Hierarchical Fault Diagnosis Using Sensor Data Fusion for Robotic System

Mohammad A. Nekoui, Amir R. Kashanipour, and Karim Salahshoor

***Abstract*—In this paper, we present a sensor data fusion based approach in a multi-layered, multi-agent architecture toward more reliable fault detection and isolation. This paper describes a sensor fusion approach to the detection of faults in robotic systems, based on multi-agent distributed diagnosis. Each of the agents uses an Adaptive Neuro-Fuzzy Inference System (ANFIS) and decision fusion is achieved by a Dempster-Shafer supervisor. In this work sensor level fusion used for generating residual signal more accurate and by considering uncertainties in sensors tried to compensate innate lack of model-based approach in detecting abrupt change. Based on distributing the diagnosis task by dedicating intelligent diagnosis agents for different parts of robot, decision fusion used in supervisory level to consider reliability of each agent, considering contingency faults scenario and failure symptoms. Adaptive Neuro-Fuzzy Inference System has been used as inference architecture for distributed sensor networks. Two types of ANFIS networks are used. An ANFIS based learning and adaptation is used for modeling the joints toward residual generation, while for residual evaluation another ANFIS is used. In this work online fault diagnosis based on sensor data fusion techniques for online fault diagnosis targeting robotic systems has proposed. Considering possibility of diagnosis one specific fault by more than one agent, practiced by using multiple ANFIS for different type of faults in each agent. Simulation results of controlled 3-Link Rigid Planar Manipulator controlled demonstrate capability of the proposed method toward achieving a fault tolerant controller.**

***Index Terms*—Fault diagnosis, signal processing, process control, neural networks, multi-agent system, hierarchical system, data fusion.**

I. Introduction

ROBOTIC platforms performing must be equipped with multiple and different types of sensors to accurately extract information about their surroundings toward performing their commanded operation. Using the information from the various sensors requires robust, real-time sensor fusion. When sensor error or failure occurs, multi-sensor fusion can reduce uncertainty in the information and increase its reliability [18]. Additionally, due to inherent sensor limitations and characteristic and the unknown environment it is very hard and sometimes impossible to predict a priori the failure characteristics. Therefore, there is a need to estimate online the cause of any failure and try to compensate it while the system is operating. Furthermore, many damages would happen to system because of possible obstacle which would lead to system parts like damaged actuators. This requires an algorithm that is able to diagnose the fault online toward achieving fault tolerant control over the system.

The demand for Fault Detection and Isolation (FDI) of nonlinear systems are significantly growing to improve system reliability, safety and efficiency. During last decade, FDI has increasingly used in many areas such as aerospace, chemical and mechanical systems. As robots are mostly designed to act autonomously and not directly supervised, and considering the special working environment they have been used in, attitude towards the use of autonomous fault diagnosis systems with minimum human interference magnifies the importance of these systems in robotic systems.

FDI techniques can be divided into two main Categories: techniques using either model of the system [1]–[3] or data-driven techniques [4, 5]. Using system model, where quantitative and qualitative knowledge-based models, data-based models, or combination of them are achievable, applied in more reliable manner. For data-driven approaches, only the availability of a large amount of historical process data is assumed. Different methods of extracting knowledge from historical data can lead to discriminate condition of the system healthy from faulty. There might be some overlap between the model-based and data-driven approaches; this classification is just based on whether or not the model of the process is required.

In model-based methods, generally speaking, the differences between measured and reference signals or simulated signals are computed continuously. Any non-zero differences, named residual, would declare a fault occurring. Using fuzzy logic and neural networks for fault detection and isolation has been demonstrated extensively in many theoretical and practical works.

