COMPUTERIZED MONITORING

Computerized monitoring is the art of extracting information from a system through computer processes for various purposes. Computerized monitoring and inspection encompasses a wide range of applications in various industries. One common application is to evaluate the condition of a system or to inspect the integrity of its components for diagnostic purposes. The concept behind a computerized monitoring system for diagnosis is to provide information on component faults by comparison of actual observations with models of normal behavior. The approach is to seek mechanisms and procedures that can detect deviations from normal operation at an early stage. Other applications include, but are not limited to, control, industry automation, manufacturing processes, aerospace engineering, laboratory automation, quality control, and robotics.

A computerized monitoring system has two major components, hardware and software. The hardware components of a typical computerized monitoring system consist of transducers (or sensors), signal conditioning, data acquisition hardware interface, and the computer itself (Fig. 1). The basic requirements for the hardware components are reliability, accuracy, cost-effectiveness, and speed.

The software component of the computerized monitoring system should provide effective information display, determine the status of the system (i.e., pattern recognition and diagnosis), and, if appropriate, provide decision-making capability. These components are generally designed with the following items in mind: reliability, speed, visual effect (i.e., effective information display), user friendliness, ease of maintenance, and provisions for upgrading.

The software component frequently incorporates soft computing technologies. Soft computing consists of methodologies that resemble the real-world model pertaining to imprecision and uncertainty. The best example of a real-world model for soft computing is the human mind. Soft computing encompasses technologies including, but not limited to, expert systems, artificial neural networks, fuzzy logic, genetic algorithms, computer vision and image processing techniques, data mining techniques, and hypermedia databases.

The input variables to a monitoring system could be anything that can bear the information about the monitored object. Examples are the current waveform of a circuit, output torque of a motor, image of an object, speed of a car, power of a nuclear reactor, or position of a spacecraft. Transducers sense the monitored variables of the system and produce the electrical signal. Typically, these are signals that must be preprocessed before they are introduced into the monitoring system software. The preprocessing (i.e., digital signal processing [DSP]) may involve filtering, digitizing, sampling, or normalizing to a certain maximum value (1,2). Some technologies that are applied in DSP include, but are not limited to, filter design, wavelets techniques, fast Fourier transform (FFT), time–frequency analysis, and time–scale analysis. Signals from components of a system carry valuable information regarding the condition of the components or the system as a whole. For example, analysis of vibration data is helpful in identifying operational problems in rotating machinery. The main function of soft computing technologies is to extract this information and to identify its correlation with the condition of the system. Computerized monitoring uses these signals and with the aid of soft computing techniques and algorithms monitors the status of the system or its components.

With the improvements in computer technology, modern instrumentation systems have the capacity to acquire a prodigious amount of data from a wide variety of sensor types, leaving the software component as the main standard by which to evaluate a computerized monitoring system. In addition, each application would require a software component with appropriate customized soft computing techniques and algorithms that are unique to the specific application.

The first basic steps in designing a computerized monitoring system are to

1. identify target parameters to be monitored,
2. design the structure of data acquisition hardware and necessary signal preprocessing,
3. design and develop the algorithm of the soft computing component of the software and design the user interface and display format, and
4. reexamine the system for reliability, cost, maintenance, and updating capability.

We will demonstrate basic concepts in computerized monitoring with two examples of monitoring and inspection applied in the nuclear industry. One uses signals from a data acquisition system and the purpose of monitoring is diagnosis and fault identification using artificial neural networks (3). The other example demonstrates an inspection system for the purpose of quality control using image analysis methodologies and fuzzy logic algorithms. In addition, a brief description of the concept of an artificial neural network and fuzzy logic, which are currently the two most popular soft computing technologies, will be provided.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks have become popular tools for pattern recognition and signal classification (4). They offer great potential for successful application in computerized monitoring systems.

