Application of advanced signal processing techniques to the diagnostic of induction motors

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Abstract. The application of signal processing tools in electrical machines-related areas has lived an extraordinary advance over recent years. This has been partially due to the extrapolation of recent techniques that have shown very satisfactory results in other scientific areas. More specifically, the application of these tools to determine the health of the machine is a research field that has attracted the interest of industry and academia. The idea is to apply these techniques to the machine quantities, regardless of its operation regime, in order to obtain additional information about its condition that is not available with the conventional tools. This paper reviews the application of diverse recent signal processing tool in the electric machines condition monitoring area. The paper discussions presented in the paper cover from the conventional tools, as the Fourier transforms, to more modern alternatives based on time-frequency analysis. The paper includes a section where a didactic explanation of the operation of some of these advanced tools is presented.

Introduction

The use of signal processing tools in the electrical machines area has lived an extraordinary advance over recent decades [1-2]. This is a classical area that has been always characterized by importing the advances and new findings in other scientific areas but with a certain delay. More specifically, the electrical machines condition monitoring research area has been applying tools and methodologies that have been employed with great success in other research fields. As an example, nuclear engineering is an area that has been pioneer in the development and application of advanced signal processing tools in order to develop techniques aimed to guarantee the reliability of nuclear processes that are often critical. Some of these techniques have been later extrapolated to the electrical machines fault diagnosis and prognosis areas [3].

This progressive use of validated and optimized signal processing tools has been very beneficial for the electrical machines diagnosis community, whose primary goal is to develop advanced methods to reliably detect the eventual presence of failure in these machines, while these failures are still in their early stages of development. In this way, the industrial users can adopt proper maintenance actions in advance, minimizing the possible economic losses derived from unplanned interruptions. The use of advanced and modern signal processing tools enables to reach a higher reliability and accuracy in the conclusions relative to the machine condition, since much more information can be obtained when applying these tools (in comparison with that obtained with the conventional methods).

A recent trend that has drawn a significant attention is the analysis of machine quantities (currents, fluxes, vibrations, voltages…) that are captured during transient operation [2-4]. Current analysis has drawn a significant attention, since this is a quantity that can be measured in a non-invasive way and the necessary equipment for its measurement and processing is rather simple [5]. However, currents and other quantities are often characterized by their non-stationary nature, a fact that makes difficult (or even impossible) the application of classical signal processing tools (as the
Fourier transform). To analyze such quantities and obtain the most information possible, advanced signal processing tools, suited for the analysis of non-stationary signals must be used. In this context, modern time-frequency tools, as wavelet transforms, Wigner-Ville distributions or Hilbert-Huang transforms have proven to provide very useful information for fault diagnosis purposes [1-2]. In fact, these tools are able to track the evolutions of multiple harmonics that are introduced by the corresponding fault in the analyzed signal (current or vibration). The detection of these harmonics evolutions is a reliable indicator or the presence of the fault, since it is very unlikely that other phenomenon leads to harmonics with such evolutions.

One interesting application within the electrical machines condition monitoring area where the use of these tools has provided very satisfactory results is the rotor assessment of induction motors [4]. Several works have shown that the application of tools as the Discrete Wavelet Transform (DWT) [4] or the Hilbert-Huang Transform (HHT) [3,6] enables to obtain very complete ‘pictures’ of the time-frequency content of the analyzed signal. More specifically, the application of these tools to the phase stator startup current yields time-frequency maps represented in different manners, where the rotor fault related harmonics can be tracked. Moreover, it is even possible to quantify the level of cage failure by computing the energies of different regions of these maps [4].

The present paper is aimed to present an overview of the basic operation of these two transforms (DWT and HHT), illustrating their operation through several didactic examples. In addition, the paper will review the application of these tools to the rotor assessment in induction motors. The results included here show the powerfulness of these signal processing techniques as well as their potential for the further extrapolation to the detection to other faults.

**Advanced Time-Frequency tools**

**Discrete Wavelet Transform (DWT).** When the Discrete Wavelet Transform (DWT) is applied to a certain sampled signal \( s(t) \), this signal is decomposed as the addition of a set of signals (wavelet signals): an approximation signal at a certain decomposition level \( n \) \( (a_n) \) plus \( n \) detail signals \( (d_j) \) with \( j \) varying from 1 to \( n \) [7].

