A Hybrid Multi-Experts Methodology for Mechanical Defects' Detection and Diagnosis

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Abstract. Compared with parametric classifiers, several advantages set Neural Networks as privileged approaches to be used as discriminating classifiers in performing diagnosis tasks. In this paper, we present a hybrid Multi-Experts neural based architecture for mechanical defects' detection and diagnosis. This solution is evaluated within vibratory analysis frame using a wavelet transform faults' detection scheme.

1 Introduction

Monitoring of mechanical systems requires development of adapted procedures compatible with the operation ranges (shapes) of the monitored devices. Generally, behaviours analysis is associated to a set of signals (called also signatures of the monitored effects"). An example of such signatures could be obtained from chemical or physical characteristics of materials composing the monitored mechanical devices or involved in their operational phases, as: current, lubricant viscosity, acoustical signatures, etc. For bearing defects, these signatures are characterized by transitory phenomena (repetitive or random) due to the shocks' effect on the structures. Such signatures compile the frame of the vibratory analysis. A number of previous works show that vibratory analysis issued signatures include pertinent information about mechanical devices' worsening [1], [2]. Note that conventional approaches of signal processing don't permit to exploit this information in its totality especially if the related signatures are not periodical signals [3].

The general frame of the present work deals with early faults' detection in industrial plants, especially with mechanical faults' detection in turning machines. For the turning machines, the main faults which could be diagnosed through vibration analysis are: imbalance, misalignment, looseness, shaft, bearing and gear damages, cavitations in pumps, turbulent flows in ducts, foundation problems and electrical faults [4]. An additional difficulty related to the above-mentioned defects is due to the fact a large part of mechanical devices in a turning machine are inaccessible, because they are generally located inside the machine. Concerning inaccessible mechanical devices, the vibratory analysis issued techniques show attractive features because they may detect vibratory effects of internal devices from a global vibratory signature.

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Fig. 1. Examples of "Unbalanced Force Defect's" effect on turning plant's rotation axis (left) and "Flaking Path Defect" in a bearing device (middle and right).

We propose different slant, associating wavelet transform, vibratory analysis (because of the aforementioned advantages) and Artificial Intelligence issued approaches. In fact, beside the vibratory analysis issued techniques' advantages, wavelet transform could act as some kind of "zoom" effect (multi-resolution capability) in order to separate appropriated frequencies' components (those related to potential faulty behavior) from monitoring signal's of others components. On the other hand, artificial intelligence is used for classification tasks (fault's nature authentication). Taking advantage from neural networks' based classifiers and their learning and generalization [5], [6], these techniques are applied for characterizing bearings deterioration. The two bearing device defects' categories we are interested in this paper are: "Unbalanced Force Defect" (UFD) and "Flaking Path Defect" (FPD). Fig. 1 shows examples of the impact of such defects on turning plants' mechanical devices. A comparative study between our hybrid technique and two neural network based architectures, Radial Basis Function (RBF) network and Learning Vector Quantization (LVQ) network, has been presented.

The paper will respect the following structure: the next section will briefly present wavelet base defect detection within the vibratory analysis frame. The section 3 will present the "expert-fusion" based classification approach: a key part of the proposed solution. Section 4 and its subsections will give validation results and discussion. Finally, the last section will conclude the paper and give a number o perspective points.

2 Vibratory Analysis and Wavelet based Defects' Detection

The detection procedure is based on the analysis of the minor (details) components of the vibratory signature's wavelet transform: the occurrence of a shock in the vibratory behaviour is highlighted by the amplitude of the wavelet coefficients. The procedure includes four steps:

1. Determining the needed resolution corresponding to the wavelet coefficients ensuring the shocks' detection,
2. Computing of detail (minor) wavelet transform coefficients,
3. Computing of indicators' values relative to the vibratory signal,
4. Defect's severity characterization by comparing the indicators' values to a set of knowledge based thresholds values.

The vibratory signature's wavelet transform based processing opens the possibility of a "multi-bands" vibratory analysis (e.g. multi-resolution detection), involving several frequency bands. Thus, the proposed detection procedure could be run for each of the obtained spectrum ranges (detail) [7], [8], [9], [10]. Fig. 2 shows an example of obtained bands from an electromechanical turning machine issued vibratory signature. The presence of one or several defects results in the apparition of new frequencies. Detection of these new frequencies allows distinguishing potential glitches, to classify them according to their typological features (unbalanced force defect, flaking path defect, etc.) and to warn their consequences.

