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# Accurate diagnosis of induction machine faults using optimal time–frequency representations

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ABSTRACT

This paper presents a new diagnosis method of induction motor faults based on time–frequency classification of the current waveforms. This method is composed of two sequential processes: a feature extraction and a rule decision. In the process of feature extraction, the time–frequency representation (TFR) has been designed for maximizing the separability between classes representing different faults. The diagnosis is realised in two levels; the first one allows the detection of different faults—bearing fault, stator fault and rotor fault. The second one refines this detection by the determination of severity degree of faults, which are already identified on the previous level. The diagnosis is independent of the level of load. This method is validated on a 5.5 kW induction motor test bench.



## 1. Introduction

In recent years, advancement of statistical signal processing methods has provided efficient and optimal tools to process nonstationary signals. In particular, time–frequency methods provide an optimal mathematical framework for the analysis of time-varying, nonstationary signals. Time–frequency analysis unambiguously represents motor currents, which makes signal properties related to fault detection more evident in the transform domain (Yazıcı and Kliman, 1999). In many classification applications, features are traditionally extracted from standard time–frequency representations (TFRs). This assumes that implicit smoothing is appropriate for the classification task. Making such assumptions can degrade classification performance. The quadratic class of time–frequency representations can be uniquely characterized by an underlying function called a kernel. In previous time–frequency research, kernels have been derived in order to fulfil properties such as minimizing quadratic interference. Although some of the resulting TFRs can offer advantages for classification of certain types of signals, the goal of sensitive detection or accurate classification is rarely an explicit goal of kernel design (Atlas et al., 1997). Those few methods that optimize the kernel for classification purpose constrain the form of the kernel to predefined parametric functions with symmetries that cannot be suitable for detection or classification (Heitz, 1995; Davy and Doncarli, 1998). Traditionally, the objective of time–frequency research is to create a function that will describe the energy density of a signal simultaneously in time and frequency. For explicit classification, it is not necessarily desirable to accurately represent the energy distribution of a signal in time and frequency. In fact, such a representation may conflict with the goal of classification, generating a TFR that maximizes the separability of TFRs from different classes. It may be advantageous to design TFRs that specifically highlight differences between classes (Gillespie and Atlas, 2001; Wang et al., 2004; Lebaroud and Clerc, 2005). The use of TFR includes two sequential processes: feature extraction and rule decision. This technique has been successfully applied for tool-wear monitoring and radar transmitter identification (Gillespie and Atlas).

In this paper, we propose a dignosis algorithm based on the designing of optimized time–frequency representation (TFR) from a time–frequency ambiguity plane. The goal is the realization of an accurate diagnosis system of motor faults, such as bearing faults, stator faults and broken bars.

## 2. Use of the kernel and ambiguity plane for diagnosis

The relation between ambiguity plane and time–frequency representations has been recognized for a long time. Any bilinear (Cohen class) TFR (Cohen, 1995) can be expressed as the

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two-dimensional Fourier transform of the product of the ambiguity plane of the signal and a kernel function:

$$TFR_x^{\varphi}(t,f) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} A(\eta,\tau)\varphi(\eta,\tau)e^{j2\pi\eta t}e^{-2\pi jf\tau}\, d\eta\, d\tau \tag{1}$$

where $t$ represents time, $f$ represents frequency, $\eta$ represents continuous frequency shift, and $\tau$ represents continuous time lag. The ambiguity plane $A(\eta,\tau)$ for a given signal $x(t)$ is defined as

$$A_x(\eta,\tau) = \int_{-\infty}^{\infty} x(t)x^*(t+\tau)e^{j2\pi\eta t}\, dt \tag{2}$$

$x(t+\tau)$ represents the signal at a future time $(t+\tau)$, and $x^*(t+\tau)$ is the complex conjugate of $x(t+\tau)$. For diagnosis, the optimization procedure of TFR (1) via parameter kernel is computationally very prohibitive. It would be better to use the optimal TFR that can be classified directly in ambiguity plane. We propose to design and use the classifier directly in the ambiguity plane of Doppler delay. Since all TFRs can be derived from the ambiguity plane, no a priori assumption is made about the smoothing required for accurate classification. Thus, the smoothing quadratic TFRs retain only the information that is essential for classification.

The discrete version (Gillespie and Atlas, 2001) of ambiguity plane (1) and (2) is

$$A[\eta,\tau] = F^{-1}_{n\to\eta}\{R[n,\tau]\} = \sum_{n=0}^{N-1} R[n,\tau]e^{-j(2\pi/N)n\eta} \tag{3}$$

where $F$ represents the Fourier transform, $\eta$ represents discrete frequency shift and $\tau$ represents discrete time lag. The instantaneous autocorrelation function $R[n,\tau]$ is defined as

$$Rp[n,\tau] = x^*[n]x[(n+\tau)_N] \tag{4}$$

This method, used to design kernels (and thus TFRs), optimizes the discrimination between predefined sets of classes. The resulting kernels are not restricted to any predefined function but, rather, are arbitrary in shape. This approach ascertains the necessary smoothing in order to achieve the best classification performance.