Artificial neural networks (ANNs) are information processing systems motivated by the goal of reproducing the cognitive processes and organizational models of neural biological systems. The individual computational processor that makes up most artificial neural systems is referred to as a processing element (PE). Each PE (also called neuron) has many inputs, but has only a single output, which can fan out to many other PEs in the network. Each connection to the ith PE has associated with it a quantity called a weight or connection strength. The weight on the connection from the jth node to the ith node is denoted W_{ij}. Figure 2 shows a processing element. The specific characteristics of an ANN is a

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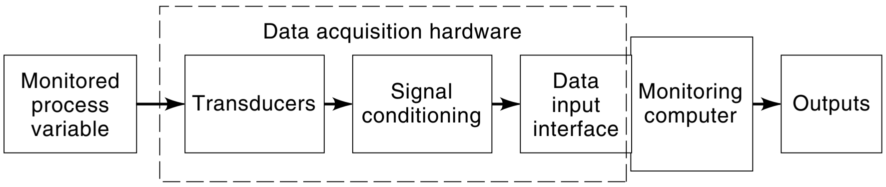

Figure 1. The minimum necessary hardware components needed to design a computerized monitoring system and the flow of information.

result of the network paradigm used. The network paradigm is specified by the network architecture and neurodynamics.

Neurodynamics and Learning Mechanisms

Neurodynamics specifies how the inputs to the PE will be combined, what type of function or relationship will be used to develop the output, and how the weights will be modified.

The inputs to the PEs are weighted and are often combined using the summation function. This is called the "interval activation." This interval activation is used to generate the output of the neuron using a continuous or noncontinuous transfer function.

The learning mechanism that handles modifications to the weights and any other organization of the network can be classified under supervised learning, unsupervised learning, or self-supervised (reinforcement) learning. Supervised learning takes place when the network is trained using pairs of inputs and desired outputs. In unsupervised learning inputs are entered and the network is able to organize its own categories. Self-supervised learning adds the feedback to unsupervised learning to correct errors in the pattern recognition process.

Network Architecture

The network architecture defines the arrangement of processing elements and their interconnections. This establishes which PEs are interconnected, the inputs to and outputs from PEs, the group or layers of PEs, and how the information flows in the network. Figure 3 shows several examples of neural network architectures.

One of the most popular feedforward neural networks that iteratively determines the weight is the backpropagation Network (BPN) [Fig. 3(a)]. A simple learning algorithm that modifies the weights between output and hidden layers is called a delta rule (5). The backpropagation algorithm is an extension of the delta rule that can train the weights, not only between output and hidden layers but also in hidden and input layers. A sequential network feeds its output back to the input units of the network [Fig. 3(b)]. A competitive neural network is a kind of unsupervised network. It employs a competitive learning algorithm that strengthens the weights

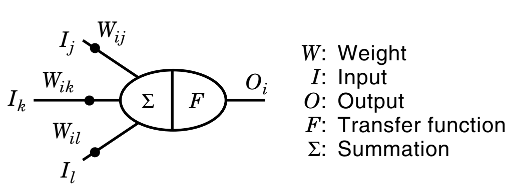

Figure 2. A processing element and its components. Two mathematical functions (Σ and F) are applied to the input in order to create the output. For a Sigmoid transfer function: $F = (1 + e^{-\Sigma})^{-1}$.

connected to the unit whose output is the biggest [Fig. 3(c)]. Weights are normalized to avoid increase without upper bound. Because only one unit becomes active as the winner of the competition, the network is called a winner-take-all network.

An adaptive resonance theory (ART) network has the ability to learn many new things without necessarily forgetting things learned in the past. Patterns of activities that develop over the nodes in the two layers of the attentional subsystem [Fig. 3(d)] are called short-term memory (STM) traces because they exist only in association with a single application of an input vector. The weights associated with the bottom-up and top-down connections between F_1 and F_2 layers are called long-term memory (LTM) trace because they encode information that remains a part of the network for an extended period.

Among the different rules and procedures developed, the handful mentioned here are accepted by the community: backpropagation, counterpropagation, Kohonen feature maps, bidirectional associative memory, neocognitron, Hopfield, and adaptive resonance theory, including ART2, ART2-A, FuzzyART, ARTMAP, and FuzzyARTMAP (6,7).

Supervised neural networks do not require a prior fault-related parameter to be identified and generate their own rules by learning from being shown original examples. This characteristic of the artificial neural network makes it attractive for monitoring purposes and diagnostic applications.

AN EXAMPLE OF COMPUTERIZED MONITORING SYSTEM FOR DIAGNOSIS

Keyvan et al. (3) have developed a prototype of a simple diagnostic monitoring system using several artificial neural networks. The system integrates the result of neural network pattern recognition with a preexisting database to classify faulty signal and through an expert system to identify the fault. The system is developed in an X-windows environment and uses Motif in a UNIX environment to build the graphical user interface (GUI). It is user-friendly and menu-driven, allowing the user to select signals and choose several neural network paradigms including ART2 and ART2-A. The system provides the status or condition of the signals tested as either normal or faulty. In the case of faulty status, the system identifies the fault and indicates the progress of the fault relative to normal as well as relative to the previous tests.