In proposed method monitored system is modeled using Adaptive Neuro-Fuzzy Inference System (ANFIS). A hybrid method harnesses both Artificial Neural Networks (ANN) and Fuzzy Logic Systems (FLS) capabilities for modeling the nonlinear systems [6]. Due to wide range of operation domain in robotic systems (here 3-DOF manipulator) and their inherent nonlinear dynamics using hybrid approach for modeling each joint in its operational point has evaluated

M. A. Nekoui, A. R. Kashanipour, and K. Salahshoor are with the Islamic Azad University, Tehran South Branch, Tehran, Iran (e-mail: Manekoui@eetd.kntu.ac.ir).

successfully. In isolation phase - determining the location of fault - by ANFIS as a classifier exact cause of fault determined. Due to burden of data in this phase, dedicating individual ANFIS to each type of faults suggested and practiced successfully.

In proposed scheme, we used distributed diagnostic agents for monitoring joints separately. Agents do not communicate by each other to decrease complexity of the overall system. Reliable decision making have achieved by availability of diagnosis of one specific fault by different agents. The overlap between duties of agents have assigned by the prior knowledge about propagation of faults in the robot. Agents have communication with supervisory system which the decision fusion takes place in it.

In many cases, different agents simply give multiple interpretations for a single event which is based on highly coupled dynamic of the system. This would bring a ambiguity and uncertainty in supervisory level for decision making. In this work each agent converts observed raw data into a preliminary declaration of fault identity. The identity declarations provided by the individual diagnosis agents are combined using decision level fusion. Many techniques for decision fusion have reported in different works such as Bayesian inference, weighted decision methods, Dempster-Shaffer Theory. In this work to handle the inherent uncertainty in fault diagnosis problems- system do not behave as it is expected and show deviation from its considered model- using Dempster-Shaffer sounds meaningful.

The proposed method is applied to fault diagnosis of a rigid 3-Link manipulator. The raw data provided form signals were measured from position and velocity sensors in each joint. Different kind of faults with variety of severity in presence of different unmeasurable disturbances simulated to evaluate the architecture. The results demonstrate the effectiveness of the method.

II. Fault Diagnosis Algorithms

In model-based diagnosis techniques, the designer uses analytical model of the plant to set up the FDI procedure. Based on relying on previous knowledge from the system or not, these methods could be categorized in two mainstreams. methods using analytical model of the process (usually known as model-based) and ones where the process model is constructed without the use of any knowledge obtained from physical laws(usually known as model-free).

In practice, owing to existence of uncertainties, it is not possible to attain an exact mathematical model of real-world processes such that it precisely mimics the system's behavior. One way to deal with the absence of a mathematical model is to build a model from input-output data. Artificial Neural Network and Fuzzy Logic/Inference systems have widely used for modeling the system behavior [7]–[10].

Basic idea behind most of these methods is using the difference between output of the healthy model and the real plant's output [11]. For detection phase, the output of the monitored system is comparing with process model, and if any magnificent change observed, occurrence of fault inferred. For isolation phase, the difference is classifying by different algorithms into corresponding classes of faults for determination the location of the fault, type of the faults and more.

Due to wide range of operational domain in robotic systems (also here in 3-DOF manipulator) and inherent nonlinear dynamics of such systems, modeling of system in its operation point to have minimum modeling error is a crucial task. Several modeling approach have suggested [12], also using multiple model in different operational point for tackling nonlinearity problem have been reported. In the most significant report [13] Local Model Networks LMNs modeling approach have suggested the division of the operating regime in parts, and then the correlation of each one with a local model approximates the plant behavior within the respective part of the operating regime. Although considering several models of the joints in the bank of models, results in a better performance, it drastically increases computational operations that are unfavorable in real-time tasks. Also, restricting the number of faults to a priory determined value does not seem reasonable. A special fault, such as variation of a parameter, can happen in a continuous domain. So it is impossible for the designer to create infinite models in the bank of models. It is a real burden to eliminate these faults using prepared models.

Implementation of these steps in this study have achieved by using ANFIS based on its modeling and identification capability. ANFIS harnesses both ANN and FLS capabilities for modeling the nonlinear systems as well as classification of data into predefined classes.

