Classification of Induction Machine Faults by K-Nearest Neighbor

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Abstract

New diagnosis method of induction motor faults based on classification of the current waveforms is presented in this paper. This method is composed of two sequential processes: a feature extraction and a rule decision. The diagnosis is realized the detection of different faults—bearing fault, stator fault and rotor fault. K-nearest neighbor (K-NN) is used as decision criterion. The flexibility of this method allows an accurate classification independent from the level of load. This method is validated on a 5.5-kW induction motor test bench.

1. Introduction

In the classification, the optimization procedure of time–frequency representation (TFR) via parameter kernel is computationally prohibitive. We propose to design and use the classifier directly in the ambiguity Doppler delay plane. Since all TFRs can be derived from the ambiguity plane, no *a priori* assumption is made about the smoothing required for accurate classification [1-2]. Thus, the smoothing quadratic TFRs retain only the information that is essential for classification [3-4].

In this paper, we have proposed a classification procedure based on the design of optimized TFR from a time–frequency ambiguity plane in order to extract the feature vector. We have used the K-nearest neighbor (K-NN) with Mahalanobis distance and Euclidean distance as decision rule. In this study, the goal is to realize an accurate diagnosis system of motor faults such as bearing faults, stator faults, and broken bars rotor faults independent from the level of load.

2. Classification algorithm

2.1. Optimal TFR method

The optimal TFR method is applied to diagnose three kinds of induction machine faults, which are the bearing fault, stator fault and rotor fault. Thus, four classes are considered:

- class of healthy motor
- class of bearing fault
- class of stator fault
- class of broken bars

The classification algorithm of these three classes of defects and the healthy class is shown in the Fig1.

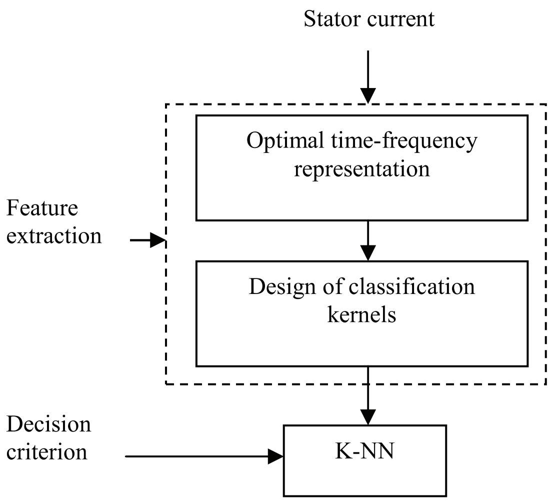

Fig.1. classification algorithm

classification algorithm is composed of the following two parts: extraction features and decision making. In the training stage, in order to build the extraction features, three optimal kernels are designed for separating four classes. The details of extraction features are described in [5]**.** A decision criterion is based on the rule of the k - nearest neighbors (k - NN).

2.2. Rule of the k - nearest neighbors (k - nn)

Let $X_a = (\underline{X}_1, \underline{X}_2, ..., \underline{X}_N)$ the training set consists of N independent vectors, each labeled with an M known classes. The principle of the rule of k - NN is to assign a new observation $\underline{X}_u$ to the class largely represented among its k - nearest neighbors. In fact, the easiest way to develop this rule is to measure the distance between the new observation vectors and each of the training set. The new observation will be assigned to Class predominantly represented among its k –NN [6]. In the choice of distance in the rule of k – NN, different distances can be used, defined by the general formulation:

$$d^2(\underline{X},\underline{Y}) = (\underline{X}-\underline{Y})^t \cdot A(\underline{X}-\underline{Y}) \qquad (1)$$

where: A is a positive definite matrix. $d(\underline{X},\underline{Y})$: Distance between $\underline{X}$ and $\underline{Y}$.

$\underline{X}$ and $\underline{Y}$:vector dimension of d' Several special cases can be drawn from this formulation:

• The Euclidean distance where A is an identity matrix:

$$d_E^2(\underline{X},\underline{Y}) = (\underline{X}-\underline{Y})^t \cdot A(\underline{X}-\underline{Y}) \quad (2)$$

• The distance Mahanalobis where A is the inverse of the total variance-covariance matrix Σ:

$$d_M^2(\underline{X},\underline{Y}) = (\underline{X}-\underline{Y})^t \sum^{-1}(\underline{X}-\underline{Y}) \quad (3)$$

Rule of k - nearest neighbors with rejection in reality, there are two main concepts of rejection: rejection ambiguity in relation to a
new observation lies between two or more classes and rejection in distance corresponds to a new observation at a distance away from classes X_a. Decision rule includes the two options will be applied for discharges $(M+2)$classes:

