Comparison Among Different Metrics in Probabilistic Neural Network for Diagnostic of Rolling Bearings Faults

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Abstract: *Reducing maintenance costs is extremely important to raise industrial competitiveness. In this context, methodologies based on predictive maintenance are a need for optimization of plant systems diagnosis in order to increase accuracy and to reduce human errors. Diagnosis process automation directly results in improved reliability for taking decisions. The present work describes an automatic diagnosis system for detection defects in bearings using a system developed with probabilistic neural network. This work intend to discuss the difference among the kinds of metrics and if there is an influence on the results. The PNNSD (Probabilistic Neural Network System Diagnosis) was developed to be able to detect defects, to identify the location of defects (inner race or outer race) and to identify the different defects in rolling bearings operating under several shaft speeds and load conditions. The measured vibratory signals were analyzed by spectral techniques. The results demonstrate that the system is an excellent tool for detect and classify bearing faults.*

Key words: *predictive maintenance, faults detection, rolling bearings, probabilistic neural network.*

1. Introduction

In order to improve industrial competitiveness, cost reduction in industrial plant maintenance is becoming increasingly important. Many methodologies, that have been used to improve production reliability as well to reduce operational costs, are based on condition maintenance (predictive or proactive). In this context, it is important to develop optimized systems of monitoring and diagnoses to increase precision in the diagnostic and to reduce human errors.

The number of monitored points in an industrial plant can be as high as a dozen of thousands among bearings (rolling, journals, etc.), gearboxes, motors, pumps, etc and vibration signals [2,3]. The most common commercial diagnostic systems compare some parameters of the measured signals to specific standard reference values. In general, the alarm threshold is established based upon energy parameters as RMS of the complete vibration signals, or for some frequency bands of these signals. An alarm is activated when the measured parameters exceed these values and, in this case, a more accurate analysis (spectral analysis, envelope, time-frequency and time scalar methods, etc.) has to be performed by a specialist to confirm the diagnosis. The amount of erroneous diagnosis is large and frequent, either because an actual alarm doesn't occur or a conclusive diagnosis is not obtained, or else because the diagnosis is false.

More sophisticated diagnostic systems use classification methods, such as statistical and geometrical classifier [7,9], neural networks [8,11,12] and fuzzy logic [1,4,5,15], to recognize machinery condition. These methods allow developing more automatic and reliable diagnostic systems. These automatic diagnosis systems should be robust to the point of dealing with a diversified source of information coming from different equipments and should be able of deal with a diversified set of defects.

The present work describes automatic diagnostic systems for rolling bearing fault identification based on the Probabilistic Neural Network (PNN) and are named as Probabilistic Neural Network System Diagnoses - PNNSD. The PNN is based on the Bayesian statistical decision criterion, and still has a restrict use, especially in the case of machinery element fault classification.

With neural network technique it is possible also makes manipulating different methods of signal processing in a integrated context as also the system developed. The PNN technique is possible to apply different metrics to explore each condition of studied problem, is interesting to explore all parameters in this method to obtain better results.

The designed system deals with vibration signal spectra collected in several bearing operation conditions (shaft speeds and load conditions). Nine different fault features were used to compose the database. Three diagnostic strategies were studied with different classification complexity.

An analyze of the impact of different metrics used in the Parzen function in the neural network performance is done.

2. The Experimental Set Up

An AC motor, that drives a shaft in which the rolling bearing was set up, composes the experimental apparatus. Connected to the bearing housing there is a mechanism that applies a known radial loading over the rolling bearing. An electronic inverter device controls the speed of the AC motor (Fig.(1)).

Rolling bearing faults may appear as a consequence of several problems: lubrication inadequacies and contamination, improper storage or installation, etc. One way to classify these faults is by means of the size of the surface defects. In order to simulate different defects sizes, four different faults types were introduced in the outer race or in the inner race of the rolling bearing: a pit (punctual size) in outer race or inner race, a localized corrosion produced by synthetic sea water during 8 and 24 hours (medium size) in outer race or inner race and a scratched surface (distributed all over the outer race or inner race surface). Therefore, eight different type of defects was generated. A perfect rolling bearing was also used to represent the normal condition. Each one of these nine patterns is named by a code, which is: *N* for normal, *Si* for scratched inner race, *So* for scratched outer race, *Pi* for pit inner race, *Po* for pit outer race, *C1i* for the corrosion during 8 hours inner race, *C1o* for the corrosion during 8 hours outer race, *C2i* for the corrosion during 24 hours inner race and *C2o* for the corrosion during 24 hours outer race.

Vibration signals from bearing housing were collected using a piezoelectric accelerometer, mounted vertically on the top of the bearing housing. The accelerometer was connected to an amplifier, with a low pass filter with 2 kHz of cut-off frequency. An A/D converter device digitized the filtered signal, with a sampling frequency of 5 kHz. Each signal is represented by 2048 points. Figure (1) shows the experimental apparatus scheme.