III. Adaptive Neuro-Fuzzy Inference System

There are three important characteristics of neural networks that make them suitable for modeling the behavior of the system: generalization ability, noise tolerance, and fast response once trained. Fuzzy logic also used for both fault detection via modeling and fault isolation via classification for nonlinear systems. An important advantage of fuzzy approaches is the fact that nonlinear systems can be modeled using set of linear model builds around a set of operating points.

A Fuzzy Logic System (FLS) can be introduced as a non-linear mapping from the input space to the output space. The mapping mechanism is based on the conversion of inputs from crisp numerical domain to fuzzy domain with the use of fuzzy sets and fuzzifiers, and then applying fuzzy rules and fuzzy inference engine to perform the necessary operations in the fuzzy domain. At the end, the result is converted back to the numerical domain using defuzzifiers.

Adaptive Neuro-Fuzzy networks are enhanced FLSs with learning, generalization and adaptively capabilities. In this paper, we use the Adaptive Neuro-Fuzzy Inference System

(ANFIS) structure and optimization processes because of their accuracy and our need for diagnose multiple faults.

To present the ANFIS architecture, two fuzzy if-then rule based on a first order Sugeno model are considered:

Rule 1: If (x is A_1) and (y is B_1) then ($z_1 = p_1 x + q_1 x + r_1$),

Rule 2: If (x is A_2) and (y is B_2) then ($z_2 = p_2 x + q_2 x + r_2$).

The ANFIS learning algorithm is then used to obtain these parameters. This learning algorithm is a hybrid algorithm consisting of the gradient descent and the least-squares estimate. Using this hybrid algorithm, the rule parameters are recursively updated until acceptable error is reached. In the defuzzification layer, crisp output is produced from the output of the inference layer. Maximum defuzzification and centroid defuzzification are used as defuzzifiers. Therefore, the resultant output is related to all the rules executed in the preceding layer. This is then compared with a threshold to determine whether or not a fault mode should be reported. The ANFIS used in this approach uses Gaussian functions for fuzzy sets, linear functions for the rule outputs and Sugeno's inference mechanism. The parameters of the network are the mean and standard deviation of the membership functions (antecedent parameters) and the coefficients of the output linear functions (Fig. 1).

In first stage, for modeling the system the position and velocity signals in combination with input torque and operation point of different joints of robot must fed into ANFIS to modeling the system. In the second stage to identify different abnormal cases different residuals of key variables must fed into fault isolation ANFIS. In the present work each of signals using by ANFIS for modeling recorded and used in normal operation mode. Multiple ANFIS have used for classify the residual toward diagnosing different faults. Combination of multiple ANFIS makes one diagnostic agents, applicable in different part of the system. Decomposing diagnosis task by local diagnosis agents reduce the computational burden of diagnosis system and increase the accuracy and rapidity of the system.

IV. Distributed Architecture

Recently there has been significant research activity in modeling, control and cooperation methodologies for

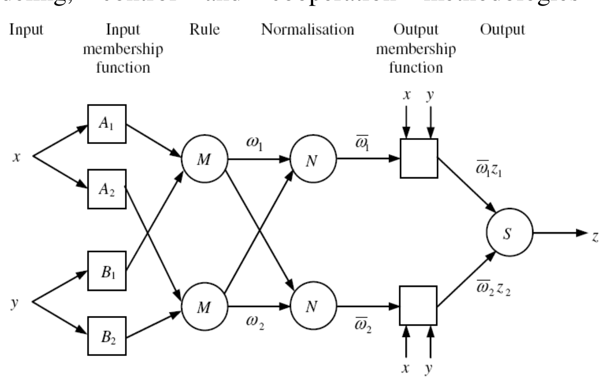

Fig. 1. ANFIS architecture to implement two rules.

distributed systems [8, 14]. Their applications especially in large-scale systems which have complex dynamic and spatially distributed and it is typically more convenient to decompose the system into smaller subsystems which can control locally, have been proved.