The signals used here are divided into two groups, the actual collected signal and the simulated signals. The collected signal is the pump power signal of the Experimental Breeder Reactor-II (EBR-II) nuclear plant; it was collected from the sensors by the plant data acquisition system on 1/29/91. This signal is used to simulate and generate faulty signals representing several levels of reactor pump shaft degradation. Figure 4 shows the plot of the collected signal data and a faulty

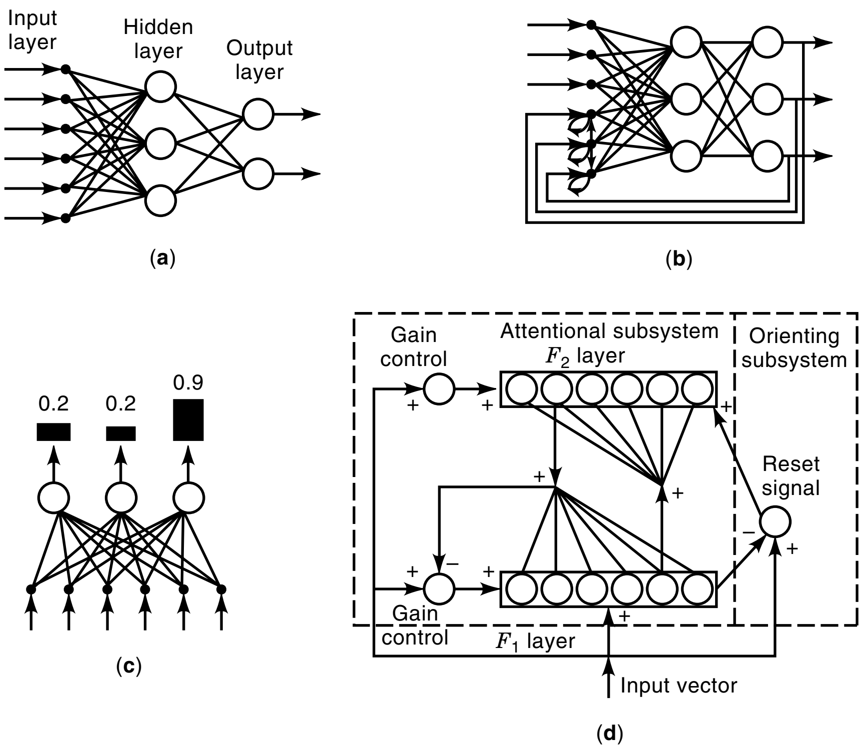

Figure 3. Examples of neural network architectures: (a) feedforward neural network, (b) sequential network, (c) competitive network, (d) ART neural network.

signal data for a 50 s time period. A comparison of these two plots reveals the sensitivity that is required of a soft computing algorithm to distinguish these signal patterns.

The neural network runs in the background and classifies the given input signal into one of three categories : normal, faulty, or unknown signal. When the signal is identified as normal or faulty, a status report is displayed as shown in Fig. 5. Note that, in the case of the faulty status report, a sample plot of the normal signal is also shown for comparison. A description of the fault can be obtained by selecting the Describe Fault button shown in Fig. 5. The fault description corresponding to the current faulty signal is identified from the existing fault data base and is displayed at this point. The faults are described as “Degradation Level 1,” “Degradation Level 2,” etc. When a new fault different from the ones currently registered in the database is encountered, the fault description will be “Unidentified fault,” as shown in Fig. 6. Figures 5 and 6 are the actual computer screen of the diagnostic monitoring system output showing a typical information display.

FUZZY LOGIC

Fuzzy logic is often incorporated in a computerized monitoring system to better model the causal effect between a system condition and its measurable signal variables.

