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Robust Slot Harmonic Extraction in Varying Speed Operations

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Abstract—It is of great interest to extract motor slot harmonics for the purpose of studying motor efficiency, heat loss, torque ripple, as well as monitoring motor health condition and estimating motor speed. However, slot harmonics are typically of small magnitudes and of varying frequency in practice for motors operating at various conditions. In this paper, we propose a robust approach to extracting motor slot harmonics from the stator current when the motor is operating at varying speed conditions. First, a sparsity-driven method is proposed to estimate the frequency variation of slot harmonics due to varying operating speed. Then a singular value decomposition(SVD)-based method is used to extract the slot harmonics after compensating the corresponding frequency variation for each time window. In addition, the motor speed is also estimated according to the relationship between the slot harmonics and the motor speed. Experiments show that our method can extract slot harmonics from very noisy measurements and estimate motor speed with improved performance compared to the traditional method.

Index Terms—Slot harmonics, varying speed operation, speed estimation, sparsity model.

I. INTRODUCTION

Motor slot harmonics are generated by motor slots due to the regular variation of reluctance and flux over the stator surface. When the motor is running at a constant speed, the variation of reluctance and flux is periodic in time, yielding constant-frequency slot harmonics in the stator current. When the motor is running at a varying speed, the slot harmonic frequency also varies with respect to the rotating speed.

The impact of slot harmonics to motor drive systems are two-sided. On one side, slot harmonics may cause side effects such as distortion of the voltage wave, decreased efficiency, extra heat loss, and undesired vibrations, *etc.* On the other side, slot harmonics may be utilized as a signal to monitor motor health conditions [1]–[4], such as eccentricity [3] and broken bars [4]. They can also be used to estimate the motor speed [5], which is useful when the motor speed is very low and traditional methods may fail to estimate the speed such as zero-frequency control. Therefore, it is of great interest to extract slot harmonics in the stator current for further study and analysis in different applications.

However, it is challenging to extract slot harmonics in practice and to analyze their magnitudes relative to the operating frequency magnitude due to several reasons. First, their Shinya Tsuruta Electric Systems Automation Mitsubishi Electric Research Laboratories Cambridge, MA, USA tsuruta@merl.com

magnitudes are much lower than the operating frequency magnitude. This is because in motor design process, slot shapes are typically optimized to improve the motor performance, leading to very small slot harmonics. Second, motors are typically operating at varying speed /varying load conditions for different applications. Therefore slot harmonics are no longer of constant frequency, but time-varying with respect to the motor speed. Third, the slot harmonics may be interfered by inverter harmonics and other noise, making it difficult to discriminate slot harmonics from other interference and further to estimate their magnitudes. The extracted slot harmonic magnitudes using traditional methods may be not robust for different the motor speed profiles.

To tackle this problem, we propose a robust sparsity-driven method to extract slot harmonics in the stator current and to estimate the magnitudes. Unlike [5], [6] which employed classical signal processing techniques such as chirp Z transform or short-time chirp-Z transform instead of short-time Fourier transform to extract slot harmonics, we further exploit the relationship of slot harmonics of different orders and the property of frequency variations between different time windows in the short-time Fourier spectra using advanced sparsity-driven signal processing techniques. As a result, the time-varying slot harmonic frequency, slot harmonic magnitudes, and the motor speed can be well identified. Our main contributions are summarized as follows.

- We proposed a sparsity-driven method to estimate frequency variation of slot harmonics due to the varying speed/load operation.
- Using the estimated frequency variation at different time windows, we compensated each time-window frequency spectra such that slot harmonic magnitudes can be extracted by performing singular value decomposition.
- Based on the estimated frequency variation, we also computed the time-varying motor speed at different time-windows and compared it with the measured speed to demonstrate its accuracy.

II. SPECTRAL ANALYSIS AND SLOT HARMONICS

Let $i_s(t)$ represent the time-domain stator current of a motor in an ideal steady-state operation. Note that the current could be a single-phase current or a combination of three phase current after proper phase alignment such as Park transform.