• $\underline{X}_u \rightarrow \Omega_c (c=1,M) : \underline{X}_u$ is classified in Ω_c.
• $\underline{X}_u$ ambiguity is rejected then: $\underline{X}_u \rightarrow \Omega_0$.
• $\underline{X}_u$ Distance is rejected then: $\underline{X}_u \rightarrow \Omega_d$.

with

Ω_d: Fictitious class of observations rejected in distance.
Ω_0: Fictitious class of observations rejected in ambiguity.
k-NN rule including two options for rejection: Reject Rejection of ambiguity and distance can be expressed by:

$$\begin{cases} \underline{X}_u \rightarrow \Omega_d \quad si \; d(\underline{X}_u, \underline{m}_c) \rangle T_c \\ \underline{X}_u \rightarrow \Omega_0 \quad si \; d(\underline{X}_u, \underline{m}_c) \leq T_c \; et \; k_c = \max\limits_{r=1,M} k_r \langle k' \\ \underline{X}_u \rightarrow \Omega_c \quad si \; d(\underline{X}_u, \underline{m}_c) \leq T_c \; et \; k_c = \max\limits_{r=1,M} k_r \rangle k' \end{cases} \quad (4)$$

3. Experimental results

An acquisition of current signals was carried out on a test bench that was made of a 5.5kW induction motor (Fig. 2). The sampling rate was 10 kHz. The number of samples per signal rises at N = 10,000 samples. The data acquisitions et on the machine consists of 15 examples of stator current recorded on different levels of load (0%,25%,50%,75%,100%).

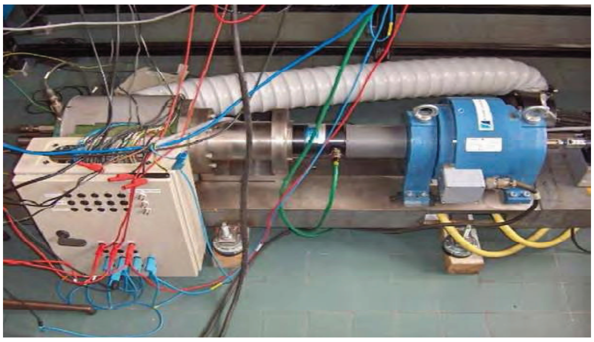

Fig. 2. Test bench of induction motor

Different operating conditions from the machine were considered: healthy, bearing fault, stator fault and rotor fault. The training set is carried out on 10 current examples. The last five current examples are used to test system classification. The design of Fisher's discriminant ratio kernel was made on two levels; the first level is used for class separation among bearing fault, stator fault and rotor fault. The second level deals with the determination of severity degree for a given type of fault. Thus, we design a kernel for each degree of severity.
Each classification consists of the separation of fault classes. The Fisher's point locations are represented in the Doppler-delay plane. We retained three point locations per kernel $\{(\xi,\tau)_1,\cdots,(\xi,\tau)_9\}$ for stronger contrast. These locations ranged in the feature vector for training $\{FV_1,...,FV_9\}$. This selection is made on the basis of contrast value and a compact localization in the ambiguity plane. We also removed the locations that have close-by values or points similar to those of other classes. The second step is the testing phase which is to classify new observations (Table. 1).

Table1. New observations X_u

new observation	contrasts
X_{u1}	12.36 20.45 15.23
X_{u2}	5.7 15.2 10.8

Classification by the k-NN rule is established for the same new observations illustrated in Table 1. uses both two distances Euclidean distance and Mahanalobis distance. In this work we have chosen three procedures of decision by the k-NN. The first is the classification of the vector test point by point. The second classification simply checks two points instead of the entire test vector to make a decision. The third classification is the center of gravity vector test.

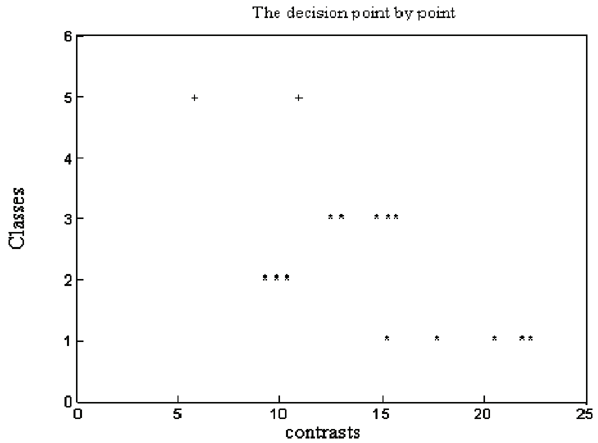

Fig.3. the decision point by point by Euclidean distance

Fig.3 shows the classification of two new observations X_{u1} and X_{u2} by the procedure "point by point" using the Euclidean distance. We note that the first point of the vector X_{u1} is assigned to the class Ω_3 that corresponds to the rotor fault but the other two points are rejected in ambiguity, therefore the decision is rejected by ambiguity vector with an error rate of 33% (the error rate is the number of misclassified points on the number of points of the vector observed), whereas the second point of the vector X_{u2} is assigned to the class i.e. the stator fault and other points are rejected distance, hence the distance vector is rejected with an error rate of 33%.