In the real world, we often must deal with fuzzy concepts or variables such as high speed, low temperature, and strong signal. Fuzzy logic provides a means to specify fuzzy concepts. Fuzzy theory provides a means for representing these uncertainties and this vagueness. In fuzzy logic, the domain of each variable is quantified into a finite number of fuzzy concepts. For example, the variable *temperature* may be fuzzily quantified into low, medium, and high. Application of fuzzy logic is most suited in (1) very complex models where understanding

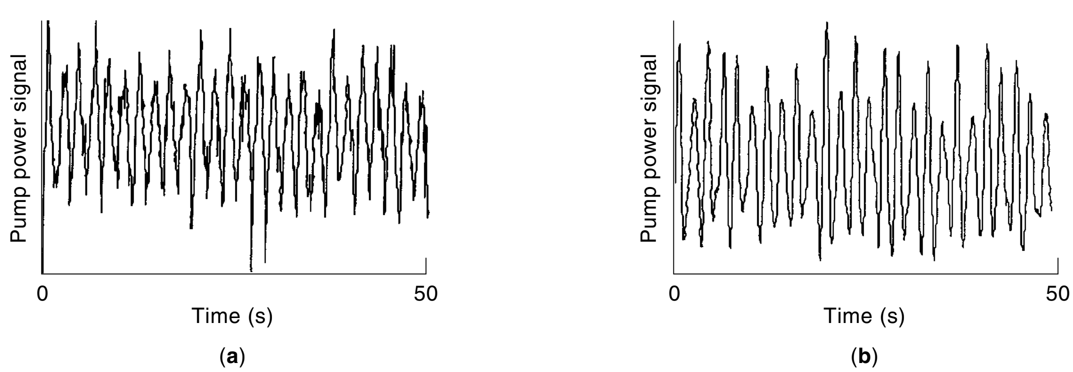

Figure 4. (a) Plot of pump #1 collected power signal for a 50 s time period; (b) plot of pump #1 simulated faulty signal for a 50 s time period.

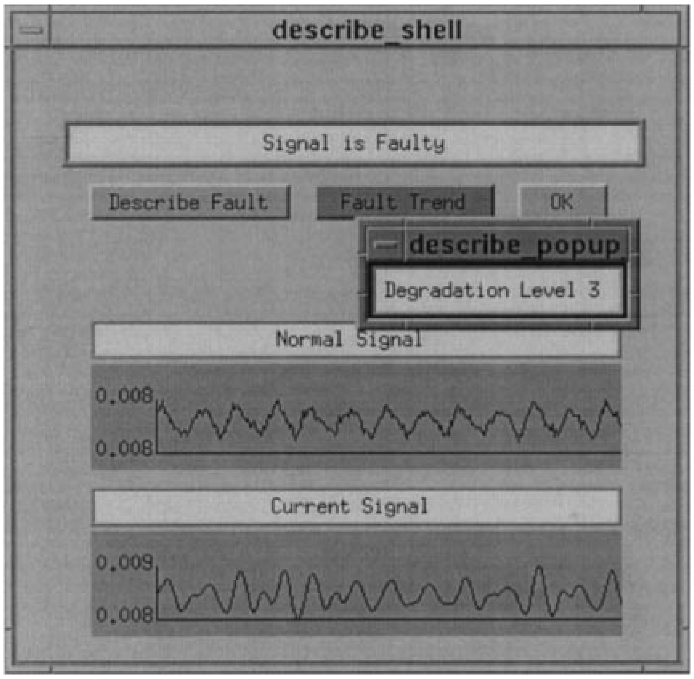

Figure 5. User interface showing the status report of a faulty signal. By choosing the “Describe Fault” option button, the user is provided with another window describing the nature of the fault, i.e., “Degradation Level 3” in this case.

is strictly limited or, in fact, quite judgmental, and (2) processes where human reasoning, human percepiton, or human decision making are inextricably involved.

Implementing fuzzy systems into computerized monitoring often relies on a substantial amount of heuristic observation to express the behavior of the system. However, the practical development of such systems presents two critical problems: finding the domain-dependent rules and tuning these rules and their membership functions (8). The conventional method first generates the initial rules and their membership functions and then refines the rules and membership functions to optimize the final system’s performance by trial and error. The input features (signals) are mapped into the fuzzy membership value based on the fuzzy membership function (fuzzification). A membership value describes the degree of which the current parameter belongs to the defined category.

As an example, a fuzzy system with two noninteractive inputs x and y (antecedents) and a single output z (consequence) is described by a collection of r linguistic IF-THEN propositions. The fuzzy rule has the following format:

$$\text{IF } x \text{ is } A_1^k \text{ and } y \text{ is } A_2^k \text{ THEN } z^k \text{ is } B^k \text{ for } k = 1, 2, \ldots, r$$

where A_1^k and A_2^k are the fuzzy sets representing the kth antecedent pairs, and B^k are the fuzzy sets representing the kth consequence. z^k is the fuzzy variable, and B^k is a fuzzy quantifier for the domain of z^k.

