Fault Diagnosis of an Industrial Machine Through Sensor Fusion

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FAULT DIAGNOSIS OF AN INDUSTRIAL MACHINE THROUGH SENSOR FUSION

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In this paper, a four layer neuro-fuzzy architecture of multi-sensor fusion is developed for a fault diagnosis system which is applied to an industrial fish cutting machine. An important characteristic of the fault diagnosis approach developed in this paper is to make an accurate decision of the machine condition by fusing information acquired from three types of sensors: Accelerometer, microphone and charge-coupled device (CCD) camera. Feature vectors for vibration and sound signals from their fast Fourier transform (FFT) frequency spectra are defined and extracted from the acquired information. A feature-based vision method is applied for object tracking in the machine, to detect and track the fish moving on the conveyor. A four-layer neural network including a fuzzy hidden layer is developed in the paper to analyze and diagnose existing faults. Feature vectors of vibration, sound and vision are provided as inputs to the neuro-fuzzy network for fault detection and diagnosis. By proper training of the neural network using data samples for typical faults, six crucial faults in the fish cutting machine are detected with high reliability and robustness. On this basis, not only the condition of the machine can be determined for possible retuning and maintenance, but also alarms to warn about impending faults may be generated during the machine operation.

Keywords: Fault diagnosis; sensor fusion; neuro-fuzzy.

1. Introduction

Fault detection and diagnosis is quite important for engineering systems, and deserves careful attention in view of the increasing complexity of modern machinery. Machine malfunction and failure will have negative implications on safety of the work environment and quality of the product/service. Poor machine performance may cause loss of throughput and financial losses. Moreover, a modern automated factory environment has to be effective, flexible and reliable. In view of these factors, it is necessary to develop intelligent systems that will provide accurate and reliable fault detection, diagnosis and prediction, which can prescribe preventive actions for modern machinery.

Fish processing is a major resource-based industry in the province of British
Columbia, Canada. The annual wastage of fish during processing reaches many million dollars in British Columbia alone. For the purpose of decreasing the meat wastage in the fish processing industry, a fish cutting machine, called the Iron Butcher [de Silva, 2000], has been designed in the Industrial Automation Laboratory (IAL) at the University of British Columbia (UBC). This machine not only improves the recovery of useful meat in a significant way, it also helps replace the manual labor of human fish processors thereby moving them away from hazardous and unpleasant working conditions of a fish processing plant.

A view of the fish cutting machine in our laboratory is shown in Fig. 1. There are three crucial sub-systems in the machine:

1. Converyer system.
2. Pneumatic system.
3. Hydraulic system.

The main functions of these three subsystems are to generate the necessary movements of the fish; the cutter in the horizontal positioning plane; and the cutter in the vertical direction, respectively.

The Iron Butcher is a complex, nonlinear, and coupled mechatronic system [de Silva, 2005], which contains different sub-systems that involve mechanical, electrical, electronic and information technologies. The failure of a sub-system can cause significant degradation of the machine performance and also incur financial losses. Therefore, an accurate and reliable system for detection and diagnosis of faults in this machine is necessary for generating appropriate warning signals and providing suitable corrective actions.

Often, a single type of sensor is not sufficient to detect all possible faults in complex machinery within practical environments. Multi-sensor approaches with data fusion methods have been considered to improve the diagnosis accuracy under these conditions. Sensor fusion first appeared in the literature in the 1960s. Today, application of sensor fusion expands into a wide range of areas: Maintenance engineering, robotics, pattern recognition, object tracking, and so on. Commonly used sensor fusion methods are reviewed in [Esteban et al., 2005]. Researchers have focused on the application of sensor fusion in fault diagnosis systems, and found that neural networks and fuzzy logic are particularly successful in engineering applications [Ghosh et al., 2007]. In recent years, applications based on neuro-fuzzy approaches have grown rapidly [Lefteri et al., 1997].

The purpose of the present paper is to design a multi-sensor fault diagnosis system with neuro-fuzzy sensor fusion for an industrial fish cutting machine. The paper first presents a system architecture, including data acquisition and processing, for fault detection and diagnosis. Next, a neuro-fuzzy scheme is presented for sensor fusion within the architecture. Subsequently experimental results from the fish cutting machine, with the developed system, are presented and discussed. The paper is concluded by indicating the advantages of the developed multi-sensor approach.

