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Mechanical Fault Monitoring in Industrial Environment: an Artificial Neural Network Based Approach

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Abstract: This paper deals with the early detection and intelligent diagnosis of mechanical faults in industrial turning machines. We develop a new strategy hybridizing conventional signal analysis based techniques and artificial neural networks issued methods. Experimental results, obtained from a real experimental industrial plant, validating the proposed strategy and issued intelligent fault detection and diagnosis system are presented and discussed.
Key words: Artificial neural networks, fault iagnois, machanical, experimantal validation.

1 Introduction

The significant increase of systems and plants complexity during last two decades made appear the fault detection (testing) and fault diagnosis tasks as major steps in all industrial processes. If the first interests have been focused on the problem of fault detection in complex system ((Isermann, 1984), (Abramovici & al. 1990), (Bahattacharya & al., 1990) and (Liu, 1991)), the fault diagnostic of those complex systems became very soon a central challenge for modern industry (Berneri & al., 1992). A large number of techniques, based on a wide range of approaches have been proposed. Major of them are reported in (Zwingelstein, 1995). However, the fault diagnosis dilemma is still an open problem (Bengharbi & al., 1997).

If the two conditions of accessibility and measurability are sufficient to ensure the success of a fault detection procedure, the fault diagnosis needs a set of supplementary conditions, which are not trivial. Among those conditions are: pertinent indicators determination, behavior or fault classification and decision tasks ((Juez & al., 2001) and (Barret & al., 2003)). So, fault's diagnosis is much more complex than its detection.

The general frame of the present work concerns early detection and diagnosis of faulty behaviors in industrial plants. We are especially dealing with mechanical faults detection and diagnosis in industrial turning machines. The used technology is the "vibration monitoring" which is employed in the frame of predictive maintenance of turning machines. It is known that vibration signature of a machine is closely related to its "health" and can thus help in the detection of early stage faults. For the turning machines, the main faults which can be diagnosed through vibration analysis are: imbalance, misalignment, looseness, shaft, bearing, gear damages, cavitations in pumps, turbulent flows in ducts, foundation problems and electrical devices related faults. In fact, many of those faults could be present simultaneously in the vibration signature, and the problem is to extract each of those faults from global signatures in order to detect and to identify the health of each component of the plant. If various vibration monitoring technology related indicators, used in industrial applications, have obtained a number of successes in detection of periodical faults, they are not always efficient to detect early stage faults, like rolling bearing defects, or hazardous shocks. We propose a different approach using hybridization of those conventional signal analysis based techniques and artificial neural networks issued methods.

This paper is organized as following. In the next section, we introduce our hybrid neural structure. Then, in section 3, the experimental setup dedicated to the validation of the presented structure will be described. Experimental results will be presented and discussed. Finally, before the references list, the last section will conclude and give the perspectives of the presented work.

2 Artificial Neural Networks based hybrid approach

The hybrid approach we propose hybridizes the action of a Neural Network based classifier and the action of a decision mechanism in order to perform an intelligent computer aided fault detection and fault diagnosis tool dedicated to mechanical plant dysfunction detection and classification. It includes three processing levels.

The first one is a pre-processing stage which processes the input data (obtained from the sensors) in order to extract relevant features related to the faulty behavior. Several signal processing based techniques, like normalization, spectral analyze or wavelet transform, could be used to transform the sensors issued information. In our case, dealing with mechanical faults detection and classification in turning electro-mechanical plants, the pre-processing stage is essentially a Fast Fourier Transform (an FFT stage) which provides a relevant information of plant's mechanical operation state. In fact, vibratory analysis issued information is frequently used to evaluate the operational state in industrial plants. That's why such information is effectively available in real-world industrial cases.

The second stage is a fault detection and classification stage. Finally, the last one is a decision stage, stating on plant's operational health. Figure 1 shows the general bloc diagram of the proposed fault detection and diagnosis architecture. Concerning the present work, the pre-processing stage is a conventional Fourier transformer performing a spectral (frequency) representation of the input sensor issued signal.

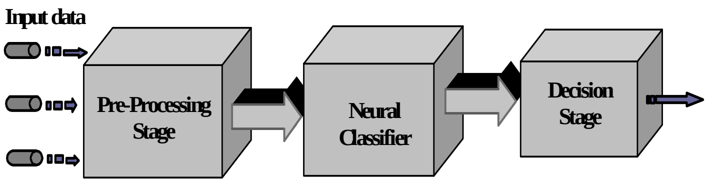


Figure 1. General bloc diagram of the proposed fault detection and fault diagnosis hybrid architecture.