The fuzzy system maps an input to an output in three steps. The first step matches the input to all the IF-part fuzzy sets in parallel. This step “fires” or “activates” the rules according to the degree to which the input belongs to each IF-

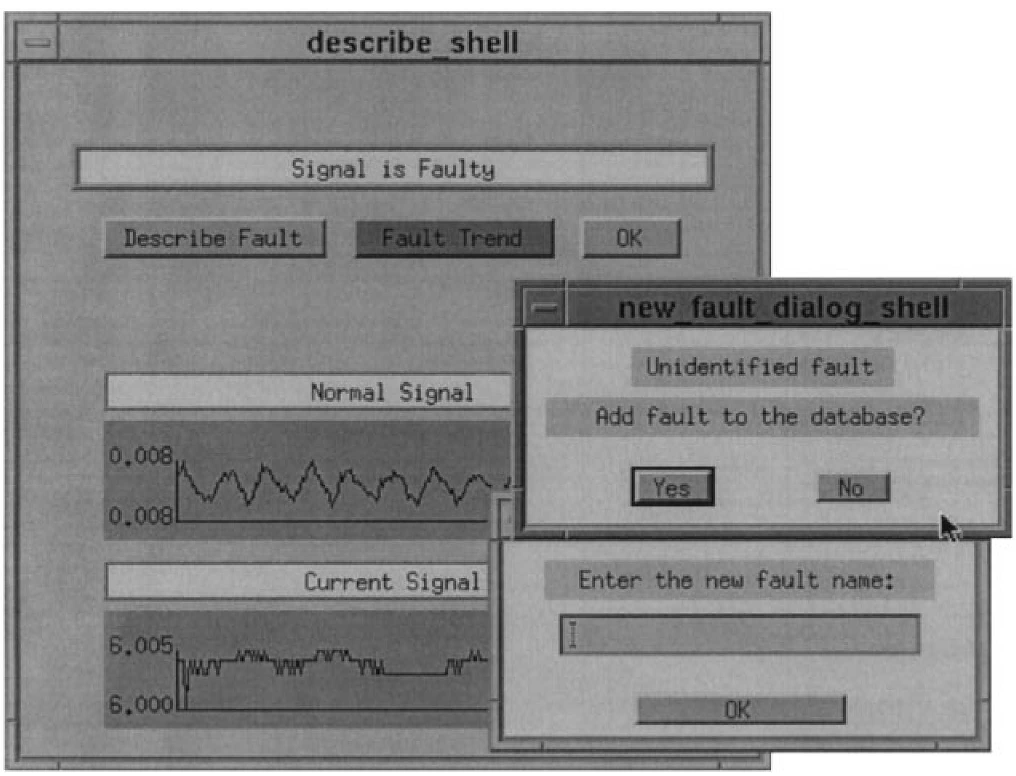

Figure 6. User interface describing a faulty signal outside of the database. By selecting the “yes” option, the user is provided with an entry box to describe the new fault.