In robotic systems diagnosing variety of faults based on variety of components (including mechanical, electrical, etc.) using commonly in these systems make robotic system a complex problem for fault diagnosis. Moreover the structure of robots, nonlinearity of the dynamic and wide range of task space, forces us to use hierarchical diagnosis system to reduce complexity of the problem. Using hierarchical architecture enables us to use its advantages like robustness, reliability, scalability and cooperation nature with high degree of flexibility and more demanded in this application quickness.

In this work decomposing task is done based on distribution of sensors and actuators also considering dynamics of robots. 3-DOF robotic manipulator system is partitioned into 3 areas; Note that diagnosis agents are trained to diagnosis neighbor area's faults for supporting each other in diagnosis task. Putting overlap between duty space of agents (toward diagnosing specific fault) guarantees redundancy of diagnosis and prevents ambiguity in decision making level.

V. Decision Fusion in Supervisory Level

Data fusion can be used to integrate information from a multisensor data array to validate signals and create features. At a higher level, fusion may be used to combine features in intelligent ways so as to obtain the best possible diagnostic information. In higher level, decision fusion is used to incorporate different fusion provided by different approach to use maximum knowledge. The combined result would yield an improved level of reliability about the system condition. However, one of the main concerns in any fusion technique is the probability of achieving a worse result than the best individual tool. The solution to this concern is to weigh a priori the tools according to their capability and performance. The degree of a priori knowledge is a function of the inherent understanding of the physical system and the practical experience gained from its operating history.

In the Dempster-Shafer approach, uncertainty in the conditional probability is considered. Dempster-Shaffer theory permits us to assign probability-like weights to a set of events (here faults) in a way that allows statements of uncertainty about verisimilitude of some of the cases. From the assign of weights we get two numbers; the degree to which a case is supported by the evidence (Belief), and the degree to which there is a lack of evidence to the contrary (Plausibility). These two numbers are the basis on which any belief-based decision is made.

Given many assigns of belief to the same set of events, there is a natural way of combining them to give a fused allocation of belief that deals both with uncertainty and with conflict between the original beliefs; we can then derive Belief and

Plausibility for the ensemble, and base our decision on this more acquisitive data.

We quantify the degree to which there is support contrary to the event (and by an obvious extension, a set of events) being considered. These two numbers, plausibility and belief, provide the basis for deciding that one event is more representative of the truth than another. If both values for a given event are higher than the corresponding values for all other events, then that event is the obvious candidate. In general, the event with the highest plausibility need not be the same as the event with the highest degree of belief. In this situation, a heuristic must be used that reflects the required strategy of the decision maker.

We consider three masses: the bottom-line mass m that we require, being the confidence in each sensor and agents of the power set; the measure of confidence m_s from sensors (which must be modeled); and the measure of confidence m_o from old existing evidence (which was the mass m from the previous iteration of Dempster's rule). Dempster's rule of combination then gives, for elements A;B;C of the power set:

$$m(C)=\left[\sum_{A\cap B=C} m_s(A)m_o(B)\right]\Big/\left[1-\sum_{A\cap B=\varnothing} m_s(A)m_o(B)\right] \qquad (1)$$

Here in this paper we are going to investigate effect of sensor data fusion in fault diagnosis using Dempster's rule. There are six possible faults in each joint and we have two sensors in each joint. Sensor reliability was evaluated according to known characteristics, accuracy and range. We assign sensors' reliabilities according to some statistical experiments and previous knowledge on sensor characteristic in such systems which are:

In each join, reliability of position sensor is more than velocity sensor.

Reliability in the first joint elements is more than the second one and in second one is more than the third.