Twenty samples of the same signal were collected for each one of the nine defects, considering six different shaft speeds (400 to 1400 rpm) and three different conditions of radial loading (200, 400 and 600N). Consequently 3240 acceleration signals form the database.

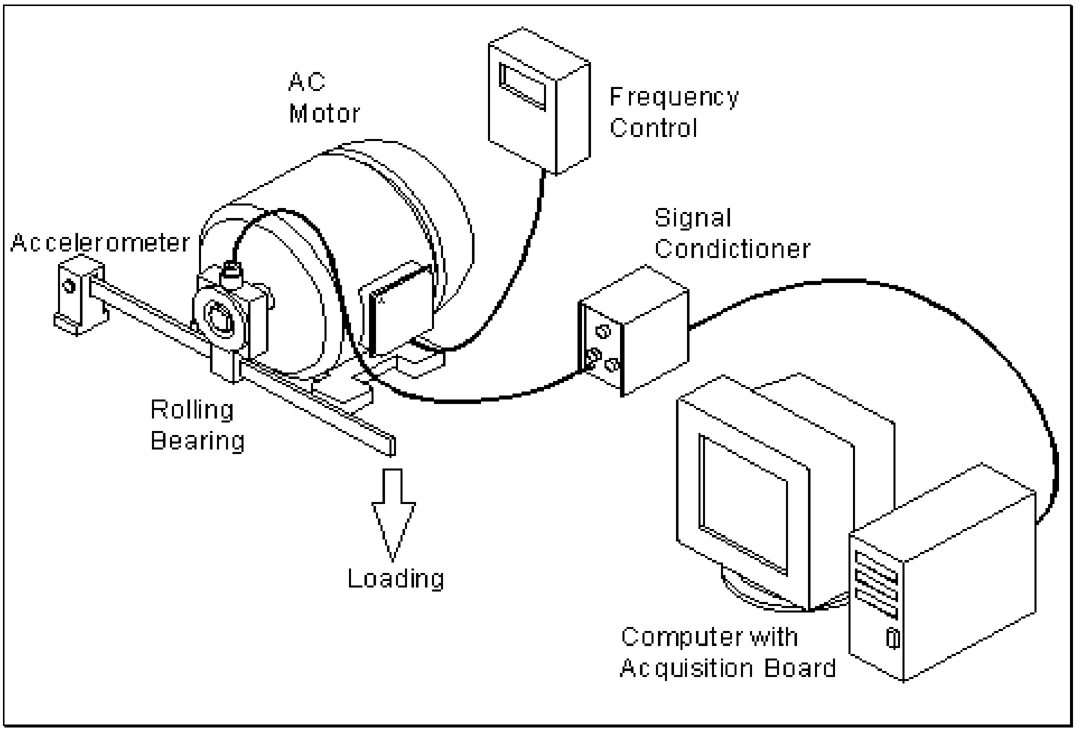

Figure 1 – Scheme of the experimental set up.

3. Pre-Processing Methodology

The pre-processing phase has the main objective of to provide the adequate feature representation of each fault pattern, in order to be presented to the neural network. The way in what that feature representation is reached has an important impact in the classification performance and in the network complexity and computational effort [1,4,11,15].. The general performance of the neural network increases with the quality of fault feature representation and with the shortest input vector size.

In this work it was used the Power Spectral Density of the vibration signals as input vectors. The signal PSDs were calculated by using Welch's Method [6], employing a Hanning window as weighting window. In order to minimize the PNN input layer each PSD vector is represented by 64 points, which implies in a timing window of 128 points and, therefore, a frequency resolution of 15 Hz.

4. PNNSD - PNN System Diagnosis

4.1 Probabilistic Neural Network

The PNN [11,12,13,14] is not a truly neural network paradigm, but an adaptation of the statistical Bayesian decision rule to the neural network formalism. Four layers compose the PNN architecture. The first one, the input layer, has its dimension dictated by the dimension (p) of the input vector. The second, the pattern layer, has the dimension (p*k) of the number of examples in the training set, while the third one, a summation layer, has the dimension (k) equal to the number of classes in the set of the examples, and one output or decision layer.

An example of a PNN architecture is shown in Fig. 2. The number of layers and the number of nodes for each layer are rigidly fixed and are defined by the training set dimension.