The frequency spectrum of the stator current i_s can be achieved by the Fourier transform as

$$I_s(\omega) = \int i_s(t) e^{-j\omega t} dt.$$
 (1)

For periodic signals in motor operations, a discrete Fourier transform (DFT) is typically used to compute the Fourier spectrum based on discrete time samplings $i_s(n)$. We ignore the detailed correspondence between the frequency and the sampling rate, and simplify the expression of Fourier spectrum as

$$[I(n_f)] = DFT[i_s(n_t)], \qquad (2)$$

where n_t and n_f represent discrete time and frequency respectively.

In the frequency domain, motor slot harmonic frequency in the stator current can be formulated as [1], [2], [7]

$$f_{slt} = \left((\kappa Z \pm n_d) \frac{1-s}{p} + \nu \right) f_s, \tag{3}$$

where f_s is the operating frequency; Z is the number of rotor slots; p is number of pole pairs; s is the motor slip, which can be calculated using the motor n_r and the synchronous speed n_s as $s = \frac{n_s - n_r}{n_s}$; $\kappa = 1, 2, 3, ...; n_d$ is the eccentricity order $(n_d = 0$ in case of static eccentricity and $n_d = 1, 2, 3, ...$, in case of dynamic eccentricity); and $\nu = \pm 1, \pm 3, \pm 5, ...$ is the order of stator time harmonics.

When the motor is operating at a constant speed, it is straightforward to extract slot harmonics according to their frequency. When the motor is operating at varying speed, slot harmonics are also changing accordingly. To capture the frequency variation of slot harmonics, we consider short-time Fourier transform (STFT) for spectral analysis. Given the STFT spectrum, we further exploit the relationship of slot harmonics of different orders and the property of frequency variations between different time windows using advanced sparsity-driven signal processing techniques. The detail of our proposed method is described in the following section.

III. PROPOSED METHOD

For slot harmonic detection at varying speed and varying load conditions, an essential task is to estimate the timevarying slot harmonic frequency. Note that the magnitude of slot harmonic signals are typically much smaller than that of the operating frequency signal, and even lower than some interference or measurement noise. Therefore, the estimation of time-varying slot harmonic frequency is sensitive to the measurement noise and other inverter interference. To improve the robustness, we propose the following robust method to estimate the slot-harmonic frequency variation. Once the frequency variation is determined, slot harmonic frequency can be well aligned after compensating the frequency variation. Consequently, the aligned slot harmonics can be extracted using conventional methods.

A. Frequency variation Estimation

Let $[I_i(n_f)]$ be the frequency spectrum of the *i*-th (i = 1, ..., N) short-time window stator current. Due to the varying speed vary load operation, the slot harmonic frequency is not constant, but exhibits a speed-dependent shift from the ideal fixed slot harmonic frequency. According to (3), slot harmonic frequency variation due to speed variation can be represented as

$$\Delta f_{slt} = (\kappa Z \pm n_d) \frac{f_s}{p n_s} \Delta n_r = \frac{\kappa Z \pm n_d}{60} \Delta n_r.$$
(4)

Note that the frequency variation is independent of the order of stator time harmonics, meaning that all orders of slot harmonics will have the same frequency variation give a speed variation.

Assume that the motor speed is fixed in a short-time window used for spectral analysis. Without loss of generality, let $\mathbf{h} = [\Delta f_{slt_1}, ..., \Delta f_{slt_i}, ..., \Delta f_{slt_N}]^{\top}$ be a column vector of the slot harmonic frequency variation across all time windows, in which the *i*-th entry $\mathbf{h}(i) = \Delta f_{slt_i}$ is the slot harmonic frequency shift corresponding to the *i*-th time window. For steady constant-speed operations, $\mathbf{h} = \mathbf{0}$. The slot harmonic frequency difference between the *i*-th and the *j*-th time windows due to speed variation is

$$L(i, j) = \mathbf{h}(i) - \mathbf{h}(j),$$

for $i, j = 1, 2, \cdots, N.$ (5)

For speed sensorless drive, the speed is not directly measured and needs to be estimated. Therefore, the slot harmonic frequency can not be tracked based on speed, but estimated by the measured current. Ideally, it is straightforward to find the frequency different by computing the cross correlation between the frequency spectrum of the *i*-th time window signal $[I_i(n_f)]$ and that of the *j*-th time window signal $[I_j(n_f)]$ as

$$\hat{L}(i,j) = \operatorname{argmax}_{n_d} \sum_{n_f} |I_i(n_f)| \cdot |I_j(n_f + n_d)|.$$
 (6)

