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Electric motor defects diagnosis based on kernel density estimation and Kullback–Leibler divergence in quality control scenario

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ABSTRACT

The present paper deals with the defect detection and diagnosis of induction motor, based on motor current signature analysis in a quality control scenario. In order to develop a monitoring system and improve the reliability of induction motors, Clarke–Concordia transformation and kernel density estimation are employed to estimate the probability density function of data related to healthy and faulty motors. Kullback–Leibler divergence identifies the dissimilarity between two probability distributions and it is used as an index for the automatic defects identification. Kernel density estimation is improved by fast Gaussian transform. Since these techniques achieve a remarkable computational cost reduction respect the standard kernel density estimation, the developed monitoring procedure became applicable on line, as a Quality Control method for the end of production line test.

Several simulations and experimentations are carried out in order to verify the proposed methodology effectiveness: broken rotor bars and connectors are simulated, while experimentations are carried out on real motors at the end of production line. Results show that the proposed data-driven diagnosis procedure is able to detect and diagnose different induction motor faults and defects, improving the reliability of induction machines in quality control scenario.

1. Introduction

In industry, Quality Control (QC) is a collection of methods that are able to improve the quality and efficiency in production processes and in many other industry aspects. In 1924, Walter Shewhart designed the first control chart and gave a rationale for its use in process monitoring and control (Stuart et al., 1995). The main concept of QC is the "proactiveness", in order to ensure the product quality, monitoring processes and related signals to detect when they "go out of control". In the last years, manufacturing industries are reversing many attentions and efforts in the monitoring and control of manufacturing systems, introducing QC methodologies in the production lines and concentrating many investigations on the introduction of QC in their production lines (Darmoul et al., 2013). One of the major problems, in which these manufacturing industries are involved, is the presence of some defective components in the lots of products they deal. Another issue where QC concept and monitoring systems are under investigation, regards the health diagnostics to improve system safety, reliability and cost reduction for maintenance operations (Wang et al., 2014; Rocchi et al., 2014).

A desirable QC solution for these manufacturing industries should be minimally invasive, effective and with a low payback period. In this paper, a solution with these characteristics is proposed: a Fault Detection and Diagnosis (FDD) algorithm is developed for defect detection and identification of electric motors. The proposed algorithm can be used at the end of a production line as a Quality Control solution to improve the reliability of induction motors (Ferracuti et al., 2013b). When the electric motor reaches the end of production line the FDD system acquires sensors measurements and detects if the product is defective or not. Moreover, by isolating and identifying the defective type, the FDD procedure helps to estimate in which subprocess the defect is introduced and to remove the defective products improving the quality of processes as a proactive measures for the QC methodology. In this paper a FDD signal-based approach is proposed instead of a model-based one. One reason concerns the system implementation requirements: the developed procedure employs only the current measurements. This solution does not require to install sensors on the electric motor because, in electric drives, these are available by inverters. Another reason, to support the signal-based methods, is that the use of models requires the knowledge of parameters; in manufacturing industries the accurate knowledge of model parameters is not often available (Ferracuti et al., 2011). Conversely, signal-based approaches

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require the use of a sample of faultless reference motors for tuning the necessary parameters in a fast training stage.

In this context vibration analysis is well known and widespread, as it is not destructive, reliable and it allows continuous monitoring without stopping the machine. Several approaches have been developed to recognize machine condition from vibration data (Ciandrini et al., 2010; Geramifard et al., 2013) and to evaluate the severity of faults to assess the proper machine condition (Jin et al., 2014a).

Motor Current Signature Analysis (MCSA) monitoring strategies involve detection and identification of current signature patterns that are indicative of normal and abnormal motor conditions. However, the motor current is influenced by many factors such as electric supply, static and dynamic load conditions, noise, motor geometry, and fault conditions. Several papers deal with MCSA for on line FDD based on supervised or unsupervised methods (Jin et al., 2014b; Soualhi et al., 2013; Zhao et al., 2014).

Authors propose a data-driven FDD algorithm based on MCSA in a QC scenario, tested on time series benchmark as well as in real experimentations. Clarke–Concordia is used to transform stator current measurements in 2-D dimensional patterns (Ferracuti et al., 2013a). A probabilistic monitoring system, for defect detection and diagnosis, is developed by employs Kernel Density Estimation (KDE) and Kullback–Leibler (K–L) divergence. KDE allows to estimate the 2-D probability density function of Concordia transformed patterns, these estimations are used as signature of the motor condition; K–L performs fault diagnosis by divergence indexes (Giantomassi et al., 2015).

Due to KDE computational cost a fast Gaussian transform (FGT) is employed to perform the numerical density estimation, such that a remarkable computational cost reduction is obtained and a near Fast Fourier Transform computational time is reached.

The proposed approach estimates the Probability Density Function (PDF) of Clarke–Concordia transformed data by KDE, which is a non-parametric method useful to assess the data distribution (Botev et al., 2010). The advantage of non-parametric approaches, respect to parametric ones, is that they offer greater flexibility in modelling a given dataset, and they are not affected by problems as stated in Botev et al. (2010) (and reference therein). Kullback–Leibler divergence is used as a distance measure between signatures computed by KDE. K–L is an index that allows to identify the dissimilarity between two determined probability distributions (that can be multidimensional): one is related to the modelled signatures and the other is related to the acquired data samples. By K–L divergence, the classification of each motor condition is performed.

