A Study on Machine Fault Diagnosis using Decision Tree

Ngoc-Tu Nguyen*, Jeong-Min Kwon* and Hong-Hee Lee†

Abstract – The paper describes a way to diagnose machine condition based on the expert system. In this paper, an expert system – decision tree is built and experimented to diagnose and to detect machine defects. The main objective of this study is to provide a simple way to monitor machine status by synthesizing the knowledge and experiences on the diagnostic case histories of the rotating machinery. A traditional decision tree has been constructed using vibration-based inputs. Some case studies are provided to illustrate the application and advantages of the decision tree system for machine fault diagnosis.

Keywords : Decision tree, Expert system, Fault diagnosis, Machine, Vibration

1. Introduction

Most machine fault diagnosis systems utilize the expert system, which is mainly based on vibration symptoms and stator currents. The principle of this method is the fact that the fault inside the machine structure can be visible as distinct frequency components in the spectrum. With knowledge of machine behavior, it is possible to perform a diagnostic analysis of the machine, which can be accomplished by experts or an expert system instead.

Fault detection and diagnosis in rotating machines have been used widely in commercial systems over the past few decades. Numerous works on machine conditions have been implemented with the aid of the MCSA (Motor Current Signature Analysis) method by W. T. Thomson [1] and the vibration-based methods surveyed in [2-4], etc. The purpose of these methods is to detect and diagnose faults in an early stage and therefore allow contingency plans to be put into place before the problems worsen. Detection or diagnosis can be achieved either manually or on the basis of the rule-based system.

The decision tree, which builds the diagnostic rules depending on the human experiences, could be used for the above purpose. As compared to other methods, decision tree has several advantages such as the simple construction and clear predictions. All vibration symptoms such as amplitude, phase, trend, and frequency should be gathered and analyzed to achieve the most reliable prediction. Because of the complication of time domain vibration, the vibration data are analyzed in frequency domain, where the frequencies describe what is wrong with the machine and the amplitudes describe the relative severity of the problem. With the collected vibration data, the user only has to answer the attribute tests in decision tree in order to obtain the problem prediction. However, most tests have only yes-no type answers and this is the main characteristic that makes the tree easy to operate.

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2. Decision Tree Construction

The decision tree is a diagnostic tool that builds the knowledge-based system by the inductive inference from case histories. A decision tree contains:

- Leaf nodes (or answer nodes) that contain class name.
- Decision nodes (or non-leaf nodes) that specify some test to be carried out on a single attribute value, with one branch and sub-tree for each possible outcome of the test.

The structure of the decision tree highly depends on how a test is selected as the root of the tree. The criterion for selecting the root of the tree is Quinlan's information theory (information gain) [5]. This criterion means the information that is conveyed by a message depends on its probability. The construction of the decision tree is based on a training set T, which is a set of cases. Each case specifies the values for a collection of attributes and for a class. Let the classes be denoted $\{C_1, C_2, \ldots, C_k\}$. Suppose we have a possible test with n outcomes that partition the training set T into subsets $\{T_1, T_2, \ldots, T_n\}$. Assume that S is any set of cases, freq (C_i, S) is the number of cases in S that belong to class C_i, and $|S|$ is the number of cases in set S. If we select one case at random from set S and announce that it belongs to class C_j, this message has probability

$$\frac{freq(C_j, S)}{|S|} \quad (1)$$

and the information it conveys is

$$-\log_2 \frac{freq(C_j, S)}{|S|} \text{ bits} \quad (2)$$

The expected information needed to identify the class of case in S is

$$\text{info(S)} = -\sum_{j=1}^{k} \frac{freq(C_j, S)}{|S|} \times \log_2\left(\frac{freq(C_j, S)}{|S|}\right) \text{ bits} \quad (3)$$

When (3) is applied to the set of training cases, info (T) measures the average amount of information needed to identify the class of a case in T.

A similar measurement after T has been partitioned in accordance with n outcomes of a test X

$$\text{info}_X(\text{T}) = \sum_{i=1}^{n} \frac{|T_i|}{|T|} \times \text{info}(\text{T}_i) \text{ bits} \quad (4)$$

The quantity

$$\text{Gain(X)} = \text{info(T)} - \text{info}_X\text{(T)} \quad (5)$$

measures the information that is gained by partitioning T in accordance with the test X. The gain criterion selects a test to maximize this information gain. Detailed descriptions of decision tree construction are presented by J. R. Quinlan in [5].