As neural classifier, we choose to work with Learning Vector Quantization (LVQ) ANN (Kohonen, 1988) because of its competitive nature, which permit to avoid classification uncertainties due to input feature space mapping problems. The decision stage operates on the basis of statistical threshold rule: the membership to a given category (class) is decided if the decision confidence exceeds 90%. However, decision stage could operate also on the basis of ANN issued decision rules. For example, even if the LVQ model is essentially used for the classification tasks, the competitive nature of its learning strategy (based on 'winner takes all' strategy), makes it usable as a decision operator.

3 Experimental Setup, Validation Protocol and Results

The validation of the proposed approach has been performed on the basis of the proposed solution's detection and diagnosis evaluation. For that, two sets of experiments have been carried out. The goal of the first set was to refine the proposed hybrid solution. Data relative to this first case has been generated by simulation based on plant's simplified model (describing its correct and faulty operation). The goal of the second set was to measure our intelligent fault detestation and diagnosis system's efficiency for data obtained from an experimental real industrial machine.

Our experimental validation is concerned, in the frame of this paper, with two particular faults: an imbalance fault (fixing a given mass on the plate) and outer race damage in the ball rolling bearing. Moreover, to increase the detection and diagnosis related difficulties only a unique sensor has been considered, making the experimental validation conform to real world industrial conditions.

3.1 Simulation and Real Industrial Plant Based Data Sets Generation

Simulated waveforms have been generated on the basis of a simplified model describing a typical industrial case relative to usual classes of turning machines turning at 1500 rpm (25 Hz). Defects are created adding some sinusoidal force to the main waveform, which represents the correct operational mode of the plant. Relation (1) gives an example of imbalance fault simulation.

$$F_1 = a_{11}\,Sin(2\pi 25\,t) + a_{12}\,Sin(2\pi\,50\,t) + a_{13}\,Sin(2\pi 75\,t) \qquad (1)$$

An additional term, appearing as a second force simulating shocks (a pseudo DIRAC impulse) is then added. This second term, depicted by F_2, takes value a_2 at time T, and *0* at all the rest of time. Finally, some white noise simulating environmental interaction, appearing as some additional random force (F_3), is added to previous ones. Thus, force which excites the machine is then: $F = F_1 + F_2 + F_3$. Supposing that the vibratory response of the machine is linear, the mechanical vibration will be the convolution product between the force *F* and the impulsional response *y*(t) of the machine. The plant's impulsional response has been simulated by relation (2), where ξ denotes the damping ratio and f_0 the natural frequency.

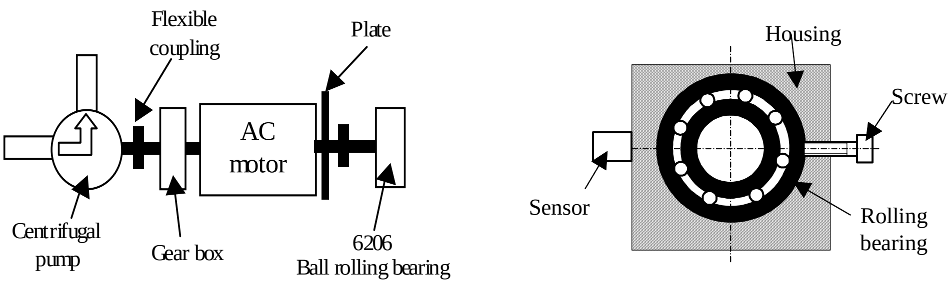
$$y(t) = e^{-x.2.p.f0.t}\,.\,Sin(2\pi\, f_0\, t) \qquad (2)$$

Based on the above-described machine's simplified model a database including 150 waveforms. 50 of them correspond to correct (faultless) operation state and others 100 patterns to faulty shape. An example of spectral representation of such waveform is given by figure 3-a for outer race damage in the ball rolling bearing.

Concerning the validation on real industrial machine, a turning machine capable to simulate various faults has been used. Among offered possibilities are: imbalance, misalignment, gear defect, cavitation in the pump and outer race damage on a ball rolling bearing. This experimental plant includes a set of modules among which:

