11-2009

Ensemble and individual noise reduction method for induction-motor signature analysis

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Abstract— **Unlike a fixed-frequency power supply, the voltage supplying an inverter-fed motor is heavily corrupted by noises, which are produced from high-frequency switching leading to noisy stator currents. To extract useful information from stator-current measurements, a theoretically sound and robust de-noising method is required. The effective filtering of these noises is difficult with certain frequency-domain techniques, such as Fourier transform or Wavelet analysis, because some noises have frequencies overlapping with those of the actual signals, and some have high noise-to-frequency ratios. In order to analyze the statistical signatures of different types of signals, a certain number is required of the individual signals to be de-noised without sacrificing the individual characteristic and quantity of the signals. An ensemble and individual noised reduction (EINR) method is proposed as the extension of the common averaging method for induction-motor signature analysis. The signals after de-noising by the proposed EINR method will preserve the individual characteristics. A number of signals are selected as an ensemble part in the proposed EINR method and are employed as the "profile" to de-noise other individual signals. The case study presented in this paper demonstrates the merits of the proposed EINR method for induction-motor signature analysis.**

Index Terms—**Noise, Ensemble and individual noise reduction, Induction motor, Signature analysis, Stator current.**

I. Introduction

Identification of the signatures of induction-motor stator currents with a fixed-frequency power supply has been discussed with several successful fault detection methods being reported [1, 13-17]. We propose applying independent component analysis (ICA) for on-line fault-detection of induction motors, and demonstrate its robustness under various load conditions [13]. Using ICA, the two most dominating features are extracted from each of the measured stator currents containing 50,100 records, leading to great simplification of the fault-detection procedure [13]. However, the fault detection of inverter-fed motor has not been as widely investigated, and it requires more attention for handling variable supply frequencies, noisy and transient operating conditions [2-3]. An inverter introduces noises and harmonics into the current waveforms, which mask small fault-related components in measured signals making the signature analysis difficult. Together with EMI and other noises, these inverter-generated noises adversely affect the accuracy of fault diagnosis [3-4]. It is therefore important to de-noise the measured signals effectively before the fault-signature analysis.

In recent years, ICA has attracted much interest as a powerful tool for blind source separation, feature extraction and process monitoring [5-7]. It was also considered as a promising tool to pre-process data in mechanical fault diagnosis applications [5]. To achieve multivariate statistical process control, ICA was used to extract the essential independent components for process monitoring [6]. Prior to induction-motor fault analysis [13], we also employed ICA for insulation diagnosis, de-noising and online source recognition of partial discharge for gas insulated substations [11].

To obtain signatures of the motor stator currents, we measured the stator-current signals from one healthy and two faulty laboratory motors for analysis by ICA. One of the main difficulties in analyzing such current signals is the presence of noises in the measured waveforms which affects the detection or classification accuracy. The basic Fourier analysis can be useful for removing some noises but it is not appropriate to deal with noises having a transitional nature. The short-time Fourier analysis can overcome this problem, but the fixed size of the window is its main drawback as it can only obtain information with limited precision [1, 12]. The wavelet transform was then introduced for overcoming the difficulties mentioned above. However, effective filtering of these noises using the wavelet transform can be extremely difficult because some noise frequencies overlap with those of the actual signals. Moreover, the noise-to-signal ratios are high at some other frequencies.

It is possible to reduce these noises by averaging a predetermined number of the corrupted signals if the signal is recurrent [8-9]. To improve the statistical stability of the spectral estimate and minimize the estimate variance, pseudo ensemble averaging or coherent averaging are often used [1]. The de-noised signal is the average of a number of signals [10]. However, by averaging the signals, some important individual characteristics are lost. In order to accurately analyze the statistical signatures of the motor stator currents, employing an enough number of individual current signals is also very important.

The aim of this paper is therefore to propose a new noise reduction method namely the ensemble and individual noise reduction (EINR) method by extending the common averaging method often used in other work. Signals after de-noising by this method will preserve the individual characteristics. Signals after de-noising are analyzed by ICA with excellent results to be demonstrated in this paper.