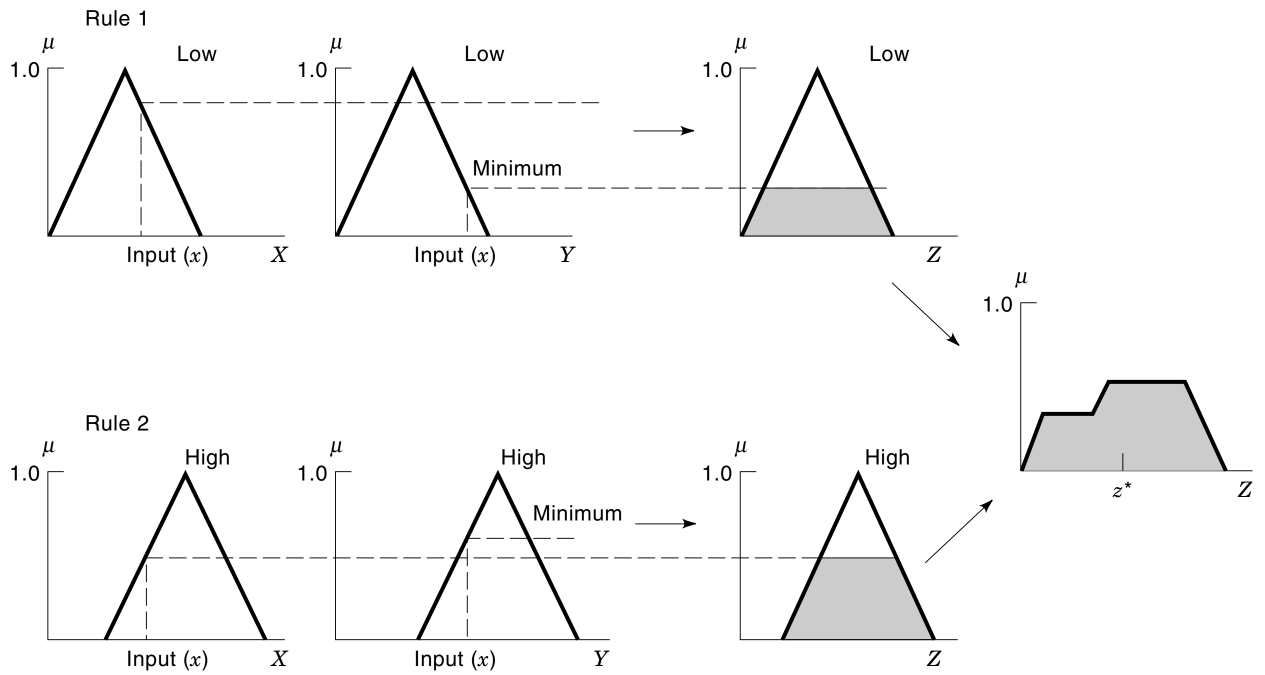

Figure 7. Graphical (max–min) inference method with crisp input (X, Y). The inference in this example is done for each rule with a minimum membership function, resulting in the shaded area of the triangles. The final output is the result of aggregation of the two shaded areas based on the disjunctive relations between these two rules.

part set. Each input fires a corresponding rule or rules. Then each fired IF-part set scales its THEN-part set. The second step adds all scaled THEN-part sets into a final output set. The third step is defuzzification. The system computes the output as the centroid or center of gravity of this final output set.

Most fuzzy systems involve more than one rule. The process of obtaining the overall consequence (conclusion) from the individual consequence contributed by each rule in the rule base is known as aggregation of rules. Fuzzy systems differ in how they fire rules and how they combine the fired rules. Aggregation strategy is based on the two extreme existing cases—conjunctive system and disconjunctive system.

In the case of a system of rules that must be jointly satisfied (conjunctive), the rules are connected by *and* connectives. In this case, the aggregated output (consequence) y is found by the fuzzy intersection of all individual rule consequent. The overall output membership function is

$$\mu_z(z) = \min[\mu_{z1}(z), \mu_{z2}(z), \ldots, \mu_{zr}(z)]$$

For the disjunctive system of rules where the satisfaction of at least one rule is required, the rules are connected by the *or* connectives. In this case, the aggregated output is found by the fuzzy union of all rule contributions, as

$$\mu_z(z) = \max[\mu_{z1}(z), \mu_{z2}(z), \ldots, \mu_{zr}(z)]$$

Suppose we have the two following fuzzy rules that are activated for input (x, y) in the fuzzy system.

Rule 1. IF X is low and Y is low, THEN Z is low.
Rule 2. IF X is high and Y is high, THEN Z is high.

The pictorial representation of the fuzzy mapping process with the input of x and y is shown in Fig. 7. Because the antecedent pairs given in the general rule structure for this system is connected by a logical *and* connective, each rule applies the THEN part with a minimum membership grade. The minimum membership value for the antecedents propagates through to the consequence and truncates the membership for the consequence of each rule. The inference (process of applying fuzzy system) is done for each rule. Then the truncated membership functions for each rule are aggregated. For a set of disjunctive rules, the aggregated output for a max–min inference or composition is given by

$$\begin{aligned}\mu(Z) = \max[&\min[\mu_{z1}(\text{input}(x)), \mu_{z1}(\text{input}(y))],\\ &\min[\mu_{z2}(\text{input}(x)), \mu_{z2}(\text{input}(y))] \cdots\\ &\min[\mu_{zr}(\text{input}(x)), \mu_{zr}(\text{input}(y))]]\end{aligned}$$

where r is the number of the rules that have been activited.

An Example of Software Component of Computerized Monitoring System for Inspection

Our second example demonstrates a computerized inspection of quality of a nuclear fuel pellet. Fabricated pellets must be of high quality before being placed into the fuel assemblies and into service in the core of a nuclear reactor. Computerized inspection in this application is expected to increase accuracy and speed of inspection and will reduce the radiation exposure of the workers. The structure of this computerized inspection system is shown in Fig. 8.