2. System Architecture

The developed architecture of the fault diagnosis system and data flow is shown in Fig. 2. Three types of sensors: Accelerometers, microphones and digital CCD cameras, are mounted on the machine. These are indicated by red circles. The outputs of the sensors are connected to a signal processing unit: A Pentium® IV computer, which carries a data acquisition board, a sound blaster card and a frame grabber. The software developed in this project contains four
main parts:

1. Data acquisition through multiple sensors and displaying the vibration and sound signals in real time on the screen.
2. Data pre-processing, feature generation, and displaying the results on the screen.
3. Displaying the results of feature-based vision tracking.

2.1. Data pre-processing

Software has been developed using Microsoft Visual Studio 2003 to acquire data from vibration and sound sensors, in the time domain. It also implements data pre-processing which generates signatures or feature vectors of the vibration and sound signals for use in the subsequent operations of fault diagnosis. After the vibration and sound signals are acquired, first they are transformed into the frequency domain using the Fast Fourier Transform (FFT) approach [Lathi, 2002], according to

$$F(r\omega_0) = \sum_{k=0}^{N_0-1} T f(kT)e^{-jr\frac{2\pi}{N_0}k}.$$  \hspace{1cm} (1)

Second, the spectrum is divided into four sub-regions as shown in Fig. 3. For each region, a summation operation is carried out to calculate the sum of amplitudes at each discrete frequency, using

$$V_i = \sum_{j=(N_0\times(i-1))/4}^{(N_0\times i)/4} M_j \quad \text{for} \quad i = 1 \text{ to } 4. \hspace{1cm} (2)$$

Finally, a feature vector $V = (V_1, V_2, V_3, V_4)^T$ is generated, which represents the signature of the acquired signal. The feature vector is normalized as

$$V_i = \frac{V_i}{\sqrt{V_1^2 + V_2^2 + V_3^2 + V_4^2}} \quad \text{for} \quad i = 1 \text{ to } 4. \hspace{1cm} (3)$$

A feature based vision tracking approach known as the Scale Invariant Feature Transform (SIFT) is applied to the vision data in
order to track in a robust manner the object of interest (fish) which is moving with the conveyor. Vision based methodology for object recognition and tracking has been widely used in industrial applications, particularly in the field of fault detection and inspection. Most of the existing commercial systems depend primarily on the approach of correlation-based template matching, which has been proved effective in some applications. However, this approach becomes infeasible under variable conditions of object pose, scale and illumination, especially when dealing with partial visibility of the tracked object. As a result, an alternative approach which is based on object features has been developed. In particular, Lowe proposed an object recognition algorithm which uses a class of local image features [Lowe, 1999; 2004]. In his algorithm, features are detected and image keys are created that allow for local gradients in multiple orientation plans and at multiple scales. The keys are used as input to a nearest-neighbor indexing method which identifies candidate object matches. Verification of each match is achieved by finding a low-residual least-squares solution.

In this paper, this tracking approach is applied to track the fish when they are moving along the conveyor, as shown in Fig. 4. A two-dimensional \((x-y)\) coordinate frame is attached to the plane of the conveyor table. At each time instant, the SIFT-based vision processing software detects and tracks the positions and orientations of the fish. A vision vector is generated for each fish, which contains the three elements: \(x\), \(y\), and the orientation angle \(\theta\). This vision vector combined with the feature vectors of the vibration and sound signals is the input to the neuro-fuzzy diagnosis system, as presented in the next section.

3. Neuro-Fuzzy Based Fault Diagnosis System

The Neuro-fuzzy approach [Tsoukalas & Uhrig, 1997], which belongs to the field of artificial intelligence, hybridizes the two soft computing technologies of artificial neural networks and fuzzy logic. Fuzzy logic is derived from fuzzy set theory to deal with approximate and qualitative reasoning rather than to make precise deductions using the classical predicate logic [Karray & de Silva, 2004]. It can be thought of as the application domain of fuzzy set theory, dealing with well thought out real world expert values for a complex problem. A neural network (NN) is an interconnected and massively parallel group of artificial neurons, which represents a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases an Artificial Neural Network (ANN) is an adaptive system that changes its structure and parameters (weights) based on external or internal information that flows through the network. In more practical terms neural networks are tools of nonlinear statistical data modeling or decision making. They can be used to model complex

![Fig. 4. Fish tracking and generation of the vision-based feature vector.](image-url)
relationships between inputs and outputs or to find patterns in data.