In practice, since the slot harmonic signal is very weak and very sensitive to noise interference, the solution of (6) may be not accurate or even quite different from the truth value. Here we use $\hat{\mathbf{L}} = [\hat{L}(i, j)]$ to represent a matrix of the frequency variation computed according to (6) and $\mathbf{L} = [L(i, j)]$ to represent the matrix of the true frequency variation according to (5). Our objective is then to recover \mathbf{h} from inaccurate estimations $\hat{\mathbf{L}}$.

Note that (5) can be re-formulated in the matrix-vector form as

$$\mathbf{L} = \mathbf{h} \mathbf{1}^{\top} - \mathbf{1} \mathbf{h}^{\top} \in \mathbb{R}^{N \times N}, \tag{7}$$

where 1 is an N-dimensional vector with all entries equal to 1. It is straightforward to verify that for any real vector $\mathbf{h} \neq a\mathbf{1}$, where a is a real scalar, we have

$$\operatorname{rank}(\mathbf{L}) = \operatorname{rank}(\mathbf{h}\mathbf{1}^{\top}) + \operatorname{rank}(\mathbf{1}\mathbf{h}^{\top}) = 2.$$
(8)

From (8) we conclude that in theory the matrix of frequency variation is a rank 2 matrix. However, in practice the estimated matrix $\hat{\mathbf{L}}$ using (6) is not rank 2 but with noise

interference. Therefore, one way to recover **h** from noisy $\hat{\mathbf{L}}$ is to use the well-known robust PCA method [8], which decomposes the observation matrix $\hat{\mathbf{L}}$ into a low-rank matrix and a sparse noise matrix. However, it is not guaranteed that the low-rank matrix decomposed by the robust PCA method is in the form of (7). Here instead of using the robust PCA, we implicitly impose low-rankness. We vectorize **L** as $l = [L(1,1), L(2,1), ..., L(i,j), ..., L(N,N)]^{\top}$ and $\hat{l} = [\hat{L}(1,1), \hat{L}(2,1), ..., \hat{L}(i,j), ..., \hat{L}(N,N)]^{\top}$. According to (5) we have

$$l = \mathbf{A}\mathbf{h},\tag{9}$$

where

$$\mathbf{A} = [\cdots, \alpha_{i,j}, \cdots]^{\top} \in \mathbb{R}^{N^2 \times N},$$
(10)

in which $\alpha_{i,j} \in \mathbb{R}^{1 \times N}$ has all-zero entries except that $\alpha_{i,j}(i) = 1$ and $\alpha_{i,j}(j) = -1$. Considering that the solution of (6) could be far away from the truth value, we impose sparsity on the estimation error. Consequently, the frequency variation estimation problem is formulated as a L1-regularized optimization problem [9], [10]

$$\min_{\mathbf{e},\mathbf{h}} \frac{1}{2} \|\hat{\boldsymbol{l}} - \mathbf{A}\mathbf{h} - \mathbf{e}\|_2^2 + \lambda |\mathbf{e}|_1,$$
(11)

where λ is the regularization parameter, and vector **e** represents sparse error of frequency variation cause by interference. When $\lambda = 0$ and $\mathbf{e} = \mathbf{0}$, (11) is reduced to the least-squares method, which works well for Gaussian noise. In our case, where there exists other interference introduced by the inverter, sparsity-inspired optimization in (11) improves the robustness.

To solve (11), we utilize the alternating minimization method by iteratively updating e and h until its stopping criteria is satisfied. The sub-problem with respect to h is a standard least-squares problem, which can be solved by

$$\mathbf{h}^{(t)} = \mathbf{A}^+ (\hat{l} - \mathbf{e}^{(t-1)}), \tag{12}$$

where \mathbf{A}^+ denotes the pseudo-inverse of \mathbf{A} , and superscripts (t) and (t-1) represent the number of iterations during the process.