The paper is organized as follows. In Section 2Clarke–Concordia transformation, KDE, FGT and K–L divergence are briefly introduced respectively. In Section 3 the training and monitoring steps of FDD procedure are discussed. The case study with the description of the experimental equipment and experiments is proposed in Section 4. Results are then reported and discussed in Section 5, while Section 6 concludes this paper with final remarks.

2. Recalled results

In this section authors present the algorithms used to develop the fault and defect diagnosis procedure. It extracts patterns by current signals using Clarke–Concordia transformation and KDE. Then K–L divergence compares these patterns to extract the motor health index.

2.1. Clarke–Concordia transformation

Due to the high correlation of three-phase induction motor currents, a two-dimensional representation is needed. In this work the Clarke–Concordia transformation (also known as the $\alpha-\beta$ transformation) is employed, which is a power invariant transformation (Martins et al., 2007; Zidani et al., 2003). For healthy motor, with three-phase without neutral connection, ideal conditions for the motor and a balanced voltage supply, the stator currents are given by Eq. (1), where i_a, i_b and i_c denote the three stator currents, I_{max} is the supply phase current maximum value, f_s is the supply frequency, ϕ is the phase angle and t is the time:

$$\begin{cases} i_a(t) = I_{max} \cdot \sin(2\pi f_s t - \phi) \\ i_b(t) = I_{max} \cdot \sin(2\pi f_s t - 2\pi/3 - \phi) \\ i_c(t) = I_{max} \cdot \sin(2\pi f_s t - 4\pi/3 - \phi). \end{cases} \tag{1}$$

The Clarke–Concordia transformation is defined as

$$T = \begin{bmatrix} \sqrt{\frac{2}{3}} & -\frac{1}{\sqrt{6}} & -\frac{1}{\sqrt{6}} \\ 0 & \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix} \tag{2}$$

Therefore, the $\alpha-\beta$ stator currents are given by

$$\begin{bmatrix} I_\alpha \\ I_\beta \\ I_\gamma \end{bmatrix} = T \cdot \begin{bmatrix} i_a(t) \\ i_b(t) \\ i_c(t) \end{bmatrix} = \begin{bmatrix} \sqrt{\frac{3}{2}} I_{max} \cdot \sin(2\pi f_s t - \phi) \\ \sqrt{\frac{3}{2}} I_{max} \cdot \sin(2\pi f_s t - \frac{\pi}{2} - \phi) \\ 0 \end{bmatrix} \tag{3}$$

In ideal conditions, three-phase currents lead a circular pattern centered on the origin of the coordinates. This is the reference pattern and allows the detection of abnormal conditions measuring the deviations of acquired patterns.

2.2. Kernel density estimation

Given N independent and identically distributed (i.i.d.) random vectors $\boldsymbol{X} = [\boldsymbol{X}_1, \ldots, \boldsymbol{X}_N]$, where $\boldsymbol{X}_i = [X_{i1}, \ldots, X_{id}]$, whose distribution function $F(\boldsymbol{x}) = P[\boldsymbol{X} \le \boldsymbol{x}]$ is absolutely continuous with unknown PDF $f(\boldsymbol{x})$. The estimated density at $\boldsymbol{x}$ is given by (Parzen, 1962):

$$f(\boldsymbol{x}) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{|H|^d} K\left(\frac{\boldsymbol{x} - \boldsymbol{X}_i}{|H|^d}\right), \tag{4}$$

A two-dimensional Gaussian kernel function is used ($d=2$) and a simplification, which follows from the restriction of kernel bandwidth $H = \left\{h^2 I : h > 0\right\}$, leads to the single bandwidth estimator; therefore the estimated density $f(\boldsymbol{x})$ becomes (Wand and Jones, 1994a)

$$f(\boldsymbol{x}) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{\left(2\pi h^2\right)^{1/2}} e^{-(\|\boldsymbol{x} - \boldsymbol{X}_i\|^2)/2h^2}, \tag{5}$$

where $\boldsymbol{x} \in \mathbb{R}^d$ whose size M is the points number at which the PDF is estimated. It is well known that the value of the bandwidth h and the shape of the kernel function are of critical importance (Mugdadi and Ahmad, 2004). In many computational-intelligence methods that employ KDE, the problem to find the appropriate bandwidth h is the issue (Comaniciu, 2003; Mugdadi and Ahmad, 2004; Sheather, 2004). In the present work the Asymptotic Mean Integrated Squared Error (AMISE) with plug-in bandwidth selection procedure is used to choose automatically the bandwidth h (Wand and Jones, 1994b). In the proposed algorithm, KDE is used to model a specific pattern for each motor condition, indeed the features of the current signals, which are mapped by the Clarke–Concordia transformation in two dimensional space, are specific signatures of the motor conditions.

2.3. Improved KDE by fast gaussian transform

In the classical formulation described in Section 2.2, the computational cost, required by KDE, is $\mathcal{O}(N \cdot M)$ evaluations of the kernel