II. Averaging Method Review

The averaging method [8] is based on the principle that each segment $x(t)(0<t<T)$ will contain the invariant segment $s(t)$, plus the noise component $n(t)$. In the averaging method, all $s(t)$ s are systematically added,

whereas the random noise components are summed and tend toward zero [9].

Signal averaging is a common method for noise reduction in bioelectric signal processing. The signal must be recurrent and a temporal reference must be available to be used as the fiducially point [8-9]. The average of the raw signal is an unbiased and consistent estimator for the signal of the interest, whose variance decreases with the number of averaged cycles. Theoretically, the signal-to-noise ratio after de-noised by the averaging method will be given as

$$SNR_{AV} = SNR \big/ \sqrt{N} \tag{1}$$

where N is the number of repetitions, SNR_{AV} and SNR are signal to noise ratio after and before de-noised. This expression gives a statistical interpretation of the de-noised signals using the averaging method related to signal-to-noise ratio.

The averaging method is described in details as the following:

$$\begin{aligned}\hat{x}(t) &= \frac{1}{N}\sum_{k=0}^{N-1} x(t+kT) \\ &= \frac{1}{N}\sum_{k=0}^{N-1} s(t+kT) + \frac{1}{N}\sum_{k=0}^{N-1} n(t+kT)\end{aligned} \tag{2}$$

Because $s(t)$ was assumed to be time invariant, equation (2) can be rewritten as:

$$\hat{x}(t) = s(t) + \frac{1}{N}\sum_{k=0}^{N-1} n(t+kT) \tag{3}$$

This $\hat{x}(t)$ is now assumed to be an estimate of $s(t)$.

The quality of the estimate is investigated by the following equation;

$$\mathrm{E}[\hat{x}(t)] = \mathrm{E}[s(t)] + \frac{1}{N}\mathrm{E}\left[\sum_{k=0}^{N-1} n(t+kT)\right] \quad (0 < t < T) \tag{4}$$

And since $\mathrm{E}[n(t)] = 0$

$$\mathrm{E}[\hat{x}(t)] = s(t)$$

Hence $\hat{x}(t)$ is an unbiased estimator of $s(t)$.

The variance of $\hat{x}(t)$ have been proved to be as the following.

$$Var[\hat{x}(t)] = \frac{1}{N} Var[n(t)] \tag{5}$$

Before the averaging procedure, $Var[\hat{x}(t)] = Var[n(t)]$, hence it may be concluded that the variance has been reduced by a factor N, and the amplitude of the signal-to-noise ratio improved with fact $N^{1/2}$. The noise is less as the number of sample is increased.

It has already been proven that the averaging method can reduce random components in the output signal if the noise is not correlated with the signals.

Each new signal $\hat{x}(t)$ is the average of a number of signals and its individual characteristic will be lost. The individual characteristic of each signal is important for signature analysis of the induction motors. This paper improves the averaging method and proposes the EINR method, which can keep the individual characteristic of the original signal.

III. ENSEMBLE AND INDIVIDUAL NOISE REDUCTION METHOD

The aim of the proposed method is to restore the original short-time spectral target signals intensity as accurately as possible for preserving the individual characteristic of each de-noised signal. For analyzing the statistical characteristic of the signatures of the signals, a large number of the signals must be obtained. Using the common averaging method, the number of the signals will be $N \times N_1$ if we want to obtain N_1 number of the de-noised signals using N number of repetitions. The performance of the averaging noise reduction method is improved as the number of averaged cycles is increased [8-10]. When one more individual de-noised signal is required, the increased number of the signals will be multiplied by the number of averaged cycles. However, using the proposed EINR method, a certain number of the signals is selected as the "profile" segment, rather than the common averaging method. $(N + N_1)$ (Number of the signals) will be enough to obtain N_1 number of the de-noised individual signals.