The kernel determines the representations and its properties. A kernel function is a generating function that operates on the signal to produce the TFR. The characteristic function for each TFR is $A(\eta,\tau)\phi(\eta,\tau)$ In other words, for a given a signal, a TFR can be uniquely mapped from a kernel. The classification-optimal representation $TFR_i$ can be obtained by smoothing the ambiguity plane with an appropriate kernel $\phi_{opt}$, which is a classification-optimal kernel. The problem of designing the $TFR_i$ becomes equivalent to designing the classification-optimal kernel $\phi_{opt}(\eta,\tau)$.

It is possible to view the class-dependent TFR and observe the time–frequency structure being exploited by the classifier:

$$RTF_{DCS}[n,k] = F^{-1}_{\eta\to n}\{F_{\tau\to k}\{\phi_{DCS}[\eta,\tau]A[\eta,\tau]\}\} \tag{5}$$

The optimal TFR method is applied to diagnose three kinds of induction machine faults: bearing fault, stator fault and rotor fault.

## 3. Induction machine faults

### 3.1. Bearing faults

Bearing faults such as outer race, inner race, ball defect and train defect cause machine vibration. These defects have vibration frequency components, $f_v$, that are characteristic of each type of defect. The mechanical vibration caused by the bearing defect results in air-gap eccentricity. Oscillations in air-gap length induce variations in flux density. These variations produce harmonics on the stator current. The characteristic current frequencies, $f_c$, due to bearing characteristic vibration frequencies are calculate by (Devaneyand and Eren, 2004)

$$f_c = |f_s \pm mf_v| \tag{6}$$

where $f_s$ is the fundamental frequency, $f_v$ the characteristic vibration frequency and $m$ is a positive integer multiplier.

### 3.2. Rotor faults

A fault on the rotor, such as a broken rotor bars, causes asymmetrical working conditions within the rotor. The current rotor bars, which are at the frequency $sf$, can be expressed into positive and negative sequence components $\pm sf$ within the rotor, where $s$ is the slip. Consequently, the negative sequence rotor current results in stator currents at frequency

$$(1-2s)f \tag{7}$$

The interaction of the $(1-2s)f$ harmonic of the motor current with the fundamental air-gap flux produces speed ripple at $2sf$ and gives rise to additional motor current harmonics at frequencies $(1\pm 2ks)f$, $k=1,2,3,\ldots$ (Filipetti et al., 1996).

With $k=1$, the frequency sidebands $(1\pm 2s)f$ of the fundamental are very commonly used to detect broken bar faults. The motor-load inertia also affects the magnitude of these sidebands (Lebaroud et al., 2005). Other spectral components that can be observed in the stator line current are (Kliman et al., 1992)

$$(k/p(1-s)\pm s)f; \quad k/p = 1,\ 3,\ 5,\ \ldots \tag{8}$$

### 3.3. Stator faults

In ideal conditions, the motor supply current contains only a positive-sequence component, leading to a constant space vector current modulus. If there is an inter-turn short circuit in the motor stator winding, the supply current will exhibit some sort of unbalance. When explained by symmetrical components theory, the stator asymmetry produces a component at frequency $-f$ (i.e., a negative sequence component). This component gives rise to torque ripples at frequencies of $2sf$, which consequently produce speed ripples of different amplitudes (Perovic et al., 2000), being differently filtered by the machine-load inertia (Lebaroud et al., 2004). The current vector of direct sequence has a circular trajectory. At the time of unbalance, a negative sequence of current appears and transforms the circular trajectory into an elliptic one (Fig. 1).

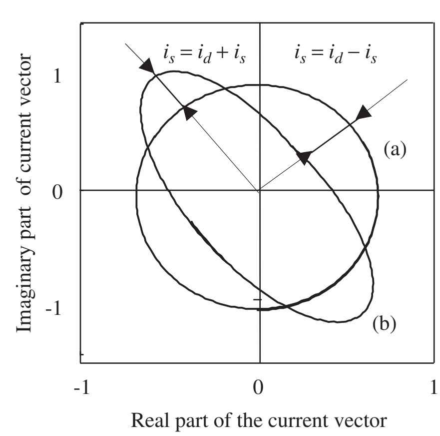


**Fig. 1.** Current vector: healthy (a) and unbalanced (b).