implemented in PDRNN agent, can realize multiple dimension and parallel time frequency prediction, and it has the high prediction precision to make its result good for the fault trend analysis. The architecture of this neural network is shown in figure 4. The transfer function of neuron adopts Sigmoid, and training method is back propagation algorithm. Details about this neural network refer to (Tianzhen Wang 2004).

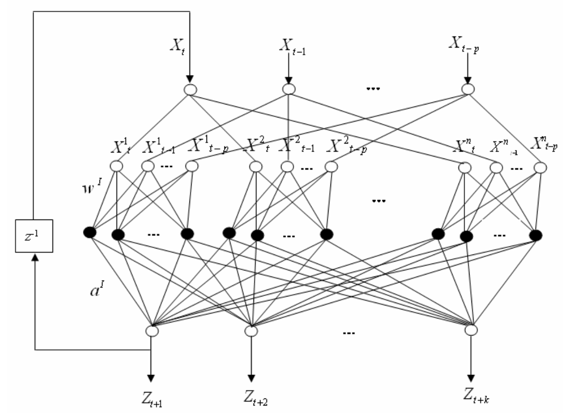

Figure 4: Architecture of PDRNN.

(5) The last step is to do system fault detection based on omen variable and parameters prediction. The core issue of fault diagnosis is to abstract signal feature and to establish the relationship between the features and different functional states. More complex modern industry system has more complex faults. One fault often demonstrates many omens, while one omen maybe includes information about many kinds of faults. The relationship between omen and fault is hard to be expressed by precise mathematic expression, so fuzzy logic diagnosis method can be used. The basic principle of fuzzy logic diagnosis is to establish the fuzzy relation matrix $\widetilde{R}$ between fault mode (cause) and omen variable according to the known information, then to select omen membership vector X. The fault mode membership matrix Y can be calculated from fuzzy relation equation $Y=X*\widetilde{R}$, thus fault causes can be diagnosed.

The uncertain relationship between fault and omen can be well expressed in fuzzy diagnosis, but the relation matrix $\widetilde{R}$ is hard to be established. On the other hand, fault diagnosis can be regarded as a kind of pattern recognition which maps the fault omen to fault causes. The relation matrix $\widetilde{R}$ reflects the mapping. For the complex system, the mapping is non-linear. A fuzzy neural network (FNN) is used to establish the matrix $\widetilde{R}$, as shown in figure 5

This FNN is realized in FNN agent, and two new fuzzy operators, the generalized probability sum operator and the generalized probability product operator, are used as transfer function to express the concepts of the generalized union and the generalized intersection calculating. Details about the FNN refer to (Tang, etc., 1998).

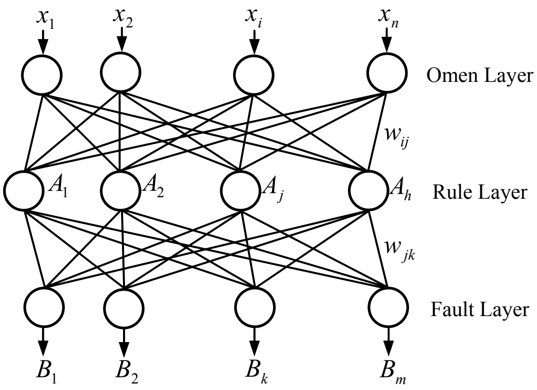

Figure 5: Architecture of fault diagnosis neural network.

4 SIMULATION EXPERIMENT

The hybrid intelligent multi-agent monitoring and diagnosis system mentioned above has been used in marine engine room, which is a typical complex and distributed system.

Marine engine room is made up principally with main engine remote control & protection system (MECS), auxiliary engine control system (AECS), ship power station automatic control system (PSCS), boiler automatic control system (BCS), cabin monitoring and alarm system (CMAS), and pump control system (PCS), etc. For every sub systems, a cooperative coalition is formed to implement monitor and diagnosis.

The overall state monitoring and fault diagnosis system for marine engine room is shown in figure 6. The architecture of a cooperative coalition is shown in figure 7.

As mentioned before, there are several different types of agents sharing the same architecture but having different capability in the proposed system, which means that the connotation of IPM is different according to the functionality of the agent. Thereby, in figure 6, the architecture of all kinds of agents is implemented in Jade, but the inner methods of IFM are coded in different programming language with consideration of coding convenience.

The monitor and alarm client interface, running on local and extended GUI agent, and the fuzzy neural network in FNN agent are coded in Visual Basic 6.0 (VB6). Other algorithms involving in the process of intelligent data mining are coded in Matlab 6.5.

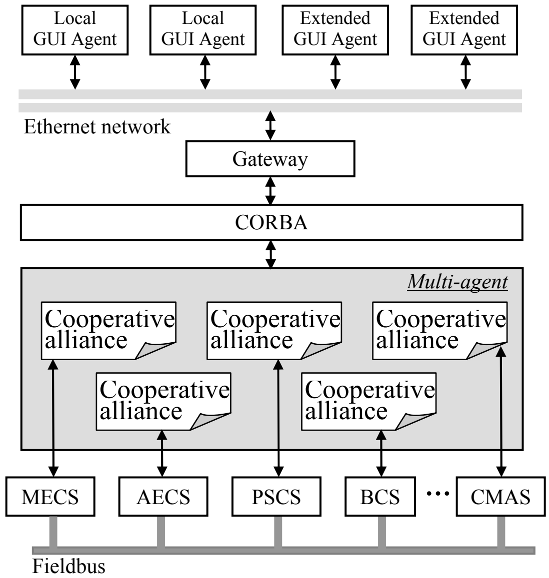

Figure 6: Architecture of marine engine room state monitoring and fault diagnosis system.