First, the input signal (the image of the fuel pellet) is acquired (using a camera) and converted to the digital signal; then, it is converted to an 8-bit gray-scale mode. Next a refer-

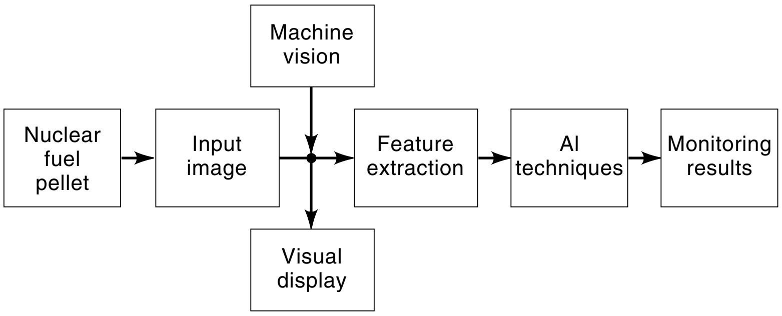

Figure 8. The structure and components of the computerized inspection system. The input images are created using a camera. Important features are extracted using machine vision techniques. The final results are obtained by applying artificial intelligence techniques to these extracted features.

ence model is generated to check the presence of a defect on the pellet image. For the nuclear fuel pellet, it is challenging to generate a universal model representing a good pellet to be checked against a defective pellet image. This is because the gray-scale value of the pixels on the same area for any two good pellets may vary greatly because of the high noise, different manufacturing process, and small variations in pellet size. For this reason, a dynamic reference model is generated on-line for each pellet individually.

The shape of gray-scale intensity distribution of the pellet image reflects the presence of a defect very well. A dynamic reference is generated by finding those rows of pixels with a distribution very close to that of a good fuel pellet. A set of good fuel pellets was selected, and their distribution surface was processed to create the reference surface model. Each row of the target image is used to match the distribution of this reference model by using

$$S = 1.0 - \sqrt{\frac{(I_{r1} - I_1)^2 + (I_{r2} - I_2)^2 + \cdots + (I_m - I_m)^2}{m}}$$

where

S = the degree of match;
m = the number of total pixels in each row of fuel pellet image;
I_i = the intensity of ith pixel in the current row; and
I_{ri} = the intensity of ith pixel in the rth reference model.

The best matching row is selected as the dynamic standard reference to reexamine the entire pellet image. Those pixels whose intensities are below or above the reference value (beyond a preselected tolerance value) are regarded as abnormal pixels and are classified into two categories—abnormal dark and abnormal light. We call those pixels above the reference distribution abnormal light and those below the reference distribution abnormal dark.

By using this dynamic model search approach, a defect is enhanced for the next step (i.e., pattern recognition). Next, six features are extracted from this enhanced defect information pool. Table 1 lists these features and their relations with the status of the input image, where each possible status of a pellet can be uniquely identified from the corresponding feature values. Each value of the feature, which is a fuzzy membership value, encodes the quality criteria of a fuel pellet.

The relation between pellet status and feature value, which are fuzzy rules, map the human inspection knowledge. The IF-THEN fuzzy rules are:

IF Abnormal dark area size is big;
$\wedge$ Abnormal light area size is zero;
$\wedge$ No related closing abnormal dark area and light area;
$\wedge$ Shape factor is small;
THEN
Banded defect.

FUTURE OF COMPUTERIZED MONITORING AND INSPECTION

Each soft computing technique has unique properties and advantages. Hence, increasing integration of a number of such techniques into a computerized monitoring system is anticipated in the near future (9,10). For example, as already mentioned, neural networks consist of highly interconnected processing units that can learn and globally estimate input–output functions in a parallel-distribution framework. Fuzzy logic systems store and process rules, with output fuzzy sets associated with input fuzzy sets in parallel. The similar parallelism properties of neural nets and fuzzy logic systems make their integration more suitable to the study of the behavior of systems that are imprecisely defined by virtue of their high degree of complexity. Because of their great learning capability, neural networks have been combined with fuzzy logic sys-

Table 1. Relationships Between Fuel Pellet Condition and Feature Value

Fuel Pellet Condition	Size—Abnormal Dark Area	Size—Abnormal Light Area	Closeness of Dark Area to Light Area	Shape Factor of Dark Area	Distance (relative to end of pellet)
Good	Zero	Zero	—[a]	—[a]	—[a]
End defect	—[a]	Big	—[a]	—[a]	Big
Banded	Big	Zero	Zero	Small	—[a]
Crack	Big	Zero	Zero	Big	Small
Chipped	Big	Big	Big	Small	—[a]

[a] No relation exists.