Neural networks and fuzzy systems represent two distinct methodologies that deal with incomplete knowledge and qualitative nature which arise with increased system complexity. Each of these two approaches has its own advantages and disadvantages. Neural networks can represent complex nonlinear relationships, and they are very good at classifying patterns and phenomena into pre-selected categories. On the other hand, the precision of the outputs is sometimes limited and the time required for proper training of (or learning through) a neural network can be long. Fuzzy logic systems address the qualitative or human-perception nature of the input and output variables directly by defining them with fuzzy membership functions, which can be used to express relations (or knowledge) in a linguistic manner. Hence, fuzzy logic systems are easier to formulate and modify, and thereby more tractable. Therefore, although neural networks and fuzzy logic are quite different, their unique capabilities can be combined in a synergistic way, thereby gaining particular advantages in the present work.

Neuro-fuzzy hybridization results in a hybrid intelligent system that combines these two techniques involving the human-like knowledge representation and reasoning of fuzzy systems with the learning and massively parallel connectionist structure of neural networks. Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Networks (FNN) or Neuro-Fuzzy System (NFS) — The more popular term, which is used in this paper. It incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model of knowledge consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximators for complex and nonlinear problems, with the ability to generate interpretable IF-THEN rules.

As discussed before, the main purpose of a neuro-fuzzy network is to approximate a nonlinear mapping between the sensor signals and potential machine faults. In this paper, a neuro-fuzzy network, which approximately maps input sensor signals to potential faults of the machine, is developed. It may be used to detect, diagnose and predict existing or expected faults. The overall architecture of the fault diagnosis module as developed in the present paper is shown in Fig. 5.

In this paper, vibration, sound and vision are the sensory data sources and the neuro-fuzzy network is the means of fusing them for fault diagnosis. In Fig. 5, the input layer will accept three feature vectors which are the vibration vector \((x_1, x_2, x_3, x_4)\), the sound vector \((x_5, x_6, x_7, x_8)\), and the vision vector \((x_9, x_{10}, x_{11})\) of the monitored signals, as defined in the previous section. First, the three vectors are sent to the fuzzy layer for inference. It uses fuzzy decision making to match the input vectors to a known system status. The outputs of the fuzzy layer are then provided as inputs into the hidden layer of the neural network for identifying potential faults. This four-layer neuro-fuzzy network has a three-node hidden layer and a six-node output layer. Each output of the network represents one of six typical faults of the fish cutting machine.

### 3.1. Fuzzy layer

As seen from Fig. 5, the neuron-fuzzy network contains two main parts: The fuzzy layer and the neural network layer. In order to elaborate on the function of the fuzzy layer, assume a two-input (i.e. \(x_1\) and \(x_2\)) and one-output (i.e. \(y\)) situation, which is shown in Fig. 6. Each input variable is represented by a Gaussian type membership function as shown in Fig. 7, which includes five values labeled as Negative Large (NL), Negative Small (NS), Zero (ZO), Positive Small (PS), and Positive Large (PL). Each function has two parameters: \(c\), the centroid of the Gaussian function; and \(d\), the width of the Gaussian function. After characterizing the Gaussian fuzzy membership function with the two parameters, the inference formula can be written as

\[
y = \max \left( \exp \left( -\frac{\| C^i - X \|^2}{D^i} \right) \right) \quad \text{for} \quad i = 1 \text{ to } T,
\]
where $T$ is the total number of fuzzy rules, which is 25 according to Fig. 7, $X = (x_1, x_2)^T$ is the input vector, $C^i = (c_{i1}, c_{i2})^T$ and $D^i = (d_{i1}, d_{i2})$ denote the center and the width vectors of the two input memberships, and $\| \bullet \|$ denotes the norm operator which gives the Euclidean distance. After the normalizing operation, the final output of the fuzzy inference will range from 0 to 1.