JMatLink, a small toolkit to connect Java with Matlab, is used to call for the data mining function in an m-file for Java monitoring agent.

To implement calling VB methods and forms from Java, Java Native Interface (JNI) mechanism is utilized.

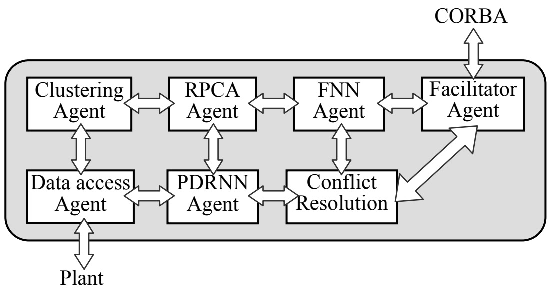

Figure 7: Architecture of a cooperative coalition.

In this experiment, several faults of main engine were adopted to test the faults diagnosis system. Ten parameters of main engine, such as engine cylinder exhaust gas temperature, maximum cylinder pressure, etc, are chosen as omen variables.

Table 1 shows the comparison between samples of normal state and three faults state and diagnosis results. The acronyms of omen variables are interpreted in Table 2.

Table 1: Fault diagnosis results.

	Normal state		Main oil pump abrasion	
	Sample	Result	Sample	Result
Pmax	0.50	0.485	0.05	0.052
Pcs	0.50	0.488	0.35	0.405
Tcs	0.50	0.499	0.35	0.381
Tex	0.50	0.446	0.20	0.228
Ntk1	0.50	0.486	0.35	0.408
Ntk2	0.50	0.496	0.35	0.408
Pti	0.50	0.495	0.35	0.416
Tto	0.50	0.513	0.35	0.404
Tko1	0.50	0.497	0.35	0.386
Tko2	0.50	0.497	0.35	0.396

Table 1: Fault diagnosis results (Cont.).

	Fuel injection late		Fuel injection pipe leak	
	Sample	Result	Sample	Result
Pmax	0.05	0.063	0.05	0.051
Pcs	0.80	0.715	0.20	0.232
Tcs	0.65	0.534	0.35	0.378
Tex	0.95	0.931	0.05	0.141
Ntk1	0.65	0.613	0.35	0.379
Ntk2	0.65	0.612	0.35	0.378
Pti	0.65	0.604	0.35	0.411
Tto	0.65	0.591	0.50	0.512
Tko1	0.65	0.596	0.35	0.407
Tko2	0.65	0.595	0.35	0.402

Table 2: Interpretation of omen variables.

Pmax	maximum cylinder pressure
Pcs	scavenging air pressure
Tcs	scavenging air temperature
Tex	cylinder exhaust temperature
Ntk1	rpm of No.1 turbocharger
Ntk2	rpm of No.2 turbocharger
Pti	inlet pressure of turbocharger
Tto	outlet temperature of turbocharger
Tko1	No.1 air cooler outlet temperature
Tko2	No.2 air cooler outlet temperature

From the table, we can see that diagnosis agent can get close results compared with the samples, and it means that fault could be detected exactly. Besides these faults in Table 1, dealing with other faults, diagnostic agent can get similar results.

5 CONCLUSIONS

This paper describes a concept of building a hybrid intelligent monitoring and diagnosing system for complex control process based on the application of MAS, and also proposed a new fault diagnosis process integrates several algorithms implemented within the MAS method, which allows the flexibility, the extendibility, and a cost-effective development of the system. Details about the overall architecture, algorithm encapsulated in IPM, and coding tools are discussed. And at last, some simulation experiment results are given to demonstrate the efficiency of the presented system.

ACKNOWLEDGEMENTS

This work was supported by National Natural Science Foundation of China (60572051) and the project from Shanghai Education Foundation (05FZ04).

REFERENCES

Edgar, T. F., Dixon, D. A., and REKLAITIS, G. V., 2000, Vision 2020: Computational Needs of the Chemical Industry, (University of Texas Press).

Parunak, V., 1994, Applications of distributed artificial intelligence in industry. In O'Hare and Jennings, (eds) Foundations of Distributed Artificial Intelligence (Chichester: Wiley Inter-Science).

Luder, A., et al., 2001, Industrial requirement and overall specification. Prepared within the PABADIS IST research project no. IST-1999-60016. Available at www.pabadis.org.

H.Worn,et al, 2002, A distributed multi-agent architecture for monitoring and diagnosis

Tianhao Tang, Tianzhen Wang. 2005, ANN-based multiple dimension predictor for ship route prediction. Proceedings of ICINCO 2005, Barcelona, Spain

Tianzhen Wang, Tianhao Tang. 2004 A Mult-dimension Predictor based on PDRNN . ICARCV, P1359-1364

Tang, T. et al 1998. A fuzzy and neural network integrated intelligence approach for fault diagnosing and monitoring. Proceedings of the 1998 UKACC International Conference on Control, vol.2, pp.975-980. Swansea, UK.

Tianhao Tang, Yao Gang. June 27-29, 2005, A Fault-tolerant Control Method Based on Adaptive Fuzzy Neural Networks for Ship Control System, 2005 International Conference on Control and Automation, Budapest, Hungary