Dempster's rule of combination then is used to assimilate the evidence contained in the mass functions and to determine the resulting degree of certainty for detected fault modes. It can be viewed as a generalization of probability theory with special advantages in its treatment of ambiguous data and the ignorance arising from them.

VI. SIMULATION

A case study of 3DOF robotic manipulator is addressed for fault diagnosis purpose in this section. The studied manipulator simulated in Simulink® and controlled by an adaptive controller. A fault detection and isolation in robotic manipulator is considered. The robotic manipulator is modeled with three rigid links of length L_1, L_2 and L_3 and point masses m_1, m_2 and m_3 at the distal ends of the links. The dynamic model of a robotic manipulator is:

$$\tau = M(q)\ddot{q} + V_m(q,\dot{q})\dot{q} + G(q) \qquad (2)$$

where q_1, q_2, q_3, $\dot{q}_1$, $\dot{q}_2$ and $\dot{q}_3$ are vectors of joint positions and velocities, respectively, τ_1, τ_2 and τ_3 are the input torque vector, $M(q)_{3\times3}$ is the inertia matrix, $V_m(q,\dot{q})_{3\times3}$ is a matrix containing centripetal and coriolis terms and $G(q)$ is the gravity vector. It is suggested that a Model-Reference Adaptive controller would be added to the system for controlling the manipulator. The Adaptive controller can stabilize the closed-loop system. The control law of the adaptive controller is:

$$T = K_p e + K_v \dot{e} + M_p \theta_d + M_v \dot{\theta}_d + M_\alpha \ddot{\theta}_d \qquad (3)$$

where K_p, K_v, M_p, M_v and M_a are:

$$\begin{cases} K_p = \alpha\int e X_S^T + K_p(0) \\ K_v = \beta\int \dot{e} X_S^T + K_p(0) \end{cases} \quad \begin{cases} M_p = \lambda\int e\theta_d^T + M_p(0) \\ M_v = \mu\int e\dot{\theta}_d^T + M_v(0) \\ M_\alpha = \nu\int e\ddot{\theta}_d^T + M_\alpha(0) \end{cases} \qquad (4)$$

and $e = X_m - X_s$ and $\dot{e} = \dot{X}_m - \dot{X}_s$.

It is shown that the closed-loop system obtained by using (3) is asymptotically stable. The stability of the closed loop system is guaranteed for any positive definite K_p and K_v, with no a priori knowledge about the system dynamics. The robotic manipulator has three input torques (τ_1, τ_2 and τ_3) and six outputs (q_1, q_2, q_3, $\dot{q}_1$, $\dot{q}_2$ and $\dot{q}_3$).

Although an adaptive controller can eliminates the faults effect after a while and take back the control of damaged or faulty (although by using wrong data acquired from faulty sensors) but diagnosing the real cause of the manipulator helps us through more reliable fault tolerant controller and maintenance purpose of manipulator.

Sensor and Actuators must accurately sense/deliver the determined value. The gains are one ($f_\alpha = 1$) while the robotic manipulator is intact. An actuator fault alarm will be set on when one of the actuators do not deliver the controller signal. Mathematically, it means that the actuator gain has become a number smaller than one.

In the proposed method, for diagnosis of the fault, no extra measurement or preprocessing is required for feature extraction. Following facts considered in the fusion process:

Position and velocity sensor faults can be approved or denied regarding velocity and sensor fault. Cross correlation between variables helps us to diagnosis sensor faults by using cluster based fusion in sensor level, here all sensor data considered in diagnosis process all Actuator fault can be detect in both position and velocity sensors in the same joint. This fact can be used for confirmation as well as combining the features existing in two recording signals.

Abnormal or large changes in the magnitude of controller signal determine an actuator fault. - If the fault represents a behavior that cannot be classified in the above categories, the fault belongs to "plant's component fault" category.