The sub-problem of e can be solved by a soft-thresholding process as [11]

$$\mathbf{e}^{(t)} = \max(0, |\hat{l} - \mathbf{A}\mathbf{h}^{(t)}| - \lambda) \odot \operatorname{sign}(\hat{l} - \mathbf{A}\mathbf{h}^{(t)}). \quad (13)$$

B. Slot harmonic extraction

Once the frequency variation vector $\hat{\mathbf{h}} = \mathbf{h}^{(T)}$ is properly estimated at iteration t = T, we can align the spectrum as circularly shift the *i*-th time window frequency spectrum by $-\hat{\mathbf{h}}(i)$, *i.e.*,

$$[\bar{I}_i(n_f)] = \operatorname{circshift}([I_i(n_f)], -\hat{\mathbf{h}}(i)), \qquad (14)$$

and form a matrix of aligned spectra as

$$\bar{\mathbf{I}} = [[\bar{I}_1(n_f)], ..., [\bar{I}_i(n_f)], ..., [\bar{I}_N(n_f)]].$$
(15)

Recalling that all slot harmonics are evenly separated by f_s according to (3), we can align all slot harmonics simultaneously by compensating frequency variation according to (14). The

slot harmonics can be extract by singular value decomposition on the compensated spectrum \bar{I} .

Let the singular value decomposition of the compensated spectrum be

$$\bar{\mathbf{I}} = \mathbf{U} \boldsymbol{\Sigma} \mathbf{V}^{\top} = \sum_{j} \sigma_{j} \mathbf{u}_{j} \mathbf{v}_{j}^{\top}, \qquad (16)$$

where \mathbf{u}_1 represents principle left singular vector of matrix $\overline{\mathbf{I}}$, or the principle spectrum of slot harmonics. Considering that slot harmonics are sparse in the frequency domain, we use a simple thresholding method to keep large frequency components. The speed-independent frequency component $\hat{\mathbf{u}}_1$ of stator current is achieved by simply thresholding the magnitude of \mathbf{u}_1 to keep the largest K frequency components, where K is related to the order of slot harmonics. In practice, considering the frequency resolution issue, we set the threshold as 10% of the largest magnitude of slot harmonics, *i.e.*

$$\hat{\mathbf{u}}_1 = \begin{cases} \mathbf{u}_1, & \text{if } abs(\mathbf{u}_1) > 0.1 max(abs(\mathbf{u}_1)), \\ 0, & \text{else.} \end{cases}$$
(17)

Note that $\hat{\mathbf{u}}_1$ is independent to the operating speed due to the slot harmonic frequency alignment, and equivalent to the slot harmonic spectrum at the constant-speed operation. Therefore it is robust for varying-speed operations. For comparison purpose, the denoised speed-dependent slot harmonic spectrum can be achieved by adding the frequency variation of each time window back to the corresponding speed-independent spectrum related to $\hat{\mathbf{u}}_1$ as

$$[\hat{I}_i(n_f)] = \operatorname{circshift}\{[\sigma_1 \hat{\mathbf{u}}_1 \mathbf{v}_1^\top(i)], \hat{\mathbf{h}}(i)\}.$$
 (18)

According to (3), given the dominant slot harmonic of static eccentricity $n_d = 0$, motor speed can also be estimated as [5]

$$n_r = \frac{60}{Z} (f_{slt} - \nu f_s),$$
(19)

where for each time window, the speed is deemed as a constant.

IV. EXPERIMENTS

A. Setup

To validate our method, we perform experiments on a 1HP three-phase squirrel-cage induction motor. The experimental setup is shown in Fig. 1. The motor is driven by a three-phase inverter. A servo-motor is mounted on the induction motor shaft and well aligned to work as a load, whose speed and torque can be controlled precisely for the experiment purpose. During motor operation, we fix the fundamental operating frequency and manually adjust the load torque (servo-motor) with an arbitrary pattern such that the motor speed changes accordingly with time, with motor slip range from 0.02 to 0.1. The three-phase stator currents are measured using current sensors and recorded via a dSPACE® Scalexio Labbox platform for further analysis.



Fig. 1. Experimental setup.

B. Results

An example of the time-domain stator current of the motor operating at a varying load condition is shown in Fig. 2, where we recorded about 53-second time-domain data with a sampling rate of 2kHz. It is clear that due to the varying load, the stator current amplitude also changes from time to time to meet the load requirement.