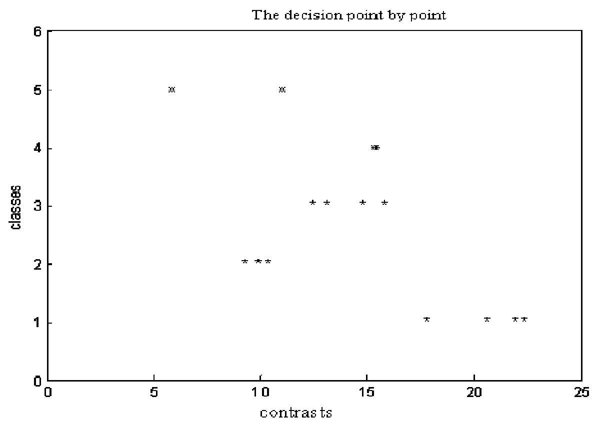

Fig. 4. Decision point by point by Mahalanobis distance

Fig.4 shows the classification of two new cases X_{u1} and X_{u2} by the procedure "point by point" but this time through the use of distance Mahanalobis. We note that the decision is the same as the Euclidean distance, that is to say the vector X_{u1} is rejected an ambiguity and the vector X_{u2} is rejected a distance. This similarity of results between the two distances is explained by the principle of Fisher, the separation between classes is greater and the point of the class is closer. The learning points are from the Fisher principle stronger contrast.

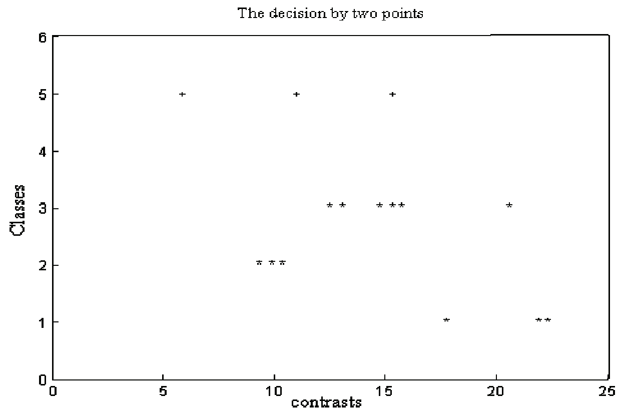

Fig. 5. Decision point by two satisfied by the Euclidean distance

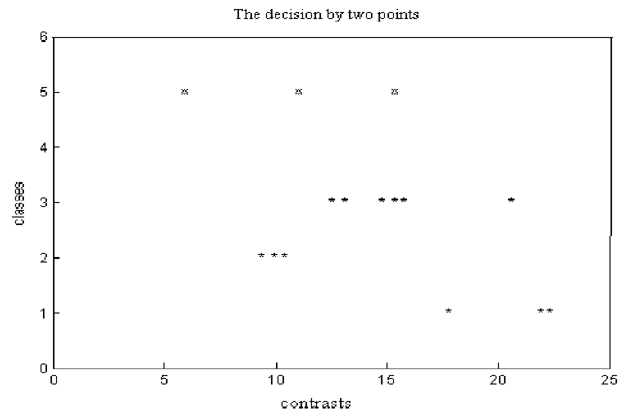

Fig. 6. Decision by two points satisfied by Mahalanobis distance

Fig.5 and 6 illustrate the case of any two points X_{u1} and X_{u2} therefore X_{u1} vector is assigned to the class Ω_3 and therefore the class of rotor failure but with an error rate of 66% and the vector is rejected X_{u2} in distance with an error rate of 33%.