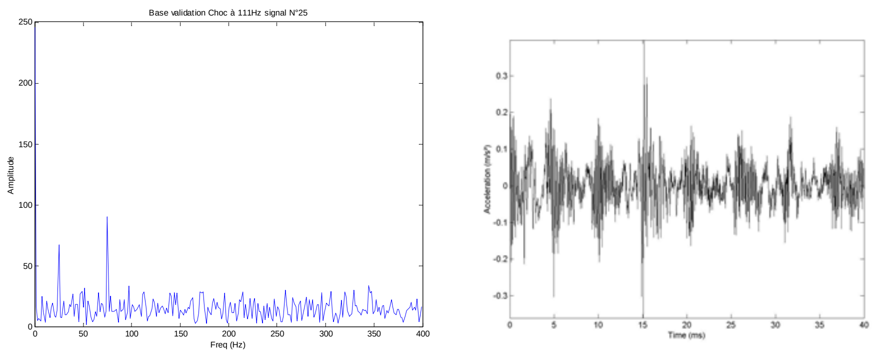
- A 1.5 kW AC motor able to reach a maximum turning speed of 1500 rpm.
- An angular-contact ball bearing (SKF 7206 or 6206) rolling bearing module.

An imbalance fault is set by fixing some given mass on the plant's plate. The outer race damage in the ball rolling bearing is artificially created with a screw (figure 2-right). Driving in the screw, one can warp the outer race of the bearing and thus create outer race damage. A piezoelectric accelerometer provides the vibration signal which will be recorded and then processed by the proposed neural network based structure.



(a) **(b)**

Figure 2. Experimental setup bloc diagram with a 6206 rolling bearing module (a). Outer race damage simulation in the ball rolling bearing (b).



(a) **(b)**

Figure 3. Spectral representation of simulated outer race damage simulation in the ball rolling bearing in presence of noise (a). Example of real accelerometer sensor issued pattern (b).

A database including 10 different waveforms sequences (corresponding to correct and faulty operation cases) with different fault magnitudes (increasing faulty behavior) has been constructed using this experimental plant. Accelerometer's output has been sampled at 1 kHz sampling period (4096 sampled values per waveform). An example of such waveform corresponding to outer race damage in the ball rolling bearing is given by figure 3-b.

3.2 Experimental Results

Firstly, we used simulation issued database to design (optimize) the neural classifier. The optimization has been done considering two parameters: the size of the learning database and the number of neurons in LVQ ANN competitive layer (hidden layer). The optimization criterion was "correct classification rate". Figures 4 and 5 give the obtained results for both categories (correct and faulty). One can remark that in the case of healthy operation recognition, the highest classification rate is obtained for a structure including 20 to 25 neurons with a learning database including not less than 25 patterns. In the same way, it could be seen that to match the machine's faulty operation, the neural structure should include 20 to 40 neurons. However, in this case the highest classification rates are obtained with smaller learning database (about 15 patterns).

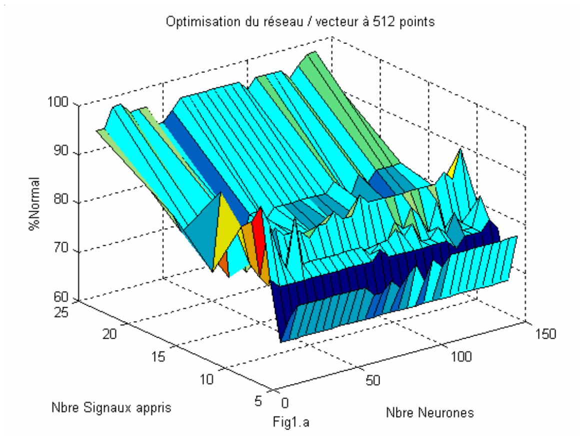


Figure 4. LVQ Neural classifier issued classification rates versus learning database size and versus number of neurons when correct functionality is learned.

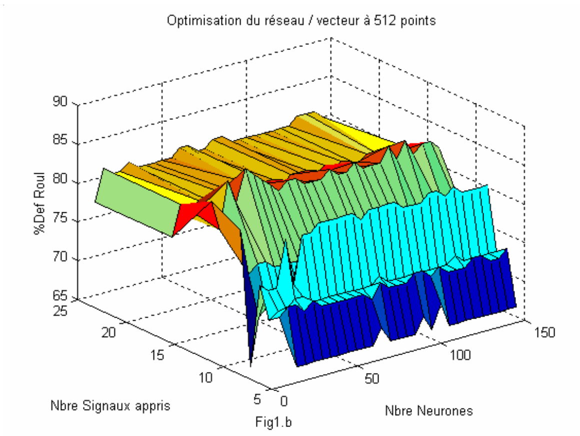


Figure 5. LVQ Neural classifier issued classification rates versus learning database size and versus number of neurons when faulty behavior is learned.