Up to now, a lot of algorithms have been developed based on this criterion such as ID3, C4.5, etc. When a decision tree is built, it can be used to classify a case by starting at the root of the tree and tracing out the path until a leaf is encountered. This paper proposes a decision tree established upon vibration-based method, where vibration data are collected from accelerator sensors and processed to become the input of the decision tree. The tree gives a final decision for machine condition from these data.

3. Vibration-based Decision Tree

Most common failures for rotating machinery appear in the vibration spectrum by some unusual frequencies. There are many types of machine faults and their brief information about the relationship with the running speed (1X) of the machine is described in [6].

This paper proposes a decision tree with 12 common causes of machinery vibration (classes of decision tree) and its tests [7-9].

Table 1. Source of vibration – common faults of induction motor

No.	Source of vibration
1	Mechanical unbalance
2	Misalignment
3	Partial rub
4	Crack
5	Mechanical looseness
6	Ball bearing damage
7	Foundation distortion
8	Oil whip
9	Static air gap eccentricity or stator damage
10	Critical speed
11	Dynamic eccentricity air gap or rotor damage
12	Gear damage

Table 2. Decision tree test and its value

No.	Test (attribute)	Value
1	What is the predominant frequency?	1X, 2X, 1X and 2X, Harmonics of 1X (multiple), Higher than 1X, Lower than 1X
2	Is 0.38-0.48X component predominant?	yes, no
3	Is bearing damage frequency predominant?	yes, no
4	Is there $2f_{line}$ frequency?	yes, no
5	Is there $2sf_{line}$ frequency?	yes, no
6	Are there harmonics of 1/2X component?	yes, no
7	Is there amplitude change?	yes, no
8	Is there phase change?	yes, no
9	Is axial amplitude larger than radial amplitude?	yes, no
10	Is orbit shape tending to banana or eight shape?	yes, no
11	How is amplitude change during coast-down (shutdown)?	constant, decrease, drop
12	Is gear damage frequency predominant?	yes, no

A list of common faults of the induction machine is given in Table 1.

In order to track to the leaf from the root of the tree, there are a set of questions or tests that have to be answered. Table 2 describes the tree's test and its value.

The decision tree is built using the C4.5 program, which is based on case history database. C4.5 is developed by J. R. Quinlan, and its algorithm has already been described in Section 2. The knowledge-based data are developed over a period of time under different conditions of machine operation. John S. Sohre has collected a useful database on machine diagnosis which is given in chart forms as shown in [10]. The proposed decision tree has been built based on these knowledge data.

When the tree processes, the system will start at the predominant frequencies and try to reach the final prediction by collecting some special symptom information. The construction of decision tree makes the diagnosis system become simpler with if-then rule sets.

4. Experiments

Some experiments are applied to induction motors (5HP, 4 poles and 1HP, 2 poles), and decision tree is established using the C4.5 algorithm. In these experiments, vibration data are collected and analyzed by FFT (Fast Fourier Transformation), and accelerometer amplitude scale is 101.5mV/g. The decision tree for this experiment is built as in Fig. 1.

4.1 Case study 1 - Looseness case

The motor is driven at 29.3 Hz (1X) input frequency. Predominant frequencies are 1X, 2X, 3X and 10X (multiple harmonic of running frequency) presented in the vibration spectrums in Fig. 2.