When an input vector $x=\{x_1, x_2, x_3, \dots x_p\}$ is presented to the network, the input layer transfers these p values to all the pattern layer nodes. This second layer is fully connected to the input layer, with one neuron for each pattern in the training set. The distance between the input vector x and the target vector x_t, that represents each one of the k classes of the pattern layer, is calculated (by some norm). After this, a transfer function *F* is used to change the value calculated at each one of the pattern layer nodes. The transfer function most widely used is the Parzen's probability density function (PDF) estimator *W*, with a Gaussian kernel function. Parzen proved that the estimated PDF of a population converges to the actual PDF as this population increases, independently of the population presenting a normal distribution or not. The transfer function of the pattern layer is given by:

$$F_1(x) = \frac{1}{ns}\sum_{i=1}^{n} W\left(\frac{\|x - x_t\|}{s}\right) \tag{5}$$

n → number of training patterns
σ → smoothing parameter (sigma parameter)

The scaling parameter sigma defines the width of the bell curve that surrounds each sample point. This value is an adjustable parameter and needed be determined for each training set.

The type of distance or metric used int the parzen function can have an important impact in the classification performance of the PNN, since it represents the resemblance or the proximity of both vectors. Several different types of metric can be used. In this paper the following three are employed and its impact in the classification performance are analyzed in section 5:

Euclidean distance $$Z_i = \sum_{j=1}^{p} \left(x_j - x_j^i\right)^2 \tag{6}$$

Cityblock $$Z_i = \sum_{j=1}^{p} \left|x_j - x_j^i\right| \tag{7}$$

Dotproduct $$Z_i = x.x^i - \frac{1}{2}\|x\|^2 - \frac{1}{2}\|x_i\|^2 = X \cdot X_i \tag{8}$$

The output of each neuron of the class *j* of the pattern layer is added at the summation layer and is available at the node S*j* . At the output layer, a comparison is then made among the S*j* values. The index *j* of the maximum S*j* among the S_1, S_2,..., S_k values, indicates to which class the input vector belongs.

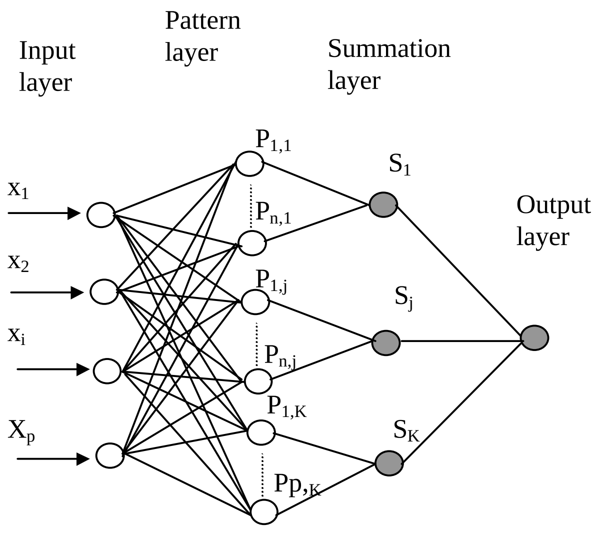

Figure 2 - Topology of PNN.

4.2. Diagnose Strategies

In this work the rolling bearing faults diagnostic problems were studied by using different classification strategies, always using PNN as a diagnostic technique and the Power Spectral Density of the vibration signal as input vectors. Three different type of metric were employed in PNN. The three different classification strategies used are shown in Table I.

TABLE I
Classification Strategies of PNNSD

	Normal	**Any Faults**	**Faults in Inner Race**	**Faults in Outer Race**	**All kinds of Faults**
Detection	x	X			
Identification	x		x	x	
Classification	x				x

In Table (1) the first strategy, named Detection, intends to identify the normal condition and the fault one, having two classification classes. It is the simplest strategy. The Identification strategy seeks to separate the normal condition, the faults in the inner race and the faults in the outer race. The last one, Classification, intends to classify all types of conditions, normal and faulty, being the more complex classification problem.

The training set is composed by 432 signals and the test set by 108 signals (20% of the total database).

5. Results and Discussion

Table 2 resumes the results obtained with the developed PNNSDs. For each diagnose strategy (Table 1) Table 2 shows the results obtained with the three metrics employed in the PNNSDs. It can be seen that for all the classification strategies the Eucledian and Cityblock norms give excellent results, but the Dotprod norm decrease the performance of the PNN with the increasing of the classification complexity.

Table 2
Main Results

Fault/Metric	**Euclidean**	**Cityblock**	**Dotprod**
Detection	98,15%	98,15%	88,89%
Identification	98,15%	98,15%	41,67%
Classification	98,15%	98,15%	5,56%

Figures 3 and 4 show examples of the correct classification results evolution with the sigma variation. These curves show the classification results ca be more or less sensible to the metric. When the Euclidean metric is used the best classification is located in a small range of sigma value and when cityblock metric is employed this range is much more wide. This fact seems to indicate that the use of the cityblock metric gives a more robust diagnostic system, regarding the choice of the best sigma value.