The principle of the EINR method is shown in Fig.1. Considering the averaging method, when increasing the number of the signals from N to N+1, we get the signal $\hat{y}(t)$

$$\begin{aligned}\hat{y}\ (t) &= \frac{1}{N+1}\sum_{k=0}^{N} x(t+kT) = \\ &= \frac{1}{N+1}\left[\sum_{k=0}^{N-1} x(t+kT) + x(t+NT)\right] \\ &= \frac{1}{N+1}\left[N \cdot \hat{x}(t) + x(t+NT)\right] \\ &= \frac{N}{N+1}\hat{x}(t) + \frac{1}{N+1}x[t+NT]\end{aligned} \tag{6}$$

Assuming that the signal to be de-noised is periodic, $S_N = N \cdot \hat{x}(t)$,

$y_n(t) = x[t + (N+n-1)T]$, then

$$\begin{aligned}\hat{y}_1(t) &= \frac{N}{N+1}\hat{x}(t) + \frac{1}{N+1}x[t+(N+1-1)T] \\ &= \frac{1}{N+1}S_N + \frac{1}{N+1}y_1(t) \\ &= \frac{1}{N+1}(S_N + y_1(t))\end{aligned} \tag{7}$$

$$\begin{cases} \hat{y}_2(t) = \frac{1}{N+1}(S_N + y_2(t)) \\ \hat{y}_3(t) = \frac{1}{N+1}(S_N + y_3(t)) \\ \cdots \\ \hat{y}_{N_1}(t) = \frac{1}{N+1}(S_N + y_{N_1}(t)) \end{cases} \quad (8)$$

A new segment S_N, which is shown in Fig.1 (b), is produced by summing the N segments as shown in Fig. 1(a). It is clear that random noise components are summed and have been eliminated after the ensemble step. The individual signals $y_1(t), y_2(t),..., y_{N_1}(t)$ shown in Fig.1(c) are de-noised using the equations (7)-(8).

Equations (7)-(8) can be rewritten as:

$$\hat{y}_n(t) = \frac{S_N + y_n(t)}{N+1} \qquad n = 1,2,..., N_1 \quad (9)$$

In the de-noised signal series: $\hat{y}_1(t), \hat{y}_2(t),..., \hat{y}_n(t)$ shown in Fig.1(d), interestingly, each newly generated segment share same "profile" due to the common factor $\frac{S_N}{N+1}$ in equations (7)-(9), yet they are differ from each other by the term, $y_n(t)$, $(n = 1,2,..., N_1)$. This is the reason we call this noise reduced method: *Ensemble and individual noise reduction method.*

IV. EXPERIMENTAL SETUP, NOISE REDUCTION RESULTS AND DISCUSSION

A. Experimental setup

To evaluate and test the proposed EINR method, our laboratory setup (Fig. 2) collects the stator-current waveforms from three inverter-fed induction motors (1 healthy, 1 with bearing fault and 1 with broken rotor bars). Each of these motors is 3-phase, four-pole, 50 Hz, 1410 rpm and rated at 1.1KW, 220-240/380-420 V. Each running motor (healthy or one with a certain problem) is supplied from a frequency converter operated at the utility frequency. The stator currents of the running motor are measured with a 4-channel digital oscilloscope with a maximum sampling rate of 1GS/s, and transferred to the computer for de-noising using the proposed EINR method.