In order to deal with the feature vectors of vibration, sound and vision signals simultaneously, three individual fuzzy inference modules are applied in this paper, which constitute the fuzzy inference layer. For each element in the vector, a Gaussian type membership function including NL, NS, ZO, PS and PL is applied with two parameters $c$ and $d$. Therefore, the dimensions of the fuzzy layers for vibration, sound and vision signals are 4, 4 and 3, respectively. By computing Eq. (4), the outputs of the fuzzy layer are generated, which range from 0 to 1. They form the inputs to the neural network layer in Fig. 5. It is commonly known that a fuzzy logic inference involves three
steps: Fuzzification, inferencing and defuzzification. However, a benefit of the present approach includes simplification of the fuzzy inference by eliminating the procedures of fuzzification and defuzzification.

### 3.2. Neural network layer

The second component of the fault diagnosis network is the neural network layer whose architecture is presented in Fig. 5. Backpropagation (BP) method [Karray & de Silva, 2004; Alpaydin, 2004] is applied in the present work. The training error of the neural network is closely related to the number of hidden nodes and epochs in the network. This relationship is shown in Figs. 8 and 9.

As shown in Fig. 5, the neural network contains three layers which are the input layer, the hidden layer and the output layer. Also, there are 3 input nodes (i.e. fuzzy layer outputs) and 6 output nodes in the neural network. The number of the hidden nodes is chosen to be 3 because it gives a relatively small error and fast convergence speed according to Fig. 8. Another advantage of this type of structure is that it is easy to code. Furthermore, too many hidden nodes in the network can lead to convergence problems. Furthermore, an overly complex model memorizes the noise in the training set and does not generalize to the validation set.

The backpropagation training algorithm is used in this paper to adjust the weights in the neural network. The detailed procedure of the algorithm is shown in Fig. 10. In the algorithm, $\text{sigmoid}(w^Tx^T)$ is given by

$$y = \text{sigmoid}(w^T x) = \frac{1}{1 + \exp(-W^T x)}. \quad (5)$$

This training algorithm can be applied in both on-line and off-line training. In this paper, off-line training is carried out before the neural network is implemented in the diagnosis system of the fish processing machine. The criterion used to stop training in the present application is: when the mean squared error is less than 2%, the training process automatically stops. It is known that a phenomenon called over-fitting will appear when training is continued for too long. In particular, as more training epochs are made, the error on the training set decreases, but the error on the validation set starts to increase beyond a certain point. Thus, training should be stopped before exacerbating problem of over-fitting. There are two factors which will indicate that the algorithm has learned correct mapping. The first indicator is whether the error is generally decreasing with the training, and the other one is whether the error stops changing (i.e. converges). Under optimized conditions, as given by Fig. 9, the neural network will properly learn the intended strategy. In the present work it takes about 16 epochs to converge, which corresponds to a fast convergence speed.

### 3.3. Neuro-fuzzy sensor fusion

Sensor fusion, which is also known as multisensor data fusion, is generally defined as the use of techniques that combine data from multiple sources and combine that information in order to achieve inferences that will be more efficient than if they were achieved by means of a single
source. It is shown that sensory data fusion from disparate sources can possibly provide a better solution than when these sources are used individually.

In this paper, vibration, sound and vision are the sensory data sources and the neuro-fuzzy network is the means of fusing them for fault diagnosis. In the present system, offline training is applied by acquiring data specimens under six typical working conditions given by:

- Blocked (jammed) fish.
- Failure of the hydraulic cylinder system.
- Failure of the conveyor system.
- Failure of the hydraulic pump.
- Failure of the hydraulic servo valves.
- Failure of the pneumatic controlled cutter.
- Normal operation.

The vibration, sound and vision signals are acquired for each of these working conditions of the fish-cutting machine. After acquiring signals from the sensors, the software extracts the three feature vectors and sends them to the neural network for fault diagnosis. Through checking the real preset fault, one output of the neural network is set to “1” and the other outputs of the network are set to “0.” A training sample is generated in this manner. Hundreds of samples are generated in this manner for each potential fault and the normal (non-faulty) operating condition. The training process is stopped when the mean squared error becomes less than 2% for each condition. It is found that after training, the neuro-fuzzy fault diagnosis network that is developed here is capable of properly identifying the faults in the fish cutting machine.