Therefore, these results show that optimization of the PNN performance depends on the perfect combination between sigma value and type of metric.

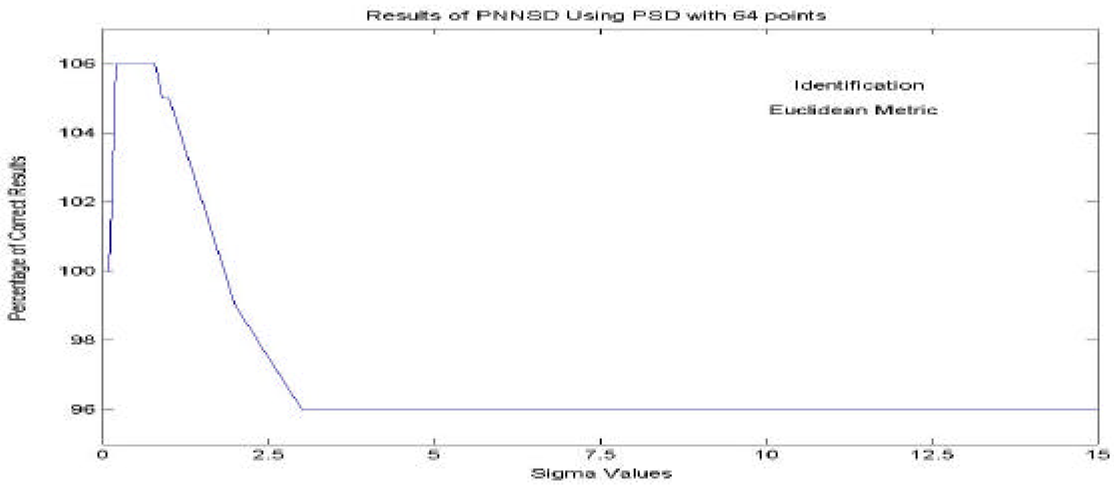

Figure 3 – Euclidean Metric.

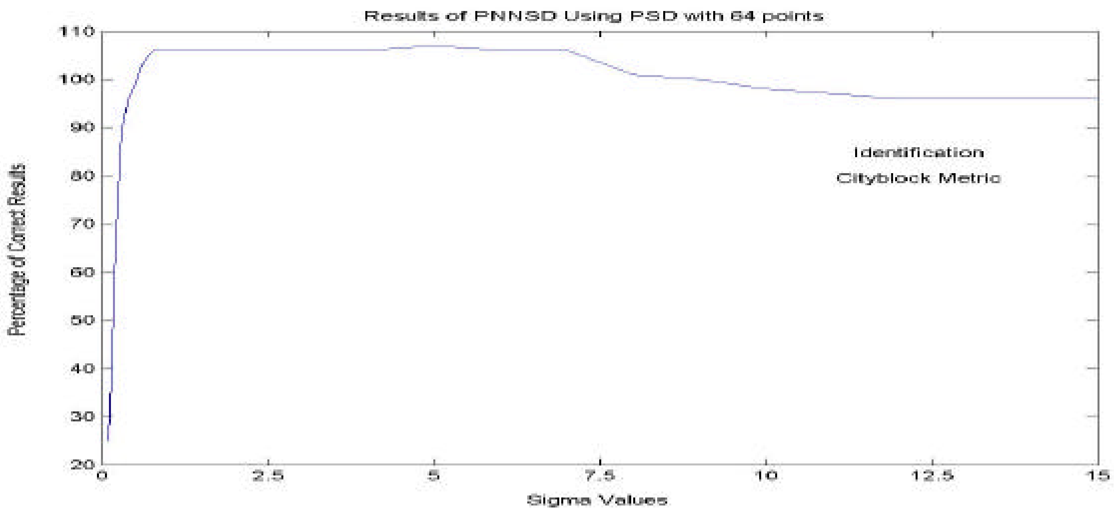

Figure 4 – Cityblock Metric

5. Conclusions

In this work a PNNDS was developed to detect and identify faults in rolling bearings in a universe of nine fault types in the outer race and inner race: a pit, a corrosion and a scratched surface. The complexity of classification task is enhanced since the vibration database is composed by signals measured at different shaft speeds and radial loads. Only one pre-processing method was used to prepare the database, the Power Spectral Density of the signals. Three different diagnostic strategies was used, with different complexity of classification.

The results have shown that excellent results can be reached (98% of correct diagnostic). These results have also shown that the type of the metric used in the Parzen function has an important effect in the PNN performance. Some metrics seems be less sensible to the classification complexity and other having an opposite behavior.

In this work only one sigma was used to model the Parzens functions. The impact of the use of multiple sigma, in order to model one Parzen function for each sample of the database, in the PNN performance need to be analyzed.

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