The Third AFSS(1998). 203－207

FAULT DIAGNOSIS OF ROTATING MACHINERY THROUGH FUZZY PATTERN MATCHING

Jesús Manuel FERNANDEZ SALIDO [a], Shuta MURAKAMI [b]

a. Faculty of Engineering, Department of Computer Science, Kyushu Institute of Technology
1-1 Sensui-cho, Tobata-ku, Kitakyushu-shi, Japan 804.
Tel:+81-93-884-3244 Fax:+81-93-884-3244 E-mail:salido@sys1.comp.kyutech.ac.jp.
b. Faculty of Engineering, Department of Computer Science, Kyushu Institute of Technology
1-1 Sensui-cho, Tobata-ku, Kitakyushu-shi, Japan 804.
Tel:+81-93-884-3244 Fax:+81-93-884-3244 E-mail:murakami@ comp.kyutech.ac.jp.

Abstract

In this paper, it is shown how Fuzzy Pattern Matching can be applied to diagnosis of the most common faults of Rotating Machinery. The whole diagnosis process has been divided in three steps: Fault Detection, Fault Isolation and Fault Identification, whose possible results are described by linguistic patterns. Diagnosis will consist in obtaining a set of matching indexes that express the compatibility of the fuzzified features extracted from the measured vibration signals, with the knowledge contained in the corresponding patterns.

Keywords: Automatic Diagnosis Systems, Rotating Machinery, Vibration Analysis, Fuzzy Pattern Matching.

1. Introduction

Unexpected failures of critical machinery can have disastrous economic consequences for production in an industrial plant. For this reason, over the years an increasing importance has been given to maintenance programs for industrial equipment. One of the maintenance policies that has proven to be most efficient is that of *Predictive Maintenance*. Under this maintenance philosophy, through continuous or periodic measurement and observation of certain properties of a machine, failures can be detected and diagnosed before they are fully developed. In this way, correction of these faults can be planned ahead, and carried out at the most convenient time.

In the case of rotating machinery (such as industrial motors, pumps, fans or gearboxes), analysis of the vibrations measured periodically at critical points of the machine can produce an abundant information about the state of development of different possible faults, like machine unbalance, axis misalignment, ball bearing or gear related faults, eccentricities, mechanical looseness, etc. The interpretation of this data is a complex process , specially since more information can now be extracted from the vibration signal of a machine through new signal processing techniques. In recent years, Artificial Intelligence techniques are starting to be applied for the implementation of automatic diagnostic systems based on vibration analysis. Different approaches for this problem have been based on traditional Expert Systems, Pattern Recognition Techniques or Artificial Neural Networks.

In this paper, a methodology based on *Fuzzy Pattern Matching* [2] for fault diagnosis in rotating machinery using vibration data is proposed. With this approach, the Vibration Analysis expert's knowledge can be implemented using linguistic terms, while the uncertainties generated in the vibration features' measurement process can be dealt with . Being a knowledge-based approach, no previous data of the fault states of the machine is needed for its implementation. Basically, the method is very similar to Fuzzy Matching techniques that have been successfully applied in Medical Diagnosis and Information Retrieval Systems, though including some specific characteristics that are necessary for the better interpretation of vibration data.

2. Elements of the Fuzzy Diagnosis System

The faults that our system pretends to diagnose are unbalance, misalignment, and three basic types of ball bearing faults. A previous step for diagnosis will be the measurement of the vibration time signal at selected points of the target machinery. Through intensive signal processing, other additional signals (frequency spectrum, cepstrum and envelope spectrum), that contain important information for fault isolation, will also be obtained. Out of these signals, a set, **F**, of those features that show a characteristic behavior in the presence of a fault, can be extracted. Some features will have an statistical nature (kurtosis, crest factor, standard deviation...) and shall be measured in the time signal. Others will be obtained from the frequency domain signals, like vibration levels or the amplitudes of the signal in the rotating frequency, defect frequencies, its harmonics and side-bands. In order to take into account different causes for uncertainty that appear during the signal measurement and features extraction process, the elements of **F** will be normalized, and through a fuzzification process, converted into fuzzy numbers with triangular shape membership functions. The resulting set, **S**, shall be called the set of fuzzy symptoms and shall be the input for the fuzzy diagnosis system.

Diagnosis will consist in determining whether the set of measured fuzzy symptoms matches the knowledge previously implemented in the system about the evolution of the different faults under study. This will be done using the three classic steps of industrial diagnosis, suggested by J. Gertler [4]:

1. ***Fault Detection:*** Noticing in something is going wrong in the system
2. ***Fault Isolation:*** Finding out the location of the fault.