4. Experimental Results

4.1. Sensor arrangement

The physical arrangement of the sensors of the test machine is shown in Fig. 11. In the present work, five types of sensors are integrated into the fish cutting machine for detecting the potential faults. Specifically there are 4 accelerometers, 2 position sensors, 4 pressure sensors, 2 microphones and 2 CCD cameras [de Silva, 2007]. Figure 11 shows the positions of these sensors, as mounted on the machine. Four accelerometers are mounted on the machine mainframe, the conveyor, the vertical cutter, and the cutting table. Between the accelerometers and the data acquisition board, there is a set of power amplifiers. A JVC CCD camera is mounted on
the left side of the cutter, to sense the movement of the conveyor system. Another JVC CCD camera is mounted on the right side of the pneumatic cutter to track the position and orientation of the fish. Moreover, there is a global three-degree-of-freedom Panasonic CCD camera providing a video stream of working conditions of the machine for the purpose of remote monitoring.

4.2. System software

The graphic user interface (GUI) of the diagnosis software is shown in Fig. 12. The interface is divided into four parts. The two parts in the left-hand side show the vibration and sound signals acquired from the sensors. Moreover, they show the frequency spectrum after FFT processing. The top right section is the vision part which carries out the function of tracking the moving fish and generating vision vectors for further diagnosis. After acquiring three feature vectors as discussed in the previous section, they are sent into the neuro-fuzzy network for fault diagnosis.

4.3. Simulated faults

Each subsystem of the fish cutting machine consists of several important components such as valves, actuators, motors, and so on. Failure of any of these components can cause abnormal working conditions in the machine, with potentially serious repercussions. In Table 1, important potential faults are identified, which are related to the three main subsystems.

4.4. Experimental results

In this section, the neuro-fuzzy fault diagnosis system as developed in the present work is applied to the fish cutting machine for experimentation and performance evaluation. This diagnosis system will mainly focus on the six potential faults which were introduced in the six previous sections. The rest of the faults which were introduced in Table 1 may be directly detected and diagnosed by using single sensors.

In the developed system, the outputs of the neural network represent the decision of the diagnosis process. When the output value is equal to or greater than 0.75, the relevant output node on the GUI software turns red, which implies that the corresponding fault may be taking place at a very high possibility. Similarly, it turns yellow when the output ranges from 0.25 to 0.75, which will imply a moderate possibility of the corresponding fault. It will be green if the output value is less than 0.25, which indicates that the machine is operating normally (i.e. fault free). In the present system, the diagnosis time is 3 s, which means that in every 3 s, new vectors of vibration, sound and vision signals are generated and sent to the diagnosis system for decision making.

Figure 13 shows the vibration signals in the time domain and the frequency domain under normal working conditions. It is a screen shot form the GUI of the running software. Because
the duration of a data processing interval is 3 s, the time graph shows a period containing 3072 discrete points (at a sampling rate of 1024 Hz). The frequency range displayed on the GUI is from 0 to 500 Hz according to the sampling theorem. Figure 14 shows the sound signals in the time domain and the frequency domain under normal operating conditions. The data updating interval is also 3 s, and its sampling rate is 44100 Hz.

Table 2 shows the feature vectors of the vibration and sound signals containing four elements. The generation of the feature vectors was discussed in previous section. They form the inputs to the neuro-fuzzy fault diagnosis network. In this normal operating condition, the six outputs of the network are 0.112, 0.153, 0.201, 0.187, 0.215, 0.098, all of which are less than 0.25. Therefore, the output nodes in the UGI appear green, indicating a normal operating condition of the fish cutting machine.

4.4.1. Failure of the hydraulic pump

Figure 15 shows the vibration signals and their frequency spectra when the hydraulic pump fails. Figure 16 shows the sound signals and their frequency spectra under the same condition. Subsequently, the vibration and sound feature vectors are generated based on the vibration and sound spectra, as given in Table 3. In this operating condition, the value of the 4th output of the neuro-fuzzy network is 0.92 which has a high probability that the hydraulic pumping is not operating properly. The other five output values are less than 0.25 which indicate that the other components of the machine are working properly. Consequently, it is observed that the 4th output of the diagnosis network on the
Table 1. List of simulated faults and sensor usage.