Result is predicted by the decision tree in Fig. 3.

```
Predominant frequency = 1x:
|   amplitude_change = yes:
|   |   2s_line frequency = yes: Dynamic air gap (5.3)
|   |   2s_line frequency = no: Partial rub (30.0/15.0)
|   amplitude_change = no:
|   |   bearing frequency = yes: Ball bearing damage (15.0)
|   |   bearing frequency = no:
|   |   |   2s_line frequency = yes: Dynamic air gap (9.7)
|   |   |   2s_line frequency = no:
|   |   |   |   0.38-0.48x = yes: Oil whip (6.0)
|   |   |   |   0.38-0.48x = no: Unbalance (34.0)
Predominant frequency = 2x:
|   Orbit shape = yes: Misalignment (50.0)
|   Orbit shape = no: Crack (50.0/20.0)
Predominant frequency = same:
|   Axial direction = yes: Misalignment (70.0)
|   Axial direction = no: Unbalance (30.0)
Predominant frequency = Multi:
|   Axial direction = yes:
|   |   Orbit shape = yes: Misalignment (30.0)
|   |   Orbit shape = no: Crack (4.5)
|   Axial direction = no:
|   |   amplitude_change = yes: Partial rub (14.9/1.9)
|   |   amplitude_change = no:
|   |   |   1/2x-multi = yes: Looseness (31.6)
|   |   |   1/2x-multi = no:
|   |   |   |   0.38-0.48x = yes: Oil whip (6.0)
|   |   |   |   0.38-0.48x = no: Crack (12.9/6.4)
Predominant frequency = Higher:
|   bearing frequency = yes: Ball bearing damage (30.0)
|   bearing frequency = no:
|   |   2_line frequency = yes: Static air gap (30.0)
|   |   2_line frequency = no:
|   |   |   Gear damage frequency = yes: Gear damage (30.0)
|   |   |   Gear damage frequency = no: Partial rub (10.0)
Predominant frequency = Lower:
|   0.38-0.48x = yes: Oil whip (42.0)
|   0.38-0.48x = no:
|   |   Shutdown = constant: Partial rub (0.0)
|   |   Shutdown = decrease: Foundation distortion (25.0)
|   |   Shutdown = drop: Partial rub (33.0)
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Fig. 1. Decision tree for machine fault diagnosis used in experiments

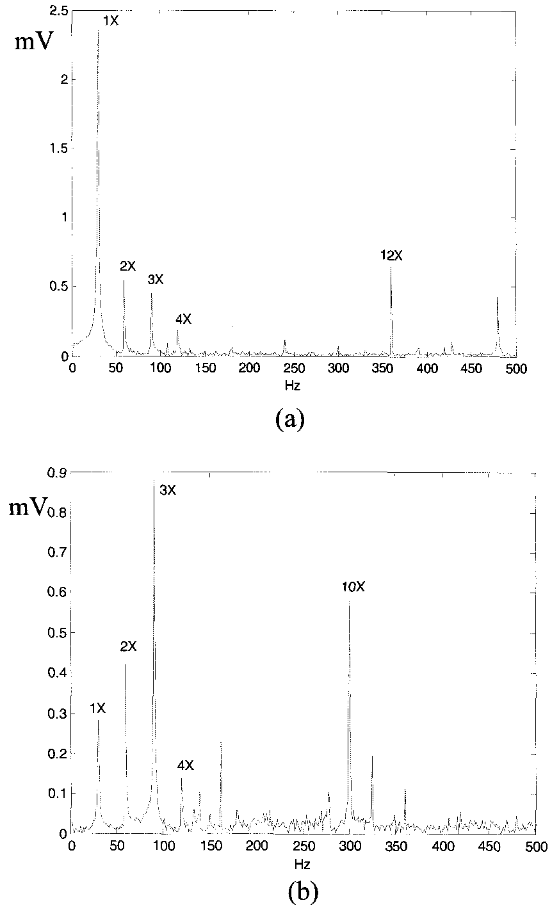


Fig. 2. Vibration spectrums (a) in radial direction (b) in axial direction

```
Predominant frequency: Multi
Axial direction: no
amplitude_change: ?
1/2x-multi: no
0.38-0.48x: no

Decision:
        Crack   CF = 0.42  [ 0.29 - 0.83 ]
        Looseness   CF = 0.38  [ 0.00 - 0.54 ]
        Partial rub   CF = 0.20  [ 0.17 - 0.71 ]
```

Fig. 3. Result of decision tree with looseness case

The decision tree is executed by answering its tests based on collected information. The question mark (?) represents an unsure answer. In this case study, the probability of looseness fault is 38%. Without the information of how the amplitude changes, the result of decision tree suggests three possible failures: crack, looseness, and partial rub. Looseness is confirmed in this case.

4.2 Case study 2 – Stator winding fault

In this case study, the component 120Hz is predominant (two times the power line frequency) from the vibration spectrums in Fig. 4.

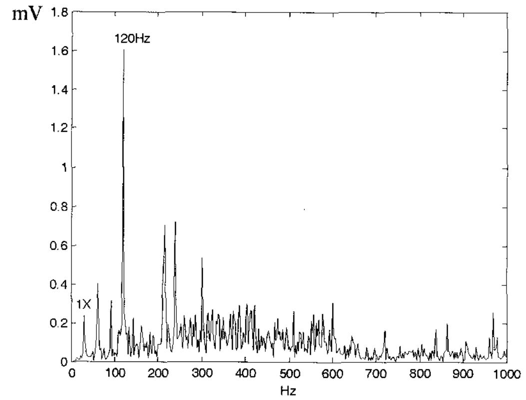


Fig. 4. Vibration spectrums of case study 2

The result of decision tree is