Table 2. Listing of Vendors of Sensors, Transducers, and Data Acquisition Boards

Production	Company	Comments
Acceleration sensors, chemical sensors, pressure sensors, biomedical sensors	Motorola Sensor Products Division Motorola Literature Distribution P.O. Box 20912 Phoenix, AZ 85036 http://design-net.com/senseon/	Sensing acceleration and deceleration for automotive, industrial, and commercial applications
Pressure sensors, disposable medial sensor, integrated accelerometer	Lucas NovaSensor 1005 Mission Court Fremont, CA 94539 (800) 962-7364 (510) 661-6000 http://www.novasensor.com/	Sensing the solid state pressure
Position sensors	BEI Sensor & Systems Company Industrial Encoder Division 7230 Hollister Avenue Goleta, CA 93117 (805) 968-0782 http://www.systron.com	A major supplier of inertial sensors and subsystems throughout the aerospace, vehicle dynamic control, navigation, intelligent cruise control, precision farming and vehicle location systems, and so on
Shock sensors, airbag sensors, ultrasonic sensors, pyroelectric infrared sensors, temperature sensors, rotary sensors, magnetic pattern recognition sensor, electric potential sensors	Murata Erie North America 2200 Lake Park Drive Smyrna, GA 30080 http://www.iijnet.or.jp/murata/	Provides various kinds of sensors
Sensor highway	Vibra·Metrics, Inc. 1014 Sherman Avenue Hamden, CT 06514 (203) 288-6158	Provides access to hundreds of predictive maintenance and process sensors using the industry standard Sensor Highway. Vibralarm is a PC-based software package that drives Sensor Highway and acquires sensor data for supervisory alarm reporting
Data acquisition boards	American Data Acquisition Corporation 70 Tower Office Park Woburn, MA 01801	Provides boards that work with DriverLink, Snap-Master, LABTECH NOTEBOOK, LabVIEW, and LabWindows/CVI
Data acquisition boards	ComputerBoard Inc. 125 High Street Mansfield, MA 02048 (508) 261-1123	Provides UniversaLibrary Programming's interface for Windows and DOS languages such as C/C++, Visual Basic, Borland C/C++, Watcom C, and Pascal
Data acquisition boards, signal conditioning products	National Instruments Company 6504 Bridge Point Parkway Austin, TX 78730 (512) 794-0100 http://www.testardmeasurement.com	This company is well known for its software products such as LabVIEW and LabWindows/CVI

Table 3. A List of Related Resources on Computerized Monitoring Technology

Web address	http://www-dsp.rice.edu
Journal	*Expert Systems with Applications* *Journal of Acoustic Emission* *Artificial Intelligence in Engineering* *Computers & Industrial Engineering* *Control Engineering Practice*
Conference	International Conference on Monitoring, Acoustics Speech, and Signal Processing International Conference on Robotics and Automation International Conference on Intelligent System Application to Power System
Transactions	*IEEE Transactions on Power Systems* *IEEE Transactions on Professional Communication* *IEEE Transactions on Control Systems Technology* *IEEE Transactions on Instrumentation and Measurement* *IEEE Transactions on Fuzzy Systems*

tems to form the initial rules of fuzzy systems and tune the rules and membership functions to manage the fuzzy system efficiently and accurately. In addition, fuzzy microprocessors, called fuzzy chips, have been successfully applied in control and robotics. Hence, it is natural to predict a more intense future application of integrated neural networks and fuzzy logic in computerized monitoring and inspection. In addition, soft computing technologies are the core of computerized monitoring and inspection. Therefore, it is expected that new advancements in these technologies, such as computer vision and data mining techniques, would greatly affect the future of computerized monitoring and inspection.

RESOURCES AND VENDOR INFORMATION

Information on several vendors of sensors, transducers, and data acquisition boards useful in computerized monitoring applications are provided in Table 2. This is not an exhaustive list of all vendors. Table 3 provides a sample of resources on the subject of computerized monitoring and inspection for interested readers.

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COMPUTERIZED NAVIGATION. See AIR TRAFFIC.