Each wavelet signal (approximation and detail) has an associated frequency band, the limits of which are well-established, once the sampling rate \( (f_s) \) of the original analyzed signal is known, in accordance with an algorithm enunciated by S. Mallat (Subband Coding Algorithm) [8]. The formulae that are employed to calculate the limits of the frequency bands associated with each wavelet signal, according to the Mallat algorithm, are specified in Fig. 1. Note how the limits of the frequency band for each wavelet signal depend on the sampling rate \( (f_s) \) as well as on the level of the corresponding wavelet signal \( (j) \). As an example, if the sampling rate used for capturing \( s(t) \) is \( f_s=5000 \) samples/second, and we perform the DWT decomposition in \( n=8 \) levels, the frequency bands associated with each wavelet signal are those shown in Table 1 [9].

![Fig. 1 DWT decomposition in wavelet signals and associated frequency bands](image-url)
Table 1. Frequency bands associated with wavelet signals for $f_s=5$ kHz and $n=8$

<table>
<thead>
<tr>
<th>Wavelet signal</th>
<th>Frequency band</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_8$</td>
<td>[0-9.7] Hz</td>
</tr>
<tr>
<td>$d_8$</td>
<td>[9.7-19.5] Hz</td>
</tr>
<tr>
<td>$d_7$</td>
<td>[19.5-39] Hz</td>
</tr>
<tr>
<td>$d_6$</td>
<td>[39-78.1] Hz</td>
</tr>
<tr>
<td>$d_5$</td>
<td>[78.1-156.2] Hz</td>
</tr>
<tr>
<td>$d_4$</td>
<td>[156.2-312.5] Hz</td>
</tr>
<tr>
<td>$d_3$</td>
<td>[312.5-625] Hz</td>
</tr>
<tr>
<td>$d_2$</td>
<td>[625-1250] Hz</td>
</tr>
<tr>
<td>$d_1$</td>
<td>[1250-2500] Hz</td>
</tr>
</tbody>
</table>

The intuitive idea underlying the application of the DWT is the next: each one of the wavelet signal acts as a filter, extracting the temporal evolution of the components of the original signal contained within the frequency band associated with that wavelet signal [4, 9]. For instance, in the previous example, the wavelet signal $d_6$ (detail signal 6) will reflect the time evolution of every harmonic component of the original signal when its frequency falls in the band [39-78.1] Hz. For instance, if the signal is a pure 50 Hz sinusoidal waveform, the whole signal evolution would be reflected in that signal $d_6$. Some examples that illustrate the operation of the DWT are presented next [9]:

**Example 1: DWT analysis of a pure sinusoidal signal**

Fig. 2 shows the DWT of a 50 Hz pure sinusoidal signal (depicted at the top). Note how, in agreement with the filtering process carried out by the DWT, the whole signal is filtered into the detail signal $d_7$. The reason for this is that this signal reflects the evolution of every component evolving within the range [39-78.1] Hz. Hence, since there is a single 50 Hz component in the original signal, $d_7$ exactly reflects the evolution of the whole component. The other wavelet signals are approximately zero, since no other frequency components exist in the original signal.

![Fig. 2 Example 1: DWT decomposition of a pure sinusoidal signal](image-url)
**Example 2: Superposition of sinusoidal signals**

Fig. 3 shows the DWT analysis of a signal $s$ (that is depicted plotted on the top) that has been built by adding four sinusoidal signals with frequencies: 5 Hz, 15 Hz, 30 Hz and 50 Hz. The result is a stationary signal in which all four frequencies are present at every time. The filtering nature of the DWT allows extracting each frequency component in a separate wavelet signal, in concordance with the values of their respective band limits. Note that the 5Hz component is filtered in $a_9$, the 15 Hz component in $d_9$, the 30 Hz component in $d_8$ and the 50 Hz component in $d_7$, remaining almost zero the rest of signals, since no other components exist within their bands. This is an illustrative example of the filtering process carried out by the transform. It also proves its ability to separate the different components of the signals, provided that they fall in different frequency bands covered by the wavelet signals [9].

![Figure 3 Example 2: DWT analysis of a signal based on the superposition of four sinusoidal signals with frequencies 5 Hz, 15 Hz, 30 Hz and 50 Hz](image)