3. ***Fault Identification***: Measuring the size of the fault.

All three processes will be accomplished through the use of Fuzzy Pattern Matching, as it is indicated in Fig.1.

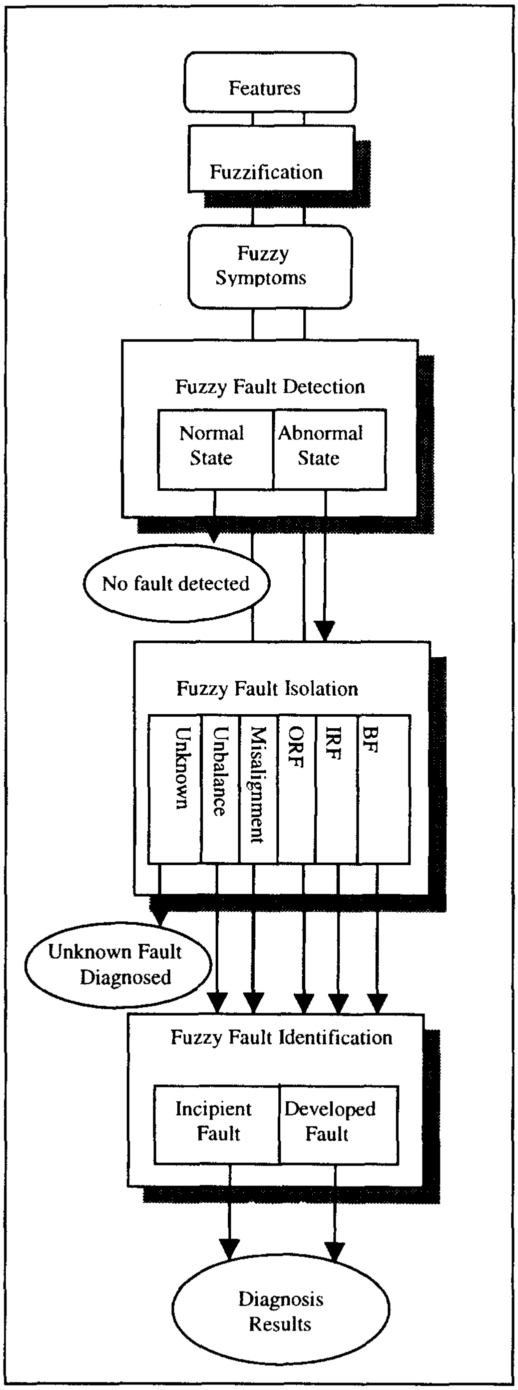

Fig. 1. Fuzzy Diagnosis Process.

2.1 Fuzzy Fault Detection

The Fuzzy Fault Detection process will try to establish whether the system has entered an abnormal (faulty) state. It is based on those fuzzy symptoms that show a characteristic behavior in the presence of *any* of the faults under study. This subset shall be called detection symptoms set, $\mathbf{S}^D \subset \mathbf{S}$. Let's denote by **S'** the set of *measured* fuzzy symptoms. The *measured* detection symptoms subset, $\mathbf{S'}^D \subset \mathbf{S'}$, shall be matched with a fuzzy pattern composed of n_r requirements of the following type:

Req.*j*: [NOT] ((S^D_k is A_a) [OR (S^D_l is A_b) [OR (S^D_m is A_c) ...]]) (j= 1 ... n_r) (1)

Example: ((*Vibration Level (5-40 KHz)* is *increased*) OR (*Vibration Level (0-1 KHz)* is *increased*))

Here, the S^D_k, S^D_l, S^D_m, ... are detection symptoms, while A_a, A_b , A_c... express different fuzzy attributes for these symptoms: *normal, increased, slightly increased, quite increased, markedly increased, decreased, slightly decreased, quite decreased* and *markedly decreased* (see Fig. 2). They have been modeled as possibility distributions with triangular and trapezoidal shapes. The variable symptoms that appear in a given detection requirement *.i* will normally be the same symptom adopting different attributes, or symptoms that are in some way related (like, as in the example, vibration levels measured over different frequency ranges).