<table>
<thead>
<tr>
<th>No.</th>
<th>Fault #</th>
<th>Use of sensors</th>
<th>Signals for diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>#2 Failure of the hydraulic pump</td>
<td>#1 Microphone</td>
<td>Sound and pressure</td>
</tr>
<tr>
<td>2</td>
<td>#3 Failure of the electro-hydraulic FCS</td>
<td>4 Pressure sensors</td>
<td>Pressure</td>
</tr>
<tr>
<td>3</td>
<td>#4 Failure of the x-axis and y-axis cylinders</td>
<td>#3 Accelerometer</td>
<td>Pressure, position and vibration</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Position sensors</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pressure sensors</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>#5 The cutting table is blocked</td>
<td>#4 Accelerometer</td>
<td>Position, pressure and vibration</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Position sensors</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pressure sensors</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>#7 Failure of the air compressor</td>
<td>#1 Microphone</td>
<td>Sound and vibration</td>
</tr>
<tr>
<td></td>
<td></td>
<td>#1 Accelerometer</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>#8 Failure of the vertical cutter blade cylinder</td>
<td>#3 Accelerometer</td>
<td>Sound and vibration</td>
</tr>
<tr>
<td></td>
<td></td>
<td>#2 Microphone</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>#9 Failure of the single action cylinders</td>
<td>#2 Accelerometer</td>
<td>Sound and vibration</td>
</tr>
<tr>
<td></td>
<td></td>
<td>#1 Microphone</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>#10 Air leakage in the pneumatic system</td>
<td>#2 Microphone</td>
<td>Sound</td>
</tr>
<tr>
<td>9</td>
<td>#12 The conveyer is blocked</td>
<td>#1 Accelerometer</td>
<td>Sound, vibration and vision</td>
</tr>
<tr>
<td></td>
<td></td>
<td>#2 Camera</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>#1 Microphone</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>#13 Wrong position and orientation of the fish</td>
<td>#1 Camera</td>
<td>Sound, vibration and vision</td>
</tr>
</tbody>
</table>

![Graphs](image)

(a) The vibration signal  
(b) The vibration spectrum

Fig. 13. The vibration signal under normal operating conditions.
Table 2. Feature vectors of vibration and sound signals in a normal operating condition.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value 1</th>
<th>Value 2</th>
<th>Value 3</th>
<th>Value 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vibration feature vector</td>
<td>0.49156</td>
<td>0.55061</td>
<td>0.50059</td>
<td>0.45234</td>
</tr>
<tr>
<td>Sound feature vector</td>
<td>0.69448</td>
<td>0.48401</td>
<td>0.41385</td>
<td>0.33491</td>
</tr>
</tbody>
</table>

GUI of the software turns red, which will generate an alarm while the other five output nodes remain green.

Figure 17 shows the outputs of the neuro-fuzzy diagnosis network when the hydraulic pump fails. The failure time is about 900 seconds. A diagnosis result is generated in each three second period. As seen in Fig. 17, the value of the fourth output remains greater than 0.75 which indicates that the hydraulic pump is failing at a high possibility.

4.5. Failure of conveyor system

Figure 18 shows the vibration signal and its frequency spectrum when the conveyor system fails, while Fig. 19 shows the corresponding
Table 3. Feature vectors of vibration and sound signals when the hydraulic pump fails.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value 1</th>
<th>Value 2</th>
<th>Value 3</th>
<th>Value 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vibration feature vector</td>
<td>0.6828</td>
<td>0.47092</td>
<td>0.42323</td>
<td>0.36454</td>
</tr>
<tr>
<td>Sound feature vector</td>
<td>0.49292</td>
<td>0.55339</td>
<td>0.50143</td>
<td>0.4465</td>
</tr>
</tbody>
</table>

sound signal and its frequency spectrum. It is observed from Fig. 18 and Fig. 19 that the pulses of vibration and sound signals in the time domain, seen to be in the normal condition, disappear when the conveyor system is down. Table 4 shows the vibration and sound feature vectors for the neuro-fuzzy diagnosis system.

Fig. 17. The outputs of the diagnosis system.
Table 4. Feature vectors of the vibration and sound signals when conveyor system is failed.

<table>
<thead>
<tr>
<th>Vibration feature vector</th>
<th>Sound feature vector</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.86514</td>
<td>0.57642</td>
</tr>
<tr>
<td>0.39742</td>
<td>0.0651</td>
</tr>
<tr>
<td>0.14608</td>
<td>0.60424</td>
</tr>
<tr>
<td>0.26881</td>
<td>0.54625</td>
</tr>
</tbody>
</table>

under this operating condition. The value of the 3rd output of the neuro-fuzzy system is 0.89 which indicates a high possibility for the conveyor system to malfunction. The output values of the other five nodes are less than 0.25, which means that the other components of this machine operate properly. Similar to the case of
hydraulic pump failure, the 3rd output of the fault diagnosis network turns red and the rest of the nodes remain green.