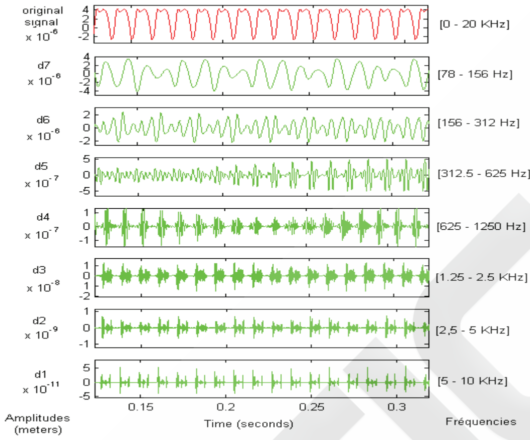

Fig. 2. Wavelet decomposition of a vibratory signal corresponding to flaking path defect (depth 157µm) at speed of 1500 rpm with wavelet sym7.

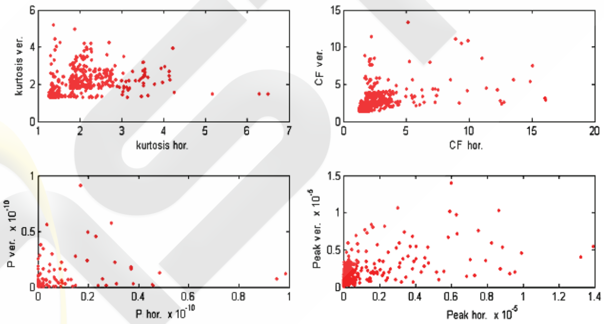

Fig. 3. Representation of the set of descriptions.

Concerning indicators, various scalar indicators as energy (*E*), peak, crest factor (*CF*), power (*P*), root mean square (*rms*), shape factor (*SF*) and kurtosis (*kur*) [10] [11] [12] could be valuable markers to define a "Multi-Features Vector" (MFV) which will be used as input for the classification unit. Concerning bearing devices such MFV are constructed for two directions of involved forces: horizontal and vertical.

$$MFV = [Feature_1, \cdots, Feature_j, \cdots, Feature_P]^T \qquad (1)$$

$$\mathrm{M}FV = [E, peak, CF, P, \ rms, \ SF, \ kur] \tag{2}$$

The analysis of data relative to the monitored plants' faulty or healthy operational modes in such feature spaces (defined on the basis of the constructed MFV) is a crucial point in defining classes' reparability boundaries and rules in order to make the classifier's action more accurate. Fig. 3 shows the data representation corresponding to different aforementioned indicators in a bi-variables feature subspace constructed from horizontal and vertical components of those indicators. It shows the possibility to identify appropriated shapes of corresponding to healthy and deficient behaviours of the concerned mechanical device (here a bearing device). So, if the classification task is of major importance in the proposed technique, the choice of pertinent indicators (via the above-mentioned data analysis in indicator's issued feature space) and a reliable detection (performed here by using a wavelet based multi-resolution approach) are two other strong points in our technique.

3 Multi-Experts based Classification

The classification strategy we propose is based on Multi-Experts principle also known as "Mixture of Experts" based approach. In such class of processing strategy the final output (the treatment's result) is constructed (obtained) from a set of local models (experts) which are specialized (devoted) either to a specific processing task or to a specific region of the processed problem's feature space. The final result is obtained from a fusion of local models' outputs or from a decision policy involving either the whole experts or a reduced number (a subset) of specialized processing units.

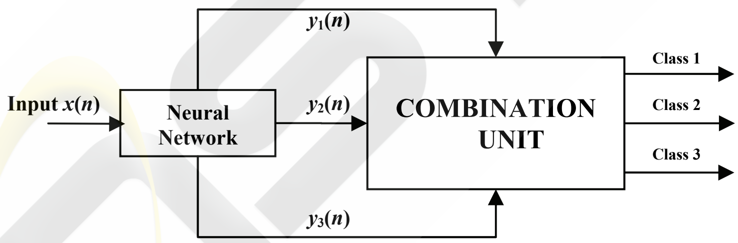

Fig.4. Single-Expert ANN based classifier.

It should be noted that the outputs' fusion operation is not exclusive (specific) to Multi-Experts schemes and may be used as a resource to perform the decision task. An example is depicted in Fig.4 where a 3-categories classification, performed using a single artificial neural network, takes advantage from a decision to carryout the final classification. The decision policy could involve either matching rules or combination policy to construct the final decision.