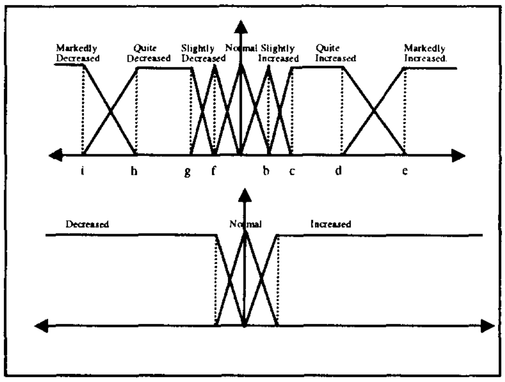

Fig 2. Possibility Distributions of the Fuzzy Attributes.

For each requirement j, a matching index, $\Pi_{\mathrm{Req}\,j}$,that expresses the compatibility of the subset of measured detection symptoms, $\mathbf{S'}^D$, with the conditions represented by the requirement, can be obtained by matching all the measured detection symptoms S'^D_k, S'^D_l, S'^D_m, ... with their corresponding fuzzy attributes A_a, A_b, A_c,... through possibility measures $\Pi_k = \sup (S^D_k \cap A_a)$, (expressed graphically in Fig. 3), and aggregating them using the maximum operator: $\Pi_{\mathrm{Req}\,j} = \Pi_k \vee \Pi_l \vee \ldots$

As it is natural, if the requirement is modified by a NOT operator, its matching index will be complemented:

$\Pi_{\mathrm{Req}\,j} = 1 - (\Pi_k \vee \Pi_l \vee \ldots)$

The global matching index, Π_D, for the detection pattern shall be obtained by aggregating all of the requirements' matching indexes through the AND operator: $\Pi_D = \Pi_1$ AND ... Π_j AND ... Π_{nr} . This index expresses the possibility that the machine is in abnormal state, according to the detection pattern. The type of AND operator chosen will clearly influence the Fuzzy Detection process' output. If, for example, a

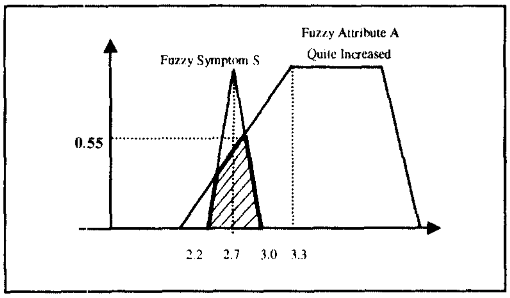

Fig.3. Matching of symptom S and attribute A using a Possibility Measure.

non compensated operator, like the minimum, is selected, it will result in a robust detection process, producing very few false detection alarms. However, the process will also be less sensible to detect small faults, in which all of the requirements may not be fully met. Therefore, and, as suggested by E. Sánchez [5], Salton's Soft- AND operator has been elected for this purpose:

$$x\ AND\ y = 1 - \left[\frac{(1-x)^p + (1-y)^p}{2} \right] \qquad (2)$$

($p \in [1,\infty)$)

Low values of p shall be used for sensible detection, while high values for p are chosen when a robust detection strategy is preferred.

2.1 Fuzzy Fault Isolation

If a fault has been considered detected, the isolation process will try to determine which of the faults under study is the one that has appeared in the system. This process is very similar to Fault Detection, although with some differing characteristics. First, the measured fuzzy symptoms, **S'**, will be matched against five patterns describing the five faults under study. The highest matching index (possibility measure) will correspond to the fault that has been considered detected. If this matching index is lower than a certain threshold, an unknown fault will be considered detected.

In Fault Isolation, the requirements that compose the different fault's patterns can have the same structure as in Fault Detection (equation 1). However, some very useful symptoms for fault isolation are the amplitudes of some special frequencies (and its harmonics and side-bands) measured in the frequency spectrum, cepstrum or envelope spectrum. In order to evaluate these features, the Vibration Analysis expert may use rules of thumb like "if *many* ORF envelope spectrum harmonics are markedly increased then an ORF fault has appeared" or "if *some* low frequency IRF power spectrum harmonics and side-bands are increased, we may have an incipient IRF Fault". This type of knowledge can be handled better with the use of *Fuzzy Quantifiers*. For this reason, some of the requirements of the Fault Isolation patterns will have the form:

Req.*j*: [NOT] (($Q_k\ S_k$ are A_a)
[OR ($Q_l S_l$ are A_b)...]]) (3)

Example: (***At least Some*** *Rotating Frequency Harmonics (Spectrum)* are *Markedly Increased*)

Here, Q_k, Q_l... are *Fuzzy Quantifiers.*

The matching process of the set of measured symptoms **S'** with the requirements that make use of Fuzzy Quantifiers is the same as for the requirements depicted by (1), though including the usual mathematical treatment for handling Fuzzy Quantifiers of the second kind [6].