**Example 3: Concatenation of sinusoidal signals**

Fig. 4 shows the DWT of a signal $s$ (that is plotted at the top of the figure) which has been built by concatenating four sinusoidal signals with respective frequencies 5 Hz, 15 Hz, 30 Hz and 50 Hz. The result is a non-stationary signal, where each frequency component is present only during its corresponding time interval. The DWT of that signal implies to filter each component in the wavelet signal covering the frequency band where it is included. Therefore, the 5Hz component is filtered in $a_9$, the 15 Hz component in $d_9$, the 30 Hz component in $d_8$ and the 50 Hz component in $d_7$. The rest of signals are almost zero since no components exist within their bands. Furthermore, the wavelet signals indicate when each component starts and ends in the analyzed signal. As an example, $a_9$ shows how the 5 Hz component is present during the initial 0.25 seconds, $d_9$ shows that the 15 Hz component is present between 0.25 and 0.5 s, $d_8$ reveals that the 30 Hz component occurs between 0.5 and 0.75 seconds and, finally, $d_7$ shows that the 50 Hz component is present between 0.75 and 1 second. This is an illustrative example of one of the most important advantages of the DWT in comparison with the FFT [9]: whereas with the FFT, the time information is lost and two rather different signals (such as those analyzed in Examples 2 and 3) could be represented by
similar FFT spectra, the DWT preserves the time information, enabling to identify which frequencies and when they occur. Hence, the DWT leads to a three-dimensional representation of the analyzed signal: frequency (because each wavelet signal covers a frequency band), time (since each wavelet signal is represented versus time) and amplitude (the amplitude of the wavelet signal informs on the corresponding amplitude of its filtered components in the analyzed signal) [9].

**Hilbert-Huang Transform.** The Hilbert-Huang transform (HHT) is a modern tool that has provided very good results in other engineering areas, as nuclear technology, to analyze multi-component signals [3, 6, 10]. In synthesis, the HHT decomposes the analyzed signal into a set of intrinsic mode functions (IMFs). Each IMF filters the components of the original signal into a certain frequency band. However, unlike what happens in the DWT, the frequency band associated to each IMF is not known ‘a priori’. The HHT performs an ‘adaptive filtering’ process so that the predominant frequencies are filtered in the first IMFs, while the latter IMFs contain the components with reduced amplitudes [10].

In order to know the exact frequencies covered and obtain a proper time-frequency representation of each IMF, it is necessary to perform the Hilbert spectrum of the IMF, that shows how all components contained in that IMF evolve in the t-f map. Some examples that illustrate the operation of the HHT are presented next [10]:

*Example 4: HHT of the addition of sinusoidal signals*

Fig. 5 depicts a signal based on the addition of two sinusoidal signals with frequencies 50 Hz and 15 Hz and respective amplitudes 5 and 1. Fig. 6 shows the application of the HHT to the previous signal (two IMFs are considered) [10]. Fig. 6(a) depicts: the IMF1 waveform (Fig. 6(a), top), the IMF1 Hilbert Huang spectrum (Fig. 6(a), middle) and the IMF1 marginal spectrum ((Fig. 6(a), bottom). Fig. 6(b) is equivalent but for the IMF2. This figure is very illustrative on how the HHT operates: the IMF1 extracts the largest component present in the signal (i.e., the 50 Hz sinusoidal
component with amplitude 5). This is observed in the imf1 waveform. On the other hand, the Hilbert Huang spectrum of this imf1, logically, shows a single line at 50 Hz at every time instant. Finally, the imf1 marginal spectrum shows a peak at 50 Hz. On the other hand, imf2 extracts the evolution of the rest of components in the analyzed signal (in this case, the 15 Hz sinusoidal component with amplitude 1); this is observed in Fig. 4(b) (top), that depicts the imf2 waveform and reveals a sinusoidal component with lower frequency (and amplitude) than that in Fig. 6(a), top. Hilbert spectrum of imf2 shows a single line at 15 Hz at every time instant. Accordingly, the marginal spectrum of imf2 reveals a single frequency peak at 15 Hz.

This example illustrates the adaptive filtering nature of the HHT, extracting the components present in the signal in the different imfs.

![Fig. 5 Signal based on the addition of two sinusoidal signals [10]](image)

![Fig. 6 Example 4: HHT of the previous signal: (a) IMF1: waveform (top), Hilbert spectrum (middle) and marginal spectrum (bottom); (b) IMF2: waveform (top), Hilbert spectrum (middle) and marginal spectrum (bottom) [10].](image)
Example 5: HHT of the concatenation of two sinusoidal signals

This example is based on the HHT analysis of the signal plotted in Fig. 7, that is the concatenation of two sinusoidal signals with respective frequencies 50 Hz and 15 Hz and respective amplitudes 5 and 1. In this case, the HHT analysis leads to a single IMF (imf1) that reflects the evolution of both components. Fig. 8 shows the HHT results: the IMF1 waveform (top), Hilbert spectrum of the IMF1 (middle) and marginal spectrum of IMF1 (bottom). The waveform of the IMF1 corresponds to that of the original signal (concatenation of the two aforementioned components). The Hilbert spectrum of IMF1 is especially interesting: a single line at 50 Hz reveals the presence of the first frequency component during the initial 0.5s. A second trace at 15 Hz shows the occurrence of the second component during the last 0.5 s. The lower color intensity of this second trace is due to the lower amplitude of the 15Hz frequency component. This Hilbert spectrum illustrates rather well the time-frequency nature of the tool, since it informs not only on which frequency components are present in the analyzed signal, but also when they occur. Finally, the marginal spectrum of IMF1 shows two peaks at the corresponding frequencies present in the signal (15 Hz and 50 Hz), the amplitudes of which reflect the amplitude of the associated sinusoidal signals [10].