Fig. 2. Time-domain stator current.

We perform short-time Fourier transform (STFT) on the stator current with sliding rectangular windows, where each window is of size 2.5 seconds, and 2-second overlap from window to window, resulting a frequency resolution of 0.4Hz, and time resolution of 0.5 second.

The STFT spectrum in the frequency range of 400Hz – 1000Hz is shown in Fig. 3, with color-bar in dB scale, with the signal-to-noise ratio (SNR) around 15.8dB. We observe that slot harmonics are very weak and interfered by strong noise in the frequency range of 600Hz-700Hz.

To recover the frequency variation, the frequency variation matrix is estimated according to (6), as shown in Fig. 4(a). After solving the optimization problem in (11), a low-rank frequency variation matrix and a sparse error matrix are



Fig. 3. Short-time Fourier transform of stator current in the frequency range of 400Hz-1000Hz.

achieved, as shown in Fig. 4(b) and Fig. 4 (c), respectively. The corresponding frequency variation vector is then recovered as shown in Fig. 4 (d).

Based on this recovered frequency variation vector, the STFT spectrum is then aligned by compensating the corresponding frequency variation of each time-window spectrum, as shown in Fig. 5 (a). After compensation, we observe that slot harmonics of different orders become straight parallel lines in the compensated STFT spectrum. The slot harmonics are then extracted using SVD, as shown in Fig. 5 (b).

To demonstrate the denoising effect, the denoised timevarying slot harmonics are achieved by adding frequency variation on slot harmonics extracted by the SVD, as shown in Fig. 6 (a). We observe that the denoised slot harmonics are much more clear than the original STFT version shown in Fig. 3, and the interference in the frequency range 600Hz-700Hz is also completely removed. For comparison, the denoised slot harmonics using least squares method are shown in Fig. 6 (b), for which we do not consider sparsity property of the interference in the frequency variation matrix, but model it as Gaussian noise. Although Fig. 6 (b) is also clean, it exhibits some bias and saw-tooth like errors at time around 26 second.

The estimated motor speed profiles using different methods and the measured speed profile are shown in Fig. 7. Due to the low bit rate A/D converter in our speed measurement platform, the measured speed exhibits discrete values in the speed profile. The estimated speed using our proposed method matches the measured curve very well, while the estimated speed using least squares method shows large discrepancy.

Since our proposed method exploits the relationship of slot harmonics of different orders and the property of frequency variations between different time windows, its implementation requires some previous time window spectra. As regarding to the computational time, it takes 8.9 seconds for our proposed method to finish loading the data, implementing the proposed algorithm, and plotting results on a Windows®desktop with an Intel®i7-8700K 3.70GHz CPU with 64G RAM using Matlab®R2022b.



Fig. 4. Frequency variation analysis. (a) Estimated frequency variation matrix $\hat{\mathbf{L}}$ using (6),(b) Recovered frequency variation matrix \mathbf{L} , (c) Recovered sparse frequency variation error \mathbf{e} in the matrix form, and (d) Recovered frequency variation \mathbf{h} of short-time windows.



Fig. 5. (a) Frequency spectrum after compensating estimated frequency variations due to speed variations and (b) Slot harmonics extracted by SVD after frequency compensation.

V. CONCLUSION

In this paper, we proposed a sparsity-driven method to extract slot harmonics of a motor operating at varying speed conditions by exploiting the relationship of slot harmonics of different orders and the property of frequency variations between different time windows. First, the frequency variation due to speed variation is estimated using a sparsity-driven optimization model. Then given the estimated frequency variation, STFT spectrum is aligned by compensating the frequency variation of each time window spectrum. Slot harmonics are then extracted from the aligned spectra using singular value decomposition. As a result, the motor speed is also computed according to the estimated slot harmonic frequency. We tested our method on experimental data of stator current. Experimental results demonstrate that our method can effectively extract slot harmonics of motor under unknown running speed, with significantly better performance than the conventional leastsquares method.



Fig. 6. Spectra of stator current in short-time windows. (a)Denoised spectrum of slot harmonics using proposed method and (b)Denoised spectrum of slot harmonics using least squares method.



Fig. 7. Comparison of motor speed using different methods.

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