```
Predominant frequency: Higher
bearing frequency: no
2_line frequency: yes

Decision:
        Static air gap  CF = 1.00  [ 0.95 - 1.00 ]
```

Fig. 5. Result of decision tree for stator winding fault case

The result shows static eccentricity air gap fault, which means there is a problem with the motor stator or power supply.

4.3. Case study 3 - Rub fault

In this case, induction motor is running at 53.7 Hz. From the vibration spectrums at Fig. 7, the predominant frequencies are multiples of 1/3X harmonic, but no shutdown data is measured. Therefore, the decision tree's result has two possibilities, partial rub (57%) and foundation distortion (43%). Rub is detected in this motor. The diagnostic outcome is shown in Fig. 6.

```
Predominant frequency: Lower
0.38-0.48x: no
Shutdown: ?

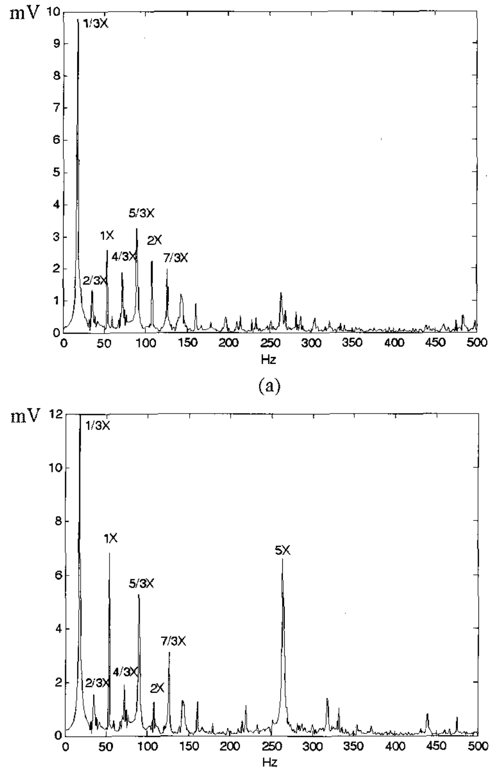
Decision:
        Partial rub  CF = 0.57  [ 0.55 - 0.59 ]
        Foundation distortion  CF = 0.43  [ 0.41 - 0.45 ]
```

Fig. 6. Result of decision tree with rub case

The result can be more reliable if there is enough information to answer all the tests of the decision tree.

4.4. Case study 4 - Unbalanced rotor

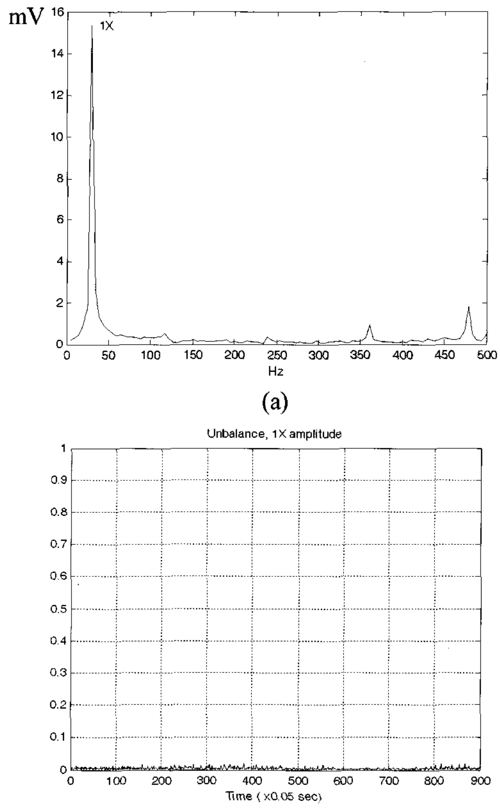
The vibration spectrum in Fig. 8a shows 1X as the predominant frequency. If there is no information for vibration amplitude change, then the probability of unbalance fault using the decision tree is 65% compared with 18% of partial rub and 18% of critical speed faults.



(a)

(b)

Fig. 7. Vibration spectrums (a) in radial direction (b) in axial direction



(a)

(b)

Fig. 8. (a) Vibration spectrums in radial direction and (b) how amplitude of 1X changes in time