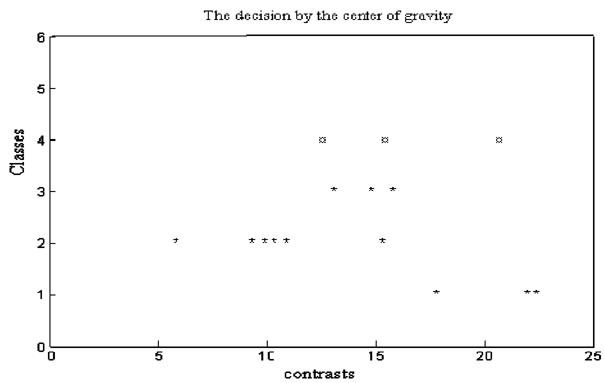

Fig.7. Decision by the center of gravity by the Euclidean distance

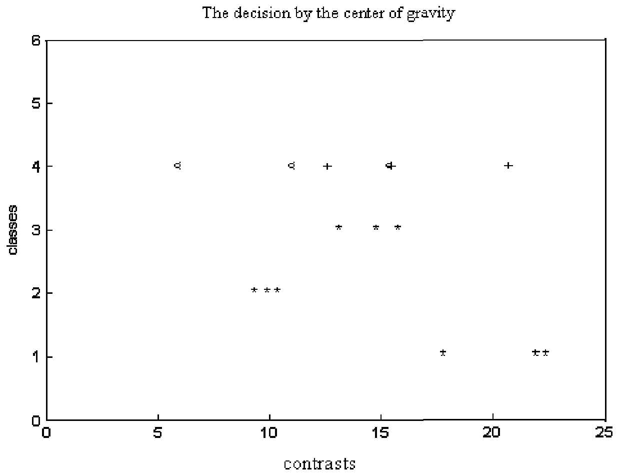

Fig. 8. Decision by the center of gravity by Mahalanobis distance

In the third step, we used the center of gravity of each vector. Fig.7 and 8 show the classification of vectors into different classes as possible. We observe that the vector X_{u1} is rejected an ambiguity, this result corresponds to the classification step by step as we have seen previously and the vector X_{u2} is rejected an ambiguity with an error rate of 66% this is due to the distance between the points of vector X_{u2}.

Table 2 and 3 summarizes the allocation of new comments to various classes of the training set: $\Omega 1$ bearing fault class, $\Omega 2$ stator fault class, $\Omega 3$ rotor fault class, Ωa the class of rejection an ambiguity and Ωd the class of rejection an distance.

Table 2. Decision by Euclidean distance

	The decision by Mahalanobis distance			
New observation	Point by point	vector	by two points	center of gravity
X_{u1}	$point1 \rightarrow \Omega 3$ $point2 \rightarrow \Omega 1$ $point3 \rightarrow \Omega a$	Ωa	$\Omega 3$	Ωa
X_{u2}	$point1 \rightarrow \Omega d$ $point2 \rightarrow \Omega a$ $point3 \rightarrow \Omega d$	Ωd	Ωd	Ωa

Table 3. Decision by Mahalanobis distance

	The decision by Euclidean distance			
New observation	Point by point	vector	by two points	center of gravity
X_{u1}	$point1 \rightarrow \Omega 3$ $point2 \rightarrow \Omega a$ $point3 \rightarrow \Omega a$	Ωa	$\Omega 3$	Ωa
X_{u2}	$point1 \rightarrow \Omega d$ $point2 \rightarrow \Omega 1$ $point3 \rightarrow \Omega d$	Ωd	Ωd	$\Omega 2$

4. Conclusions

In this study we proposed a method of time-frequency representation for the classification of faults. We have used k-nearest neighbor technique for three procedures of classification of new observations: point by point, by two point and the center of gravity. Using Euclidean distance and Mahalanobis distance, results shows that the classifications through the center of gravity of vector test is the most simple and powerful and also the results of the two distances (Euclidean and Mahalanobis) is close because the points of the training set points is more high contrast are relatively close to each other. The classification by the k-nearest neighbor method is the more efficient and interpretable in terms of classification results.

5. References

[1] M. Wang, G. I. Rowe, and A. V. Mamishev, "Classification of Power Quality Events Using Optimal Time–Frequency Representations—Part 2: Application," *IEEE Trans. Power Del.*, vol. 19, no. 3, pp. 1496–1503, Jul. 2004.

[2] B. W. Gillespie and L. Atlas, "Optimizing Time–Frequency Kernels for Classification," *IEEE Trans. Signal Process.*, vol. 49, no. 3, pp. 485–496, Mar. 2001.

[3] M. Davy and C. Doncarli, "Optimal kernels of time–frequency representations for signal classification," in *Proc. IEEE-SP Int. Symp. Time-Freq. Time-Scale Anal.*, 1998, pp. 581–584.

[4] M. Wang, G. I. Rowe, and A. V. Mamishev, "Classification of Power Quality Events Using Optimal Time–Frequency Representations—Part 2: Application," *IEEE Trans. Power Del.*, vol. 19, no. 3, pp. 1496–1503, Jul. 2004.

[5] A. Lebaroud and G. Clerc, "Classification of Induction Machine Faults by Optimal Time frequency Representations," *IEEE Trans. on Industrial Electronics,* vol. 55, no. 12, december 2008.

[6] Zouhal, L.M.; Denoeux, T.; "An evidence-theoretic k-NN rule with parameter optimization", Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on Vol 28, pp: 263 – 271, May 1998.