In our approach, the proposed scheme is a Multi-Expert neural based classifier including three neural networks (operating as local features' classification modules) where the final output (classification result) matches three possible turning plant's operational categories. Two among those three categories correspond to a faulty bearing device and one to a healthy bearing device meaning a “Normal” state (N) of the concerned mechanical device. The two bearing device defects’ categories are “Unbalanced Force Defect” (UFD) and “Flaking Path Defect” (FPD), respectively. The decision unit operates on the basis of combinatory matching rules in order to carryout a unique class (category) among the three above-mentioned possible categories.

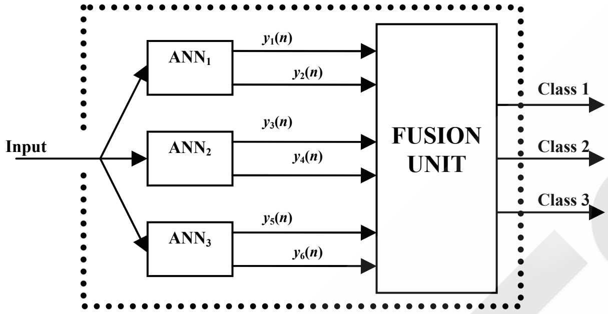

Fig. 5. Multi-Expert ANN based classifier’s bloc-diagram.

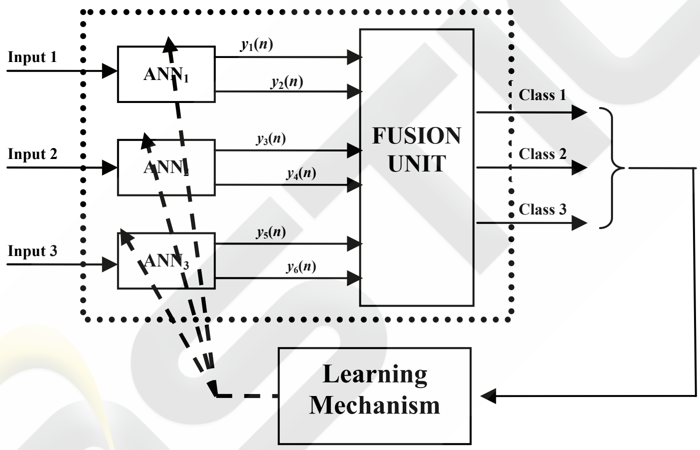

Fig. 6. Training scheme of Multi-Expert ANN based classifier.

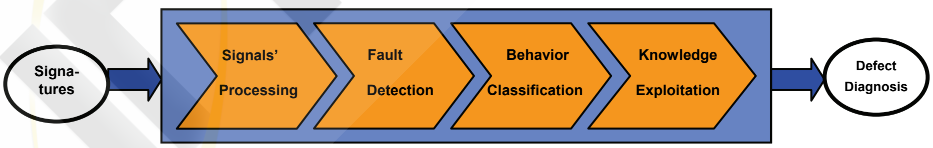

Fig. 7. Global bloc-diagram of the proposed solution.

Concerning the experts, each of them is specialized in matching between two classes: one of them is concerned with FPD and N classes’ discrimination, the other deals with the classification of UFD and N functioning categories and the last one distinguishes between FPD and UFD classes of bearing defects. Fig. 5 gives the classifier’s bloc diagram. The neural based classifier’s knowledge construction is done over a training process involving each of the three neural networks separately. Fig. 6 gives the learning mode's bloc diagram. Two kind of local neural network based experts have been implemented and compared: Learning Vector Quantization (LVQ) neural structure and Radial Basis Function (RBF) neural model. The global bloc-diagram of the proposed solution is shown in Fig. 7.

4 Validation, Results and Discussion

4.1 Experimental Set-up and Protocol

The experimental protocol for validation of the above-described automated diagnosis chain has been based on detection and diagnosis (authentication) of the two afore-mentioned defects in SKF-6002 bearing device. Table 1 gives topological and dynamical characteristics of the SKF-6002. So, three operational categories (classes) have to be detected and recognized: the normal class, the unbalanced defect class and the flaking path defect class (correspondent to a diagnosis of the defect detected which is being a failing of the flaking path of the outer race). According to the previously identified indicators, a training database containing 1594 MFV has been constructed, including a number of MFV corresponding to each possible class. The ratio of each class in the learning database is reported in table 2. The same table gives the ratio of each class within the testing database which includes 798 MFV. The two kinds of above-described defects are present with different degrees of impairment as well in learning database as in testing one. Concerning the unbalance forces' related defects, the considered rotation axis dislocations correspond to misbalancing forces covering 10 to 100 g.cm. While, the flaking paths defects correspond to fissures of 280 µm average deep and a varying width covering the range of 30 to 910 µm.