It is vital to detect all faults in minimum possible time after their occurrences. Manipulator links should track special paths. Hence, the desired position and velocity of each link, at each instance, is predetermined. For fault detection, the difference between the position sensor and velocity sensor and model output are calculated. The desired trajectory for all links is considered to be continuous sinusoidal signal and frequency of 1/2π Hz. In simulation, some faults that occur at diverse times and result in abnormal conditions in robotic manipulator performance are considered.

The cross-dependence between the position and velocity measured signals (angle and angular velocity) is a major issue considered in dedicating duties to diagnosis agents and designing supervisory logic. If any fault occurring due to joints or manipulator both position and velocity sensors will report effects. If any damage occurs to position sensor which is directly using by controller, diagnosis agents would find out by using both position and velocity sensor.

These facts are obvious in Figs. 2 and 3 which shows the effect of actuator fault in sensor and velocity sensor of joint number 1.

Moreover, due to highly couple dynamic of the robotic manipulator, any actuator fault in any of joints would be detected in other joint sensor as shown in Fig. 4 as well as sensor faults shown in Fig. 5. These two facts play a main role through decision fusion in supervisory unit. The availability of diagnosis of fault in neighbor areas by neighbor agents needs overlapping of agent's duty. It may also seems extra computational task, but it must be noted that diagnosis of faults by neighbor agents brings the overall system extra redundancy and reliability.

Through the isolation phase, the joint position and velocities residual are utilized ANFIS inputs (the residual of the joint positions is a small range signal and must be amplified). The ANFIS outputs are trained to present integer number in output (i.e. signal 1 in the case of fault number 1) and 0 in healthy.

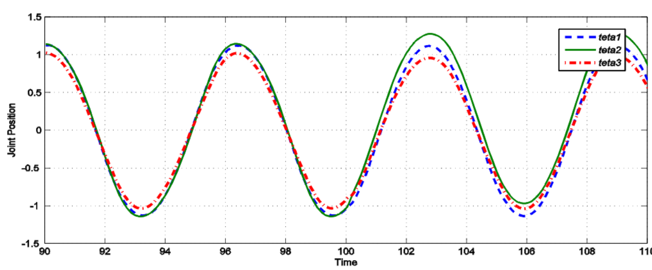

Fig. 2. Joint No. 1, actuator fault in position/angle sensor.

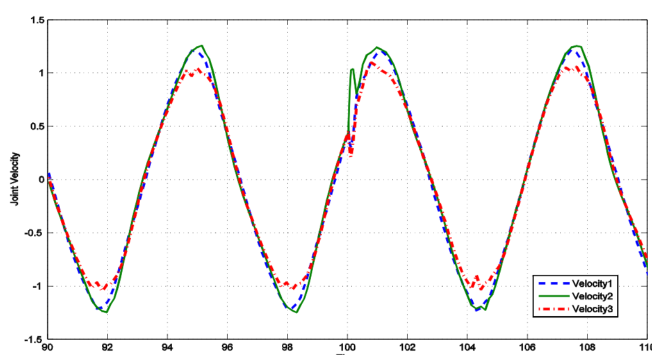

Fig. 3. Joint No.1, actuator fault in velocities sensor.

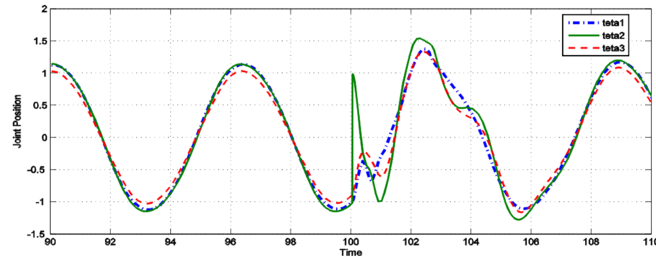

Fig. 4. Fault No. 1 in joint 2 recorded in position sensor No. 1.