Another important notion that is included in Fault Isolation is that of symptom-fault sensibility. In this paper, the numeric sensibility of symptom k to Fault i, will be expressed as T_{ik}. It is a non dimensional factor that expresses how much the presence of Fault i affects the magnitude of symptom k, and can be estimated numerically as [3]:

$$T_{ik} = \frac{\Delta S_k}{\Delta F_i} \frac{F_i}{S_k} \qquad (4)$$

Usually, the numerical estimation of a fault's size can be a difficult task, and it may not always be feasible to apply this equation. In these cases, the sensibility values will be set according to the expert's opinion.

It is obvious that if a symptom j is very sensible towards a fault i (high T_{ij}), it will be a more discriminating indicator of the presence of fault i than a less sensible symptom. As it is assumed that all of the symptoms that appear in every requirement j of the pattern for isolation of Fault i have similar symptom-fault sensibilities, the sensibility concept can be used to attach to every requirement j a weight, w_{ij}, that expresses its importance towards isolation of Fault i:

$$w_{ij} = \frac{T_{ij}}{\max_k T_{ik}} \qquad (5)$$

(for non negated requirements)

$$w_{ij} = 1 - \frac{T_{ij}}{\max_k T_{ik}} \qquad (6)$$

(for negated requirements)

After all the requirements' matching indexes have been obtained (Π_1, Π_2, ...) for the isolation pattern for Fault i , they will be aggregated taking into account the weights w_{ij}. Again, Salton's weighted Soft- AND operator [5] is used:

$$(x, w_x)\ AND\ (y, w_y) = 1 - \left[\frac{w_x^{\ p}(1-x)^p + w_y^{\ p}(1-y)^p}{w_x^{\ p} + w_y^{\ p}} \right]^{\frac{1}{p}} \qquad (7)$$

(here, w_x and w_y are the weights of variables x and y). This formula can easily be extended for more than

Table 1. Diagnosis Results.

#	Results / Fault Type	DETECTION			ISOLATION						IDENTIFICATION		
		Abnormal State	Normal State	R	ORF	IRF	BF	Unbal.	Misal.	R	Developed State	Incipient State	R
1	**Incipient ORF**	**1.0**	0.0	✓	**0.608**	0.019	0.008	0.0	0.0	✓	0.075	**0.659**	✓
2	**Incipient ORF**	**1.0**	0.0	✓	**0.695**	0.019	0.007	0.0	0.0	✓	0.090	**0.885**	✓
3	**Incipient ORF**	**0.676**	0.324	✓	**0.603**	0.019	0.007	0.0	0.066	✓	0.091	**1.0**	✓
4	**Incipient ORF**	**0.545**	0.455	✓	**0.598**	0.02	0.007	0.0	0.0	✓	0.0	**0.370**	✓
5	**Developed ORF**	**1.0**	0.0	✓	**0.530**	0.019	0.007	0.0	0.0	✓	**0.695**	0.188	✓
6	**Developed ORF**	**1.0**	0.0	✓	**0.765**	0.019	0.01	0.0	0.0	✓	**1.0**	0.091	✓
7	**Developed ORF**	**1.0**	0.0	✓	**0.889**	0.020	0.010	0.001	0.054	✓	**1.0**	0.091	✓
8	**Developed ORF**	**1.0**	0.0	✓	**1.0**	0.020	0.007	0.130	0.0	✓	**1.0**	0.091	✓
9	**Developed IRF**	**1.0**	0.0	✓	**0.145**	0.020	0.007	0.115	0.016	✗	**0.781**	0.081	✓
10	**Developed IRF**	**1.0**	0.0	✓	0.060	**0.994**	0.007	0.0	0.066	✓	0.0	**1.0**	✗
11	**Developed IRF**	**1.0**	0.0	✓	0.060	**1.0**	0.007	0.0	0.0	✓	**1.0**	0.0 .	✓
12	**Developed IRF**	**1.0**	0.0	✓	0.060	**1.0**	0.007	0.0	0.0	✓	**1.0**	0.0	✓
13	**Incipient IRF**	**0.857**	0.143	✓	0.029	**0.449**	0.007	0.0	0.0	✓	0.104	**0.677**	✓
14	**Incipient IRF**	**0.514**	0.486	✓	0.029	**1.0**	0.010	0.0	0.0	✓	0.076	**0.799**	✓
15	**Incipient IRF**	**1.0**	0.0	✓	0.029	**1.0**	0.007	0.016	0.066	✓	0.126	**0.306**	✓
16	**Incipient IRF**	**1.0**	0.0	✓	0.029	**1.0**	0.007	0.0	0.0	✓	0.126	**0.399**	✓
17	**No Fault**	0.410	**0.590**	✓									
18	**No Fault**	0.430	**0.570**	✓									
19	**Developed Misalignment**	**0.978**	0.022	✓	0.073	0. 0	0.087	0.027	**1.0**	✓	**1.0**	0.0	✓
20	**Developed Unbalance**	**1.0**	0.0	✓	0.126	0.0	0.0	**1.0**	0.066	✓	**1.0**	0.0	✓
21	**Developed Unb. & Mis.**	**1.0**	0.0	✓	0.023	0.156	0.002	0.027	**1.0**	✓	**1.0**	0.0	✓
22	**Developed Unb. & Mis.**	**1.0**	0.0	✓	0.126	0.0	0.0	**1.0**	0.066	✓	**1.0**	0.0	✓
23	**Developed Misalignment**	**1.0**	0.0	✓	0.023	0.157	0.002	0.027	**1.0**	✓	**1.0**	0.0	✓
24	**Developed Unbalance**	**1.0**	0.0	✓	0.126	0.0	0.0	**1.0**	0.066	✓	**1.0**	0.0	✓