Table 1. Technical and geometrical features of deep grove ball bearing SKF-6002.

Ball diameter	4.762 mm
Inner race diameter (d)	18.738 mm
Outer race diameter (D)	28.262 mm
Radial clearance (γ)	20 µm
Maximum amplitude of waviness (Πp)	3 µm
Initial amplitude of waviness (Πo)	2 µm
Radial load (W)	6 N
Mass of rotor (m)	0.6, 1.0 and 2.4 kg
Damping factor (c)	200 Ns/m
Number of balls (Nb)	9
Number of wave lobes (N)	8
Angular location (S)	π/4
Constant for Hertzian contact elastic deformation (k)	$7{,}055.10^{9}$ N/m$^{3/2}$

Table 2. Number of Multi-Feature Vectors (MFV) used in training and testing phases as well as the ratio of signatures: healthy, unbalanced defect and flaking path defect (%).

Number of MFV	Normal	Unbalanced force	Flaking path defect
1594 (for training)	34.6	29.9	**35.5**
798 (for testing)	**49.9**	**30.1**	**20.0**

For validation experiments we have considered two following cases: a detection/authentication chain based with a single neural network classifier and our hybrid multi-experts scheme. As well for the single neural network based classifier as for the hybrid solution, two kind of neural models (LVQ-like neural net and RBF-like model) have been implemented.

4.2 Experimental Set-up

Table 3 summarizes results relative to obtained performances using single neural network based scheme. For each kind of classifiers different MFV have been considered. The considered MFV are composed by previously introduced (in section 2) scalar indicators measures in horizontal and vertical directions. They differ in number of components (number of indicators composing the MFV). The number of components varies from 4 (corresponding to horizontal and vertical measures of 2 indicators) to 14 (corresponding to same measures of 7 indicators) and defines the number of neurones of the input's layer. The output layer of each neural classifier contains 3 neurons corresponding to the 3 possible operation categories.

Table 3. Performances of the single neural network based classifier – plant's rotation speed is 400 rpm.

Neural Network Type	Sequences of observations	Dimension of Input Vector	Number of Data Sets			Correct Detect Rate			Average Detection Rate
			N	UFD	FPD	NR	UDR	FDR	
LVQ	Memorization	4	551	477	566	$\frac{446}{551}$	$\frac{388}{477}$	$\frac{539}{566}$	$\frac{1373}{1594} = 86{,}14\ \%$
	Generalization	4	398	240	160	$\frac{297}{398}$	$\frac{206}{240}$	$\frac{97}{160}$	$\frac{600}{798} = 75{,}19\ \%$
	Memorization	14	551	477	566	$\frac{371}{551}$	$\frac{426}{477}$	$\frac{542}{566}$	$\frac{1339}{1594} = 84{,}00\ \%$
	Generalization	14	398	240	160	$\frac{299}{398}$	$\frac{222}{240}$	$\frac{112}{160}$	$\frac{633}{798} = 79{,}32\ \%$
RBF	Memorization	4	551	477	566	$\frac{450}{551}$	$\frac{427}{477}$	$\frac{561}{566}$	$\frac{1438}{1594} = 90{,}21\ \%$
	Generalization	4	398	240	160	$\frac{298}{398}$	$\frac{213}{240}$	$\frac{145}{160}$	$\frac{656}{798} = 82{,}21\ \%$
	Memorization	14	551	477	566	$\frac{494}{551}$	$\frac{78}{477}$	$\frac{405}{566}$	$\frac{977}{1594} = 61{,}29\ \%$
	Generalization	14	398	240	160	$\frac{362}{398}$	$\frac{55}{240}$	$\frac{81}{160}$	$\frac{498}{798} = 62{,}41\ \%$

In the same way and considering the same MFV, Table 4 gives the obtained results for hybrid Multi-Experts chain. The local neural experts are RBF-like neural networks.