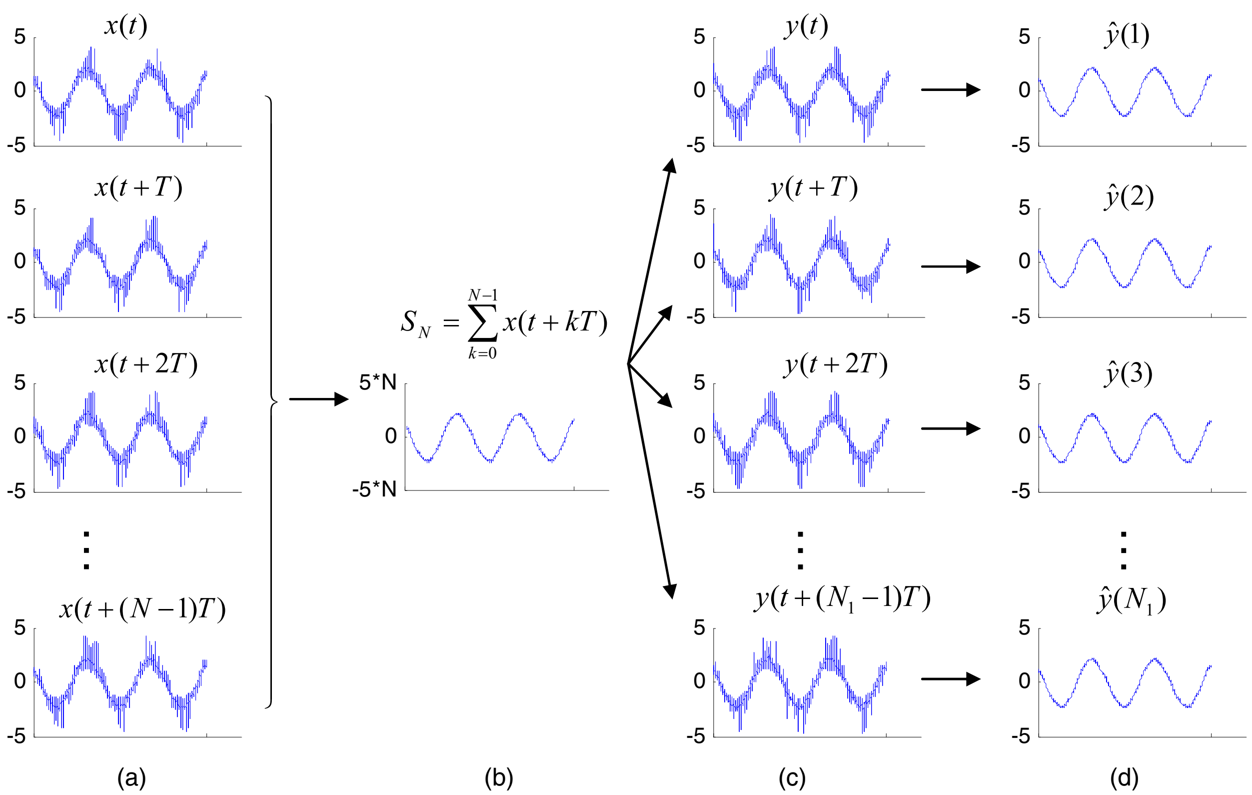

Fig. 1 The principle of the ensemble and individual noise reduction (EINR) method

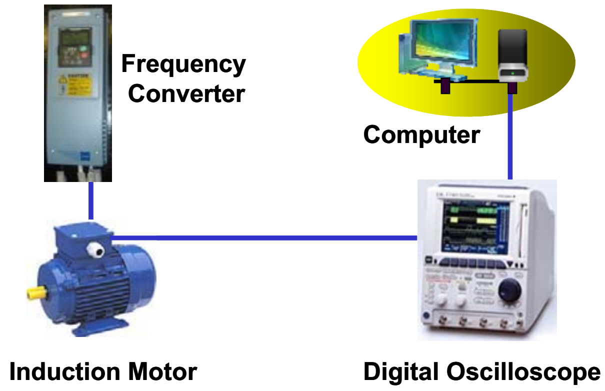

Fig. 2 Experimental setup for measuring noisy signals

B. *Performance of the proposed EIRN method compared to wavelet transform*

The EINR method is proposed with the assumption that the nature of the noisy signals is unknown and extensive signals have to be reduced to find the statistical signatures of these signals. In such cases, the EINR method can obtain a number of de-noised signals to be analyzed without requiring too much data.

Fig. 3 and Fig. 4 show the stator-current waveforms after de-noising using the proposed EINR method and wavelet method. Fig. 3(a) and Fig. 4(a) show the original signals. Fig. 3(b) and Fig. 4(b) show the signals after de-noising by the proposed EINR method and wavelet method respectively. Fig.3 (c) and Fig. 4(c) show the noise signals extracted from the original signals. It is seen that both of these two noise reduction methods have visually de-noised the signals, but the wavelet transform has actually eliminated both the noises as well as some useful components of the signals that contain the characteristic of the faulty motor (Fig. 8).