Table 1. Test conditions and results. 3 databases have contributed to following results: two simulation issued databases (DB N°1, DB N°2) and one real plant issued database (DB N°3)

Concerned database	Database & Conditions	Diagnosis Category	Classification Rate
DB N°1	Simulated / Noiseless	Unfaultable	93 %
		Faulty	83 %
DB N°2	Simulated / Noisy	Unfaultable	99 %
		Faulty	90 %
DB N°3	Real Machine / Noisy	Unfaultable	100 %
		Faulty	100 %

Using these results, we have implemented a neural structure including some 20 neurons. Concerning the learning phase, it has been performed on the basis of a learning database including 50 patterns (25 correct-function representatives and 25 faulty-function representatives). For validation, 3 different databases have been generated. The first one, called DB N°1, includes 150 model based simulated noisy waveforms (50 correct-function representatives and 100 faulty-function representatives). The second one, called DB N°2, contains 160 model based simulated noisy waveforms with simultaneous presence of two different faults (100 correct-function representatives and 60 faulty-function representatives among which 30 patterns with simultaneous faults). The last one, called DB N°3, has been constructed using real plant's accelerometer (sensor's output). It contains 10 different sequences corresponding to different levels of outer race damage in the ball rolling bearing. Table 1 gives results corresponding to simulated database.

Of course, all of 50 patterns of the learning database have been correctly learned (100% correctly recognized). It could be remarked from Table 1 that correct-function representatives are better matched than those corresponding to the faulty-function related patterns. This is verified independently from the fact that the processed data be noisy or noiseless. It could also be remarked the fault detection could be realized with a 99% success (on the basis of correct plant's functionality matching).

Conclusion

To avoid difficulties related to faults detection and diagnosis in modern industrial environments, we proposed a new approach using hybridization of conventional techniques and artificial neural networks issued methods. A scheme of such hybrid intelligent fault detector and classifier has been proposed including 3 stages. The preprocessing stage (the first in the processing chain) has been chosen in the frame of the vibratory analysis issued signatures preprocessing. It consists of a Fast Fourier Transform device which transforms the sensor issued signals (obtained from the monitored plant) in relevant information in term of vibratory information matching. We have designed (optimized) our system and we have validated it on the basis of simulated waveforms but also, using real industrial plant issued waveforms. An average of more than 90% of correct fault detection and diagnosis has been achieved. Obtained results show the viability of such hybrid approach to be implemented in real industrial environment.

We are actually working on generalization of our system to detection and classification of different kind of industrial plants faulty behaviors. Of course, the expected goal is to build an intelligent computer aided fault detection and fault diagnosis tool with generalization ability, adaptable to a wide variety of mechanical or electro-mechanical (mechatronical) plants.

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References

Abramovici M., Breuer M. A. and Friedman A. D., *Digital systems testing and testable design*, Computer Science Press, 1990, ISBN 0-7167-8179-4.

Bahattacharya D., Hayes J.P., *Hierarchical modeling for VLST circuits testing.* Kluwer Acad. Pub., 1990, ISBN 0-7923-9058-X.

Barret M., Madani K., Durastanti JF., *An Application of Wavelet Transform to the Detection of Incipient Spalling in Rolling Bearings*, IAR-Workshop on Advanced Control and Diagnosis – IAR-ICD 2003, November 2003, Duisburg, Germany, ACD proc. pp. 79-82..

Bengharbi A., Amarger V. and Madani K., *Multi-Fault Diagnosis of Analog non Linear Circuits by Smart Classification Technique*, Proc. of IEEE European Test Workshop 97, Torino, Italy, May, 1997.

Berneri A., Betta C. and Pietrosanto A., *An integrated measurement approach for fault diagnosis in electrical systems*, Proc. of 5th IMEKO TC4 Int. Symp, Vienna, Austria, April 1992.

Isermann R., *Process fault detection based on modeling and estimation methods* – A Survay, Automatica, vol. 20, 1984, pp. 387-404.

Juez J., Sainz G. I., Moya E. J. and Peran J. R., *Early detection and diagnosis of faults in an AC Motor*, Bio-Inspired Applications of Connectionism (J. Mira and A. Prieto (Ed.)), Lecture Notes in Computer Science Series, Spinger Verlag, pp. 595-602, 2001.

Kohonen T., *Learning Vector Quantization*, Neural Networks, vol. 1, suppl. 1, p. 303, 1988.

Liu R-W, *Testing and diagnosis of analog circuits and systems*, Van Nostrand Reihold Publisher, 1991, ISBN 0-442-25932-8.

Zwingelstein G., *Diagnostic des Défaillances*. HERMES, Traité des nouvelles technologies – Diagnostic and Maintenance Series (in French), 1995.