two variables.

Low values of p shall be used for sensible isolation, while high values for p are chosen for robust isolation.

2.3 Fuzzy Fault Identification

Fuzzy Fault Identification pretends to measure the fault's size. Now, the measured symptoms are matched to two patterns: incipient or well developed state. The requirements are similar to the ones of Fault Isolation. However, as there is no need to discriminate between different fault types, weights have not been attached to the Identification requirements.

3. Application of the Diagnosis Method

Table 1 shows the results of applying the proposed diagnosis method to a set of 24 vibration samples obtained from a test machine in which unbalance, misalignment and two types of ball bearing faults (Outer Race Fault and Inner Race Fault) have been induced. A set of over 200 fuzzy symptoms measured in everyone of these vibration samples, was matched with a generic detection pattern and with isolation and identification patterns that described unbalance, misalignment, Outer Race Fault (ORF), Inner Race Fault (IRF), and Ball Fault (BF). As the results prove, the method can be applied with a good degree of reliability for diagnosis of these faults. However, when several faults occur at the same time, the method has a difficulty for diagnosing all of the faults. A more profound diagnosis study (with the implementation of isolation patterns that describe several faults appearing at the same time) is needed for these cases.

Application of the diagnosis method also showed the importance that the values taken by the weights of the isolation requirements have in order to get good performance results. The best results (shown in Table 1) were obtained after the isolation weights were tuned using a diagnosis optimization method based on Genetic Algorithms. With this optimization method, diagnosis performance can be improved for a specific machine if enough fault data for this machine is available. This will be the topic of a future research paper.

4. Concluding Remarks

A knowledge-based diagnosis method for rotating machinery using vibration data has been developed that takes into account several sources of imprecision. The system's knowledge base can be implemented in linguistic terms, resulting in a simple interface with the Vibration Analysis expert. The system's performance has been validated with a set of 24 vibration samples, giving satisfactory diagnosis results.

References

1. A. Barkov, N. Barkova, J. Mitchell. "Condition Assessment and Life Prediction of Rolling Element Bearings", Sound and Vibration, 10-17, June 1995. http://www.inteltek.com/articles/ .

2. D. Dubois, H. Prade, C. Testemale. "Weighted Fuzzy Pattern Matching", Fuzzy Sets and Systems, **28**, 313-331, 1988.

3. J. Fernández, L.J. de Miguel, J.R. Perán. "Applying Fuzzy Logic to Rotating Machinery Diagnosis", Proc. of the 4th International Conference on Soft Computing IIZUKA'96, 859-862, Iizuka, Japan, 1996.

4. J. Gertler, "Survey of Model-Based Failure Detection and Isolation in Complex Plants", IEEE Control Systems Magazine, 3-11, December 1988.

5. E. Sánchez, "Importance in Knowledge Systems", Information Systems, **14**, 455-464, 1989.

6. L. A Zadeh, "A Computational Approach to Fuzzy Quantifiers in Natural Languages", Computers and Mathematics, **9**, 149-184, 1983.

Acknowledgements

The vibration samples corresponding to the results shown in this paper have been kindly provided by Mr. Martin Weichselbaumer, from the German diagnosis company Prüftechnik AG.