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Real-time implementation of the digital Taylor–Fourier transform for identifying low frequency oscillations

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ABSTRACT

This paper proposes the use of the digital Taylor–Fourier transform (DTFT) for identifying low frequency oscillations in power systems. The implementation has been performed on the CompactRIO (cRIO) platform and its associated libraries, using a computational efficient DTFT calculation. The platform generates the signal spectral decomposition, yielding mono-component signals extracted by a filter bank. The spectral analysis is accomplished by means of a sliding-window that advances each new sample, providing reconstructed signals, their amplitude estimates, and information of their instantaneous damping and frequency. The identification process is applied on both simulated and actual signals. Experimental results confirm the proposition's performance, precision, and reliability.

1. Introduction

The real-time identification of low frequency oscillations (damping and frequency) through phasor measurement strategies represents a challenge for power systems monitoring. Nowadays, it is possible to take advantage of advanced hardware, including phasor measurement units (PMUs), fast microprocessors and newfangled algorithms that allow supervising the power systems operation [1]. The identification process assumes that the PMUs data are processed timely, accurate, and effectively, so that it extracts the maximum information about the oscillatory phenomenon evolution, as well as trends on the system behaviour.

Low frequency oscillations (LFOs) may arise for different reasons, and have been extensively studied. Their presence in power system threaten the system's stability [2,3]. Therefore, because the impact of LFOs over the stability, their rapid and effective identification are required in order to take the corresponding actions for preventing ulterior consequences. Typically, LFOs lie in the range 0.1–2.0 Hz and may be divided into two categories: (i) *local*, and (ii) *inter-area*. The former one varies within the interval [1.0, 2.0] Hz, while the latter one ranges within [0.1, 1.0] Hz. Because power systems become the interconnection of many sub-systems, the inter-area modes are of main concern, since they may involve large geographical zones. Thus, modal identification represents a remarkable issue in power system [4–8].

Several approaches have been developed for the LFOs identification hinged on PMU measurements. Some relevant techniques are discussed in [3–9]. Among these, the following are highlighted: (i) Fourier transform (FT); (ii) Hilbert–Huang transform (HHT); (iii) Prony analysis (PA); (iv) Eigensystem Realization Algorithm (ERA); (v) Matrix Pencil (MP); (vi) Kalman filter. Some of these techniques have been implemented under the North American SynchroPhasor Initiative (NASPI), especially in the oscillation monitoring system [8], where the Prony, Matrix Pencil, and Hankel Total Least Square algorithms are used for the analyses. Thus, for the power engineering community it is relevant to develop measurement and instrumentation systems in order to study the low frequency oscillations' phenomena. The use of information related to the oscillatory phenomena and the ability to provide their estimates in real-time, may be quite valuable for power system's operators.

On the other hand, power system monitoring has been profited of the signal processing techniques evolution and the advancement of processing devices, making feasible the real-time implementation [9]. Currently, the digital signal processing may be accomplished using a digital signal processor (DSP) [10,11], a field programmable gate array (FPGA) [12], or a general-purpose microprocessor [13], according to the application's requirements. In this paper, for identifying electromechanical oscillations [14–16], the implementation has been embedded into a FPGA and microprocessor platforms in a reconfigurable-embedded chassis with integrated real-time controller known as compactRIO [12]. Besides, in this proposal a continuous phasor measurement strategy is

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assumed, enabling to detect slow events in the electrical grid. Previously, such strategy has been used to estimate a blood pressure oscillometric signal with low frequency components in [17]. Also, its performance under fast transient events has been explored in [18]. Likewise, it has been proposed for measuring synchrophasors, frequency, and rate of change of frequency (ROCOF) in power systems [19], and it has been implemented for phasor estimation purposes [20].

Respect to different implementations [5–9], this proposal reduces the sampled data collected over a time-window, using a window of several seconds instead of minutes [9], while fictitious modes are not introduced [5,21]. Experimental results for actual and generated signals are exhibited. Thus, this paper extends the DTFT applicability for frequencies lower than 1 Hz, instead of applying it just for measuring syncrophasors at nominal frequency [20]; this proposal highlights the phasor measurement technique, which is founded on the Taylor–Fourier transform.

The novelty of the paper is to provide an alternative analysis tool for monitoring and extracting modal information from the power system's oscillating signals, utilizing a novel technique known as Taylor–Fourier-Transform (TFT). The paper introduces the computational aspects for its real-time implementation. That is attained by handling the TFT depending on the modes of concern in order to provide the best frequency decomposition, achieving the precise estimation of frequency and damping.

2. Taylor–Fourier transform

For identifying electromechanical modes [21], the digital Taylor–Fourier transform (DTFT) is described in the following. The DTFT's expands the Fourier subspace by incorporating Taylor terms greater than zero. Thus, the Taylor–Fourier subspace is shaped, and it is spanned by using the vectors of the Fourier matrix as Taylor terms' harmonic modulators included in the Kth Taylor polynomial.