Figure 20 shows the outputs of the neuro-fuzzy network when the conveyor system fails. The duration of the failure is 900 s. A diagnosis result is generated in every 3 s. As seen from the Fig. 20, the third output remains greater than 0.75 which indicates that the conveyor system has failed at a high possibility.

4.6. Advantages of the multi-sensor fusion approach

In this section, a comparison between the fault detection using the single sensor approach and the multi-sensor fusion approach, as developed in the present work, is given and the performance is discussed, when faults occur in the hydraulic system. Through this comparison, the benefits of the multi-sensor fusion approach are highlighted.

As discussed in the previous sections, the hydraulic system failure can be caused by several factors such as failure of the hydraulic cylinder, failure of the hydraulic pump, and the presence of blocked/tangled fish. When these faults occur, it is very difficult for a single sensor (sound, vibration or vision sensors) to determine the fault source because the sound signal can only be used to detect the failure of the hydraulic pump; the vision signal can only be used to judge the failure of blocked fish; and the vibration signal can only be applied to detect the motion of the cutting table. If the cutting table does not work properly, failure of any of these components (the hydraulic pump, cylinder, etc.) may be the reason for this problem. In this case, multi-sensor fusion technology becomes necessary because the signal sensor approach is not adequate to detect and diagnose all fault sources. The experiment presented below will demonstrate this case and validate the multi-sensor fusion approach in detecting and diagnosing faults in a complex system.

Figure 21 shows vibration and sound signals when the hydraulic cylinder fails. Non-moving cutting table is the symptom of this failure. Although a single vibration sensor can detect the motion of the cutter, it cannot indicate which component of the hydraulic system has failed. In this situation, by combining the sound and vision signals, the neuro-fuzzy sensor fusion system is able to determine that the hydraulic pump operates normally, and no fish is blocked.

Figure 22 shows how the diagnosis network has identified the three types of failure in the hydraulic system. In this experiment, the machine was first run under normal conditions for 30 s. Then a fault of blocked fish was simulated on the machine from the 30th to the 40th s. It is observed from Fig. 22(a) that the value of the first output of the diagnosis network has increased significantly while the other outputs still remain at low values. Because the first output of the network corresponds to the fault of “failure of blocked fish”, Fig. 22(a) demonstrates that the network has correctly identified the pump failure in that period.

Next, another failure — The hydraulic cylinder failure — was simulated at approximately 69th s. Again, this fault has been correctly captured by the neuro-fuzzy network, as shown in Fig. 22(b). Finally, at the 153rd s, the hydraulic pump was suddenly shut down to simulate the fault “hydraulic pump failure.” Figure 22(d) shows that the value of the fourth output of the network has increased suddenly at that time, which indicates that there exists pump failure.

5. Conclusion

In this paper, a fault diagnosis system based on a neuro-fuzzy sensor fusion approach was developed for a real engineering system — An industrial fish cutting machine. Vibration, sound and vision signals were detected by three types of sensors: Accelerometer, microphone and CCD camera, which were used as inputs to the diagnosis system. A feature vector was defined and extracted from the fast Fourier transform (FFT) frequency spectra of the acquired signals. Also, a feature based vision tracking approach known as the Scale Invariant Feature Transform (SIFT) was applied to the vision data to track the object of interest (fish moving with the conveyor) in
Fig. 20. The outputs of the diagnosis system.

Sound Signal

Vibration Signal

Fig. 21. The signals under failure of the hydraulic cylinder.
Fig. 22. The outputs of a sensor fusion diagnosis experiment.
a robust manner. A four-layer neural network including a fuzzy layer was developed to analyze and diagnose a range of primary faults. The system was implemented in the industrial fish cutting machine and experiments were conducted to evaluate the performance of the developed system. By training the neural network with sample data for typical faults, six crucial faults in the fish cutting machine were accurately detected in these experiments. Using the developed system, alarms to warn about impending faults may be generated as well during the machine operation.

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References


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