It is interesting to note from Table 3 that in the case of RBF-like single neural network based classifier the generalization (e.g. testing) using MFV including 2 indicators (e.g. 4 components) performs better results than those obtained with a 7 indicators MFV (e.g. 14 components). This could be explained by the fact that considering more indicators leads to increase the input feature space dimensionality for a same number of learned (representative) patterns and thus, the RBF-like classifier (which operates on the basis of a patters' distance issued matching policy) has to map a larger feature space with the same number of learned patterns. While the same table shows that LVQ-like neural classifier leads to quite similar (rates of defects' correct detection and classification between 75 and 80 %) either using MFV including 7 indicators or exploiting 2 indicators MFV (even if the obtained results are slightly better when 7 indicators are used). This is due to the conjunction of two facts. The first one is related to the fact that in LVQ-like neural model the matching is obtained in "competitive layer" of such network performing a "Winner Takes All" (WTA) policy. In fact, the two defects' categories as well as the healthy operational state are matched essentially on the basis of two (among seven) indicators, but as the matching is obtained from a WTA based decision policy (excusive decision), the increase of the input feature space's dimensionality remains of a limited effect on classification performance. Beside this first factor, another reason avoiding the classification rate decreasing here is related to the fact that the major data is discernible enough regarding the above-described matching policy in 2-D feature space obtained from the first two indicators. The similar performances obtained with RBF-like classifier (82% correct classification) when 2 indicators are used confirms this purpose

Table 4. Performances of the Multi-Experts based classifier – plant's rotation speed is 400 rpm.

RBF architecture		Number of Data Sets N	UFD	FPD	Correct Data Rate NR	UDR	FDR	Individual Average Detection	Average Detection Rate
Memorization 4 indicators	ANN_1	551	0	566	$\frac{462}{551}$	–	$\frac{566}{566}$	$\frac{1028}{1117}$ = 92,03 %	92,71 %
	ANN_2	551	477	0	$\frac{494}{551}$	$\frac{455}{477}$	–	$\frac{949}{1028}$ = 92,32 %	
	ANN_3	0	477	566	–	$\frac{419}{477}$	$\frac{559}{566}$	$\frac{978}{1043}$ = 93,77 %	
Generalization 4 indicators	ANN_1	398	0	160	$\frac{324}{398}$	–	$\frac{145}{160}$	$\frac{469}{558}$ = 84,05 %	89,73
	ANN_2	398	240	0	$\frac{360}{398}$	$\frac{231}{240}$	–	$\frac{591}{638}$ = 92,63 %	
	ANN_3	0	240	160	–	$\frac{211}{240}$	$\frac{159}{160}$	$\frac{370}{400}$ = 92,50 %	

However, the slightly better results obtained with RBF architecture with MFV including 2 indicators (4 components) seems to privilege the use of this neural classifier against in spite of the LVQ based classifier. That is why the Multi-Experts architecture has been implemented including three RBF networks. Results are reported in Table 4. It is pertinent to note the significant enhancement of classification rate. Fig. 8 completes the results of the two last tables by giving learning and generalization performances versus the number of involved (exploited) indicators. If Fig. 8-a confirms the results consequences of the first table (Table 3), the second (e.g. Fig. 8-b) reveals an additional interesting point. In fact it is interesting to note the enhancement of classification rate as well when a 4 component MFV is exploited as when the input MFV includes 14 components (a 15% classification rate increasing). That shows the experts' mixture strategy's pertinence (efficiency).

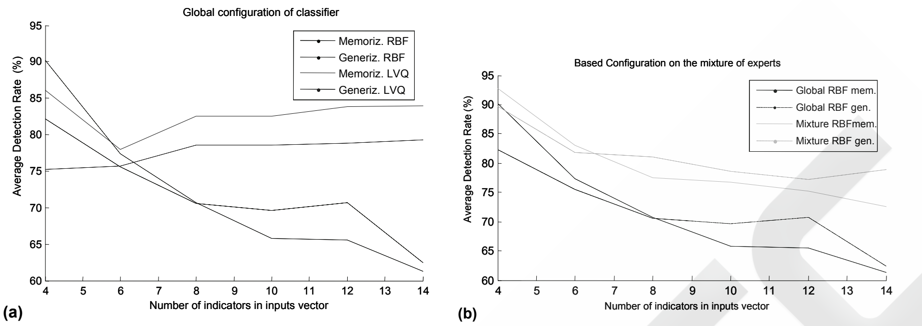

Fig. 8. Performances of training and generalization versus number of involved features for single neural network based classifier (a) and Multi-Expert solution (b).

5 Conclusions and Perspectives

We have presented a hybrid Multi-Experts neural network based architecture for mechanical defects detection and authentication in turning plants, which are massively present in industrial production chains. The pertinence of the experts' mixture strategy has been shown and validated. On the other hand, the advantage of a wavelet transform based multi-resolution detection leads to capability of simultaneous detection of different kind of mechanical defects. Finally, the use of vibratory analysis technique make possible the inaccessible mechanical devices' monitoring from a global vibratory signature obtained from relatively low cost standard sensors.

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