2.1. Taylor–Fourier subspace

Signals $\boldsymbol{s}$ projected onto the Taylor–Fourier (TF) subspace are expressed by the following linear combination,

$$\hat{s} = \mathbf{B}\hat{\xi} \qquad (1)$$

where $\mathbf{B}$ is the Taylor–Fourier matrix for N filters,

$$\mathbf{B} = (\boldsymbol{T} \quad \boldsymbol{E}^1\boldsymbol{T} \quad \bar{\boldsymbol{E}}^1\boldsymbol{T} \quad \boldsymbol{E}^2\boldsymbol{T} \quad \bar{\boldsymbol{E}}^2\boldsymbol{T} \quad \cdots \quad \boldsymbol{E}^N\boldsymbol{T} \quad \bar{\boldsymbol{E}}^{N-1}\boldsymbol{T}), \qquad (2)$$

$\boldsymbol{T}$ stands for the first $K+1$ Taylor terms defined in (3); matrix $\boldsymbol{E}^i$ includes the samples of the first Fourier vector on its diagonal $\boldsymbol{E}^i = diag(e^{j2\pi f_i t})$, where f_i is the ith frequency of concern. Vector $\hat{\boldsymbol{\xi}}$ contains up to the Kth derivative of the dynamic phasor and their complex conjugates,

$$\boldsymbol{T} = \begin{pmatrix} 1 & t_n & \frac{t_n^2}{2!} & \cdots & \frac{t_n^K}{K!} \end{pmatrix}. \qquad (3)$$

$$\hat{\boldsymbol{\xi}} = (\boldsymbol{\xi} \quad \dot{\boldsymbol{\xi}} \quad \ddot{\boldsymbol{\xi}} \quad \cdots \quad \boldsymbol{\xi}^{(K)} \quad \bar{\boldsymbol{\xi}} \quad \bar{\dot{\boldsymbol{\xi}}} \quad \bar{\ddot{\boldsymbol{\xi}}} \quad \cdots \quad \overline{\boldsymbol{\xi}^{(K)}})^{\boldsymbol{T}}, \qquad (4)$$

$t_n = nT_s$, where $n \in \left[-C\frac{N}{2}, C\frac{N}{2}\right]$, and C is the number of fundamental cycles taken into account. Thereby, the signal $\hat{\boldsymbol{s}}$ is the linear combination of the first $(K+1)$ time derivatives, corresponding to each Taylor term for the defined set of harmonics. That is, each matrix $\boldsymbol{E}^i$ in (2) is modulated by each time derivative in the Taylor–Fourier coefficients $\boldsymbol{\xi}^{(\boldsymbol{K})}$ in (4), at its corresponding harmonic frequency. Then, signal $\boldsymbol{s}$ is projected towards the Taylor–Fourier subspace as $\hat{\boldsymbol{s}}$, Fig. 1. This is done in order to provide the best approximation through the TF estimates.

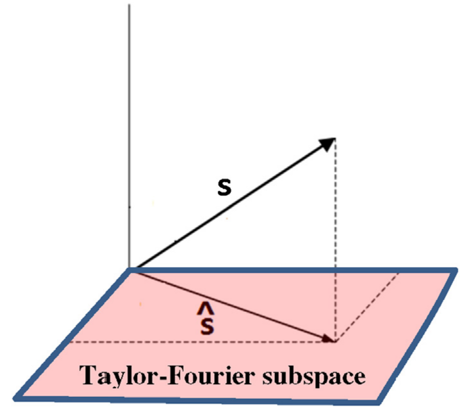

Fig. 1. Projection onto the Taylor–Fourier subspace.

2.2. Digital Taylor–Fourier transform

Once the Taylor–Fourier subspace is shaped, the filtered algorithm is performed using the least-squares solution, and it may be concluded that its best Taylor–Fourier estimates become [14–17],

$$\hat{\boldsymbol{\xi}} = [\mathbf{B}^H\mathbf{B}]^{-1}\mathbf{B}^H\boldsymbol{s} = \mathbf{B}^{\dagger}\boldsymbol{s}, \qquad (5)$$

where $\mathbf{B}$ is expressed as in (2).

The DTFT computational complexity is reduced because $\mathbf{B}$ includes just the frequencies of concern [17,21]. From (5), the best Taylor–Fourier coefficients are estimated for each of such frequency in (2). In this paper, the DTFT is implemented using expressions (1)–(5), with $K = 3$, $C = 4$, the frequencies of concern, and the sampling frequency.

On the other hand, the signal reconstruction is carried out through the synthesis Eq. (1) [14], while the amplitude estimates are expressed by,

$$\hat{\boldsymbol{a}}(t) = 2|\hat{\xi}| \qquad (6)$$

From (1) the analytic representation of the reconstructed signal $\hat{\boldsymbol{s}}_{CN}$ is computed. Each component $\hat{\boldsymbol{s}}_j$ may be decomposed as

$$\hat{\boldsymbol{s}}_j = Re\{\hat{\boldsymbol{s}}_j\} + Im\{\hat{\boldsymbol{s}}_j\} \qquad (7)$$

where $Re\{\hat{\boldsymbol{s}}_j\}$ is the real part of $\hat{\boldsymbol{s}}_j$, denoted by $\boldsymbol{s}_{Re}$, and $Im\{\hat{\boldsymbol{s}}_j\}$ is the imaginary part of $\hat{\boldsymbol{s}}_j$, denoted by $\boldsymbol{s}_{Im}$. Therefore, the instantaneous frequency may be numerically calculated via the Hilbert transform using (8) [22],

$$\hat{f}_j(t) = \frac{\boldsymbol{s}_{Re}(t) * \dot{\boldsymbol{s}}_{Im}(t) - \boldsymbol{s}_{Im}(t) * \dot{\boldsymbol{s}}_{Re}(t)}{2\pi(\boldsymbol{s}_{Re}^2(t) + \boldsymbol{s}_{Im}^2(t))} \qquad (8)$$

From the time derivative, the phase $\hat{\varphi}_j(t)$ and its derivative $\widehat{\dot{\varphi}}(t)$ are estimated by (9) and (10