```
Predominant frequency: 1x
amplitude_change: ?
2s_line frequency: no
bearing frequency: no
0.38-0.48x: no

Decision:
        Unbalance  CF = 0.65  [ 0.62 - 0.85 ]
        Partial rub  CF = 0.18  [ 0.15 - 0.38 ]
        Critical speed  CF = 0.18  [ 0.00 - 0.23 ]
```

Fig. 9. Result of unbalance case without amplitude_change information

```
bearing frequency: no
2s_line frequency: no
amplitude_change: no
0.38-0.48x: no

Decision:
        Unbalance  CF = 0.83  [ 0.77 - 1.00 ]
        Foundation distortion  CF = 0.17  [ 0.00 - 0.23 ]
```

Fig. 10. Result of unbalance case with amplitude_change information

In case that amplitude_change attribute is known as in Fig. 8b, the probability of unbalance is increased to 83% as indicated in Fig. 10.

4.5. Comments and Suggestion

In many cases, it is usually impossible to gather enough information to trace a leaf exactly under the given situation. As a result, the final decision may include several outcomes that have their own probability. The reliability of the decision strongly depends on the information related with the symptom. The experimental results also demonstrate that the more information is collected, the more reliable the result becomes. It is clear from these experiments that the decision tree is a simple application system once it is built completely.

In Table 2, there are some attributes that could be treated as continuous attributes such as "Is amplitude changed?" and "How is amplitude changed during coast-down (shutdown)?" beside other crisp attributes. If these attributes are considered as crisp ones, there will be some problems when they have values near the boundary. Then at some moments, if there is only a small change of attribute value near the boundary, it can cause an erroneous decision. In order to reduce this weakness, these attributes can be reconstructed to fuzzy attributes. This establishes a fuzzy border in the region between two attribute values, resulting in two values being overlapped in some region. As a result, even if some uncertainties exist in the attribute values, the decision tree will not give a completely wrong decision except a set of predicted probabilities. Many works on fuzzy decision tree have been published in [11-13].

The attribute's membership function can be linear or nonlinear and strongly depends on practical experiments. In this paper, a linear membership function is supposed and defined as Fig. 11.

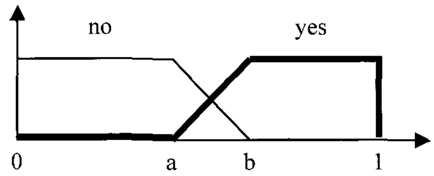


Fig. 11. Fuzzy membership function with 2 fuzzy sets: yes and no

$$\mu(yes) = \begin{cases} 0 & \text{if } x \le a \\ \dfrac{x-a}{b-a} & \text{if } a \le x \le b,\ 0 \le x \le 1 \\ 1 & \text{if } x \ge b \end{cases} \tag{6}$$

$$\mu(no) = 1 - \mu(yes) \tag{7}$$

Thus, decision tree's branches, which have fuzzy attributes, can be described as shown in Fig. 12. The fuzzy tree can be constructed from the original decision tree without any modification except the continuous attributes classification. The attributes of the fuzzy tree do not have any output membership function, and each of them only has an input membership function, which is used to give the probability of attribute values. An example of soft foot (foundation distortion) is considered from the attribute value where amplitude_change is yes (probability is 0.22) and no (probability is 0.78).

The example is given to illustrate fuzzy tree advantage. The soft foot (foundation distortion) fault with "Is amplitude changed?" attribute value in the fuzzy region is presented in Fig. 13. The diagnostic result is shown in Fig. 14.

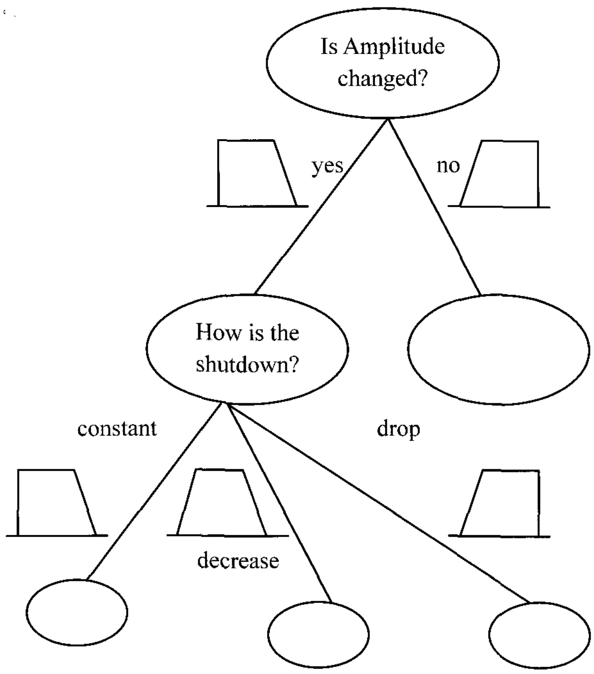


Fig. 12. A sample fuzzy decision branch

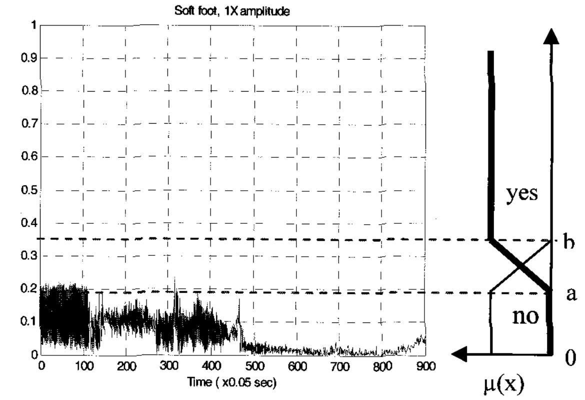


Fig. 13. Vibration amplitude change with soft foot case

The result of the tree now is