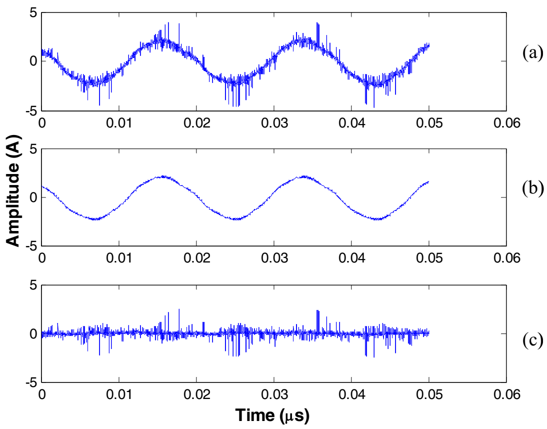

Fig. 3 Performance of de-noising by the proposed method on high-noise signals

Fig. 5 shows the signatures extracted using ICA (known as ICA signatures) from the low-noise signals [13], which are obtained from motors supplied from a fixed-frequency and near-sinusoidal source. Fig. 6 shows the ICA signatures without de-noising from the high-noise signals measured from motors fed from an inverter. Compared to the signatures obtained from low-noise signals as shown in Fig.5, high-noise signatures obtained from the healthy and faulty motors overlap each other as in Fig. 6 without de-noising. It is thus difficult to separate signatures of the healthy motor from those of the faulty ones without de-noising. This is due to noises from the inverter, which hide the useful information.

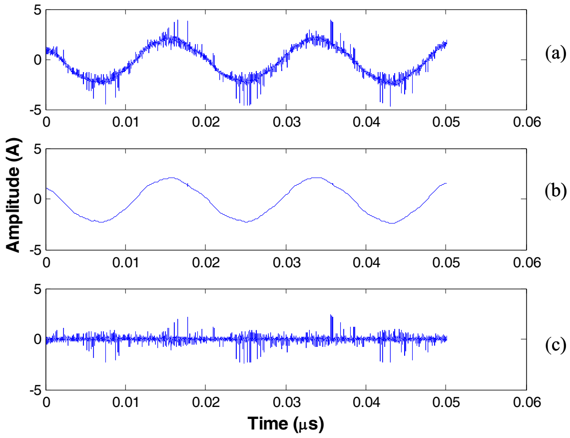

Fig. 4 Performance of de-noising by the wavelet method on high-noise signals

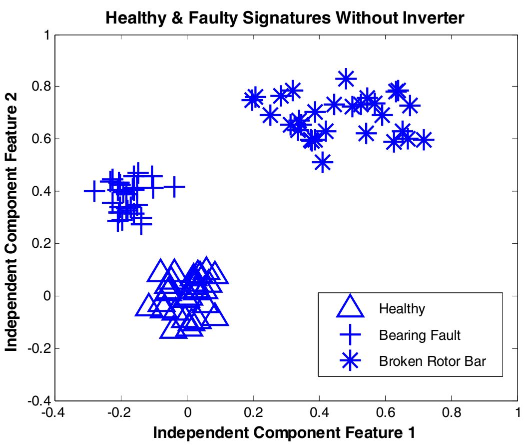

Fig. 5 Signatures of low-noise signals obtained from near-sinusoidal supply

Using the same high-noise data as those in Fig. 6, Fig.7 and Fig.8 show the ICA signatures after de-noising using the proposed method and wavelet respectively. From Fig. 7, the proposed EINR method classifies perfectly after de-noising on each type of ICA signatures according to the type of healthy or faulty motor. Although seen visually as an excellent noise reducer (Fig. 4), the wavelet method has not provided (Fig. 8) the similar effectiveness of de-noising as given by the proposed EINR method. By comparing Fig. 8 with Fig. 6, the wavelet method has in fact provided very little improvement over the case of no de-noising. This supports our notion that the wavelet transform eliminates both the noise as well as a part of useful components of the signals that describe the respective motor fault.

The EINR method has also been used to de-noise the current signals obtained at other frequency, such as 20Hz, 25Hz, 31.5 Hz, 37.5 Hz, 43.5 Hz and 55 Hz. The effectiveness of the proposed EINR method has thus been demonstrated.