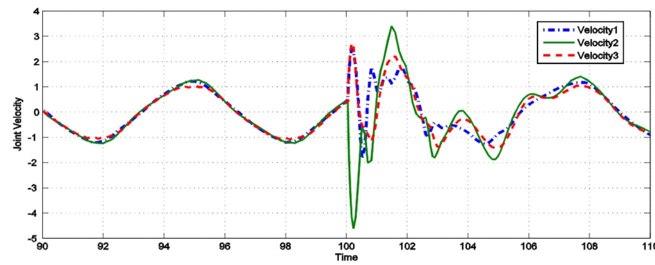

Fig. 5. Joint 2 of position sensor fault recorded in velocity sensor 1.

The fault criteria are: five consecutive signals in the ANFIS output have to be greater that 0.5 to a fault to be detected. The sensitivity of FDI system can be prejudiced adopting these criteria. However, if the sample rate is low, it does not represent a serious problem. For each fault a dedicated ANFIS classifier has been occupied to discriminate between two normal and faulty states. This strategy has been used to maximize the efficiency of diagnosing in time and computational burden aspects, according to size and nonlinearity of target dynamic. If all the faults in were put in single diagnosis unit or using just one central fault diagnosis agent ,as it is usual ,it will make the diagnosing process slower and the classification accuracy lower. Simulated faults details are given in Table I.

After training 15 different faults related to each joint Sensor reliability in Table II is evaluated according to known characteristics, accuracy and range.

Here experiment's data with the standard Dempster-Shafer

TABLE I
SIMULATED FAULTS DETAILS

Fault Type	**Place of Occurrence**	**Observed in Sensors**
Joint Lock	Actuator	Position and Velocity of Each Joint
Actuator Gain	Actuator	Position and Velocity of Each Joint
Actuator Bias	Actuator	Position and Velocity of Each Joint
Sensor Bias	Position/Velocity Sensor	Velocity/Position of Each Joint
Sensor Lost	Position/Velocity Sensor	Velocity/Position of Each Joint

TABLE II
RELIABILITY OF SENSOR BASED ON STATISTICAL STUDIES

	Fault	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6
	Sensor	Reliability (percent %)					
Joint 1	Position	66	68	60	72	74	76
	Velocity	64	66	68	70	72	74
Joint 2	Position	64	66	68	70	72	74
	Velocity	62	64	66	68	70	72
Joint 3	Position	62	64	66	68	70	72
	Velocity	60	62	64	66	68	70

method results are shown in Table III. In the Table III, the reliability in each agent for different fault shown and final result for overall diagnosis system show the efficiency of proposed method.

The proposed method using separate diagnosis agent on each joint of robot, each are capable to diagnose different type of fault by using multiple ANFIS, and a supervisory unit using Dempster-Shaffer based decision fusion to localize the exact place of occurred fault by the data it receive from the diagnosis agents. This decentralization of diagnosis task helps us to diagnose and localize the fault in any demanded robot with any degree of freedom as well as mobile robots, with a rather fast and accurate efficiency. Using fusion in supervisory level help the overall system improve its efficiency in a meaningful way Simplicity and transparency in structure, high accuracy and speed, conformation with human's experience, no need for extra measurement or pre-processing are some advantages of the proposed method.

The generalization of this method relies on using distributed diagnostic agents for different parts of the system and considering relations in robotics systems in fusion process which would occur in supervisory level.

VII. CONCLUSION

This paper presented computationally simple, fast and accurate expert system for fault diagnosis of robotic systems. In this paper, a hierarchical fault diagnosis for large faults number applying to unknown nonlinear systems was investigated. Simplicity, transparency, rapidity and generalization are the dominant features of the proposed technique. Neuro-fuzzy modeling capabilities were employed to create some transparent models using fault-free input-output data. The proposed method can be extended to other applications with little modifications.