```
bearing frequency: no
2s_line frequency: no
amplitude_change: yes:0.22,no:0.78
Shutdown: ?
0.38-0.48x: no

Decision:
        Unbalance  CF = 0.65  [ 0.60 - 0.90 ]
        Foundation distortion  CF = 0.17  [ 0.02 - 0.32 ]
        Partial rub  CF = 0.09  [ 0.08 - 0.38 ]
        Critical speed  CF = 0.09  [ 0.00 - 0.30 ]
```

Fig. 14. Result of soft foot case with using fuzzy attribute amplitude_change

At the region near the boundary, amplitude_change value is only yes or no with the crisp decision tree. But, in case of the fuzzy decision tree, it gives probability values for both yes and no. If the above experiment is applied to the crisp tree, the tree with amplitude_change = yes predicts partial rub (0.43), critical speed (0.43) and soft foot (0.15). Meanwhile, the tree with amplitude_change = no predicts unbalance (0.83) and soft foot (0.17). It is clear that fuzzy decision tree used in this case can improve the reliability to predict the fault condition. Thus, the fuzzy decision tree is better in a sense of accuracy and reliability compared to the crisp tree.

5. Conclusions

Many methods have been developed to monitor machine condition, and this paper has also tried to suggest a way to investigate this objective. This work has studied how to use the expert system, which focuses on decision tree algorithm as a fault diagnostic technique for induction motors. This paper demonstrates the accuracy and simplicity of the decision tree to identify the possible vibration cause in induction motors. Decision trees have simple construction that can be easily managed by users, and they also provide acceptable accuracy even though information is insufficient to predict the condition of the motor. The problems with them are that decision trees are sensitive to noises and the discrete output cannot predict the severity of a fault. Generally, decision trees have been proved as an appropriate tool for fault diagnosis, but much work is still needed to be done. Some future works are to optimize the fuzzy attributes in both membership function and its parameters and to develop the experiment database used to construct the decision tree.

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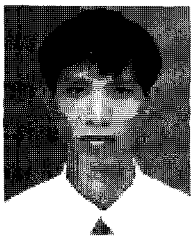

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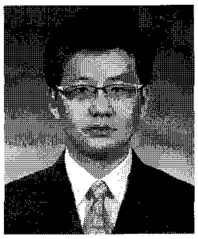

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