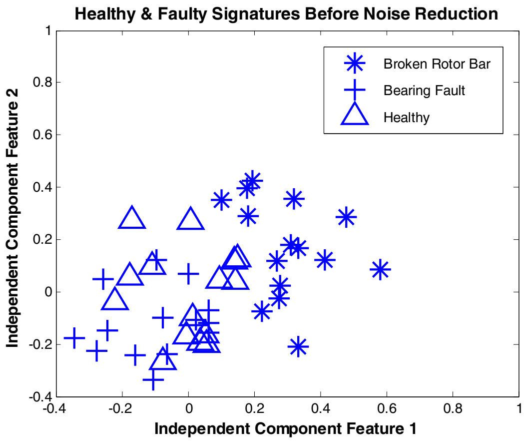

Fig. 6 Signatures of high-noise signals obtained from inverter without de-noising

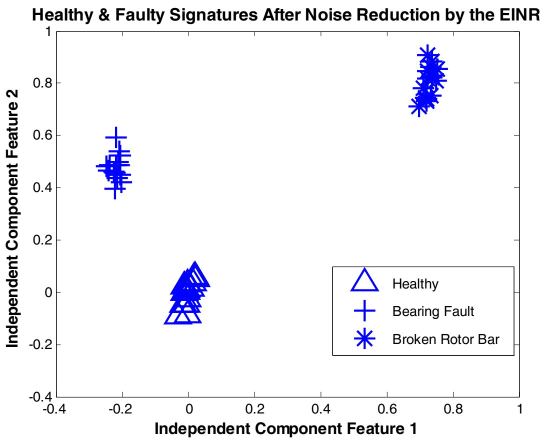

Fig. 7 Signatures of signals obtained from inverter and de-noised by the proposed method

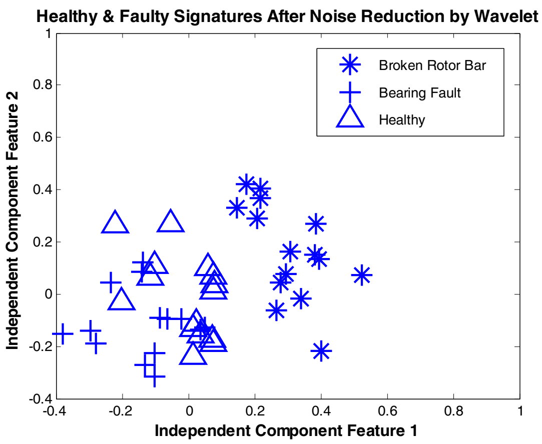

Fig. 8 Signatures of signals obtained from inverter and de-noised by the wavelet method

C. *Advantages of the EIRN method compared to the common averaging method*

The two main advantages of the proposed EIRN method are:

(1) The proposed EINR method reduces the computational complexity and signal size required by the common averaging method. For example, the number of the obtained de-noised signals for both the proposed and common averaging methods is set for 45 for the three types of motors (15 for bearing problems, 15 for broken rotor bar problems and 15 for healthy motor) for providing sufficiently accurate analysis of the statistical characteristic of measured signals. The number of repetitions is set to 30 in this study. Using the common averaging method, the number of the signals in each type will be 450(=30×15), and the total number of the signals of the three types is 1350(=450×3). Using the proposed EINR method, 30 of the signals is selected as the "profile" segment to de-noise the other 15 signals and 45(=30+15) signals are enough to get the 15 individual de-noised signals. The total number of the required signals is 135 (=45×3).

(2) As shown in equation (9) and Fig. 7 after de-noising by the proposed EINR method, each signal preserves its own characteristic, which is essential for statistical signatures analysis.

V. CONCLUSIONS AND FUTURE WORKS

To obtain the signatures of motor stator currents, maintaining sufficient individual current signals is very important. The ensemble and individual noise reduction method is proposed as an alternative to the wavelet and the common averaging methods for the induction-motor signature analysis. The proposed EINR method is superior to the common averaging method for reducing the computational complexity and data size, and better than wavelet for preserving all the fault-related components of the measured signals. The signals de-noised by the proposed EINR method retain individual characteristics. The case study in this paper demonstrates the merits of the proposed EINR method.

Our work will be extended to on-line fault detection of more induction-motor fault conditions, such as gearbox problems. This EINR method is being extended to de-noise the in the frequency domain signals. A fault detection method based on hybrid time-frequency domain analysis is being investigated with promising initial results, which will be detailed soon.

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