Fig. 7 Signal based on the concatenation of two sinusoidal signals [10]

Fig. 8 Example 5: HHT of the previous signal: waveform of the IMF1 (top), Hilbert spectrum of IMF1 (middle) and marginal spectrum of IMF1 (bottom) [10].
Application of Signal Processing Techniques to Fault Diagnosis

As explained before, the application of some of the aforementioned signal processing tools in the electric motor condition monitoring area has provided very beneficial results; these tools enable a more accurate tracking of the evolutions of the fault related components in the analyzed signals (e.g. the startup current). These evolutions are reliable indicators of the presence of the failure since it is very unlikely that other phenomena can lead to the same evolutions.

A clear example that illustrates all these statements relies on the determination of the rotor condition in induction motors. In previous works [5], it has been shown that when the rotor of an induction motor is faulty, several harmonics appear in the stator current signal (i.e. the current demanded by the motor). The most relevant harmonics are known as sideband components; their frequencies are given by the well-known expression (1) (with \( f = \) supply frequency and \( s = \) slip). The lower sideband component (LSC) is the one with negative sign in (1), whereas the upper sideband component (USH) is that with positive sign [5].

\[
f_{sc} = f \cdot (1 - 2s)
\]  

(1)

In recent works [4, 6], it has been shown that the application of advanced tools, as the DWT or the HHT, enables to track the evolution of both harmonics (especially, the evolution of the LSC that is the most relevant component) during the startup transient. During this transient, as the slip changes from 1 to near 0 in a direct-on-line start), the frequency of the LSC (\( f_{LSC} \)) drops from \( f \) (=50 Hz in Europe) to 0 and then increases again to near \( f \). This evolution can be clearly identified with the aforementioned tools, as proven in recent works [4].

Fig. 9 shows the DWT of the startup current for a healthy motor (Fig. 9(a)) and for a motor with broken rotor bars (faulty rotor, Fig. 9 (b)). Note the appearance of a \( \Lambda \)-shaped pattern in the high-level wavelet signals for these latter case [4]. This pattern is caused by the time-frequency evolution of the LSC during the startup; as its frequency changes in the way commented before (50→0→50Hz), some oscillations appear in the wavelet signals covering that frequency band. These oscillations are reflecting the evolution of the LSC and their detection enables to diagnose the presence of the fault [4].

Moreover, it is even possible to determine the severity of the rotor failure; to this end, several fault indicators have been developed based on the amplitudes or energies of the wavelet signals affected by the evolution of the LSC [4, 11]. The practical experience has shown that indicators based on the energies of signals as \( d7 \) in Fig. 9 have provided very good results for the diagnostic. The indicators have been defined in such a way that a low value indicates faulty condition, while high values show a healthy condition of the rotor [12].

The application of the HHT to the startup current has provided also good results for rotor fault diagnosis purposes. In this case, the HHT can provide complete maps (either in 2-D or 3-D) of the time-frequency content of the startup current signal. These maps enable to visualize the fault components evolutions and, among them, the evolution of the LSC [3, 6]. Fig. 10 shows the 3-D Hilbert Huang spectrum of the imf2 of the startup current for the healthy motor (Fig. 10 (a)) and for the motor with faulty rotor (Fig. 10(b)). The time-frequency evolution of the LSC, that was previously described, is clearly noticed in that figure.
Conclusions

This paper reviews the application of advanced signal processing techniques to the electric motors condition monitoring area. More specifically, the work describes the utilization of two time-frequency decomposition tools (the Discrete Wavelet Transform and the Hilbert-Huang Transform) for the rotor assessment of induction motors. The paper includes a didactic explanation of both tools, including several examples that illustrate the operation of these transforms. As justified in the work, these tools enable a reliable diagnostic of the possible rotor failures based on tracking the evolutions of fault-related harmonics in the time-frequency map. The results included in the paper, obtained with real machines, prove the usefulness of the extrapolation of advance tools that have shown very satisfactory results in other scientific fields.
References