TABLE III
DECISION FUSION RESULTS IN SUPERVISION LEVEL

Fault No.	Joint 1	Joint 2	Joint 3	Diagnosis
	Belief Value in percent			Efficiency
1	97.76	97.12	96.4	99.99770%
2	98.32	97.76	97.12	99.99890%
3	98.8	98.32	97.76	99.99950%
4	99.2	98.8	98.32	99.99980%
5	99.52	99.2	98.8	100.00000%
6	99.76	99.52	99.2	100.00000%

REFERENCES

[1] P. Frank, “Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy. A survey and some results,” Automatica, Vol. 26, pp. 459−474, 1990.

[2] R. Isermann, “Process fault detection based on modeling and estimation methods—A survey,” Automatica, Vol. 20, 1984.

[3] Gertler, “Survey of Model-Based failure Detection and Application in Complex Plants,” in Control Magazine, 1989.

[4] F. L. George Vachtsevanos, Michael, Roemer, Andrew Hess, Biqing Wu, “Intelligent fault diagnosis and prognosis for engineering systems,” John Wiley & Sons, Inc., 2006.

[5] L. Xiong, J. Liang, and J. Qian, “Multivariate Statistical Process Monitoring of an Industrial Polypropylene Catalyzer Reactor with Component Analysis and Kernel Density Estimation,” Chinese Journal of Chemical Engineering, Vol. 15, pp. 524−532, 2007.

[6] O. M. Al-Jarrah and M. Al-Rousan, “Fault Detection and Accommodation in Dynamic Systems using Adaptive Neuro Fuzzy Inference Systems,” Vol. 148, IEE Proc-Control Theory App, 2001.

[7] H. Schneider and P. Frank, “Observer-Based Supervision and Fault Detection in Robot Using Nonlinear and Fuzzy Logic Residual Evaluation,” IEEE Transaction On Control Systems Tech, Vol. 4, 1996.

[8] Y. Pencole and M.-O. Cordier, “A formal framework for the decentralised diagnosis of large scale discrete event systems and its application to telecommunication networks,” Artificial Intelligence, Vol. 164, pp. 121−170, 2005.

[9] V. Palade, C. D. Bocaniala, and L. Jain, “Computational Intelligence in Fault Diagnosis,” Springer, 2006.

[10] J.-D. Wu, Y.-H. Wang, and M. R. Bai, “Development of an expert system for fault diagnosis in scooter engine platform using fuzzy-logic inference,” Expert Systems with Applications, Vol. 33, pp. 1063−1075, 2007.

[11] H. A. Talebi and K. Khorasani, “An intelligent sensor and actuator fault detection and isolation scheme for nonlinear systems,” in IEEE Conference on Decision and Control, 2007, pp. 2620−2625.

[12] A. T. Vemuri, M. M. Polycarpou, and S. A. Diakourtis, “Neural Network Based Fault Detection in Robotic Manipulators,” IEEE Tran. on Robotic and Automation, Vol. 14, 1998.

[13] Skoundrianos E.N and Tzafestas S.G, “Finding fault - fault diagnosis on the wheels of a mobile robot using local model neural networks,” in IEEE Robotics & Automation Magazine, Vol. 11, 2004, pp. 83−90.

[14] R. Olfati-Saber and N. F. Sandell, “Distributed tracking in sensor networks with limited sensing range,” in IEEE American Control Conference, 2008, pp. 3157−3162.

[15] R. C. Luo, M. G. Kay, “Multisensor integration and fusion in intelligent systems,” IEEE Transactions on Systems, Man and Cybernetics 19 (5), 1989, pp. 901−931.

[16] S. Thrun, W. Burgard, D. Fox, “Probabilistic Robotics,” MIT Press, MA, 2005.

[17] M. A. Abidi, R. C. Gonzales, “Data Fusion in Robotics and Machine

[18] Intelligence,” Academic Press, San Diego, CA, 1992.

[19] R. R. Brooks, S. S. Iyengar, “Multi-Sensor Fusion,” Prentice Hall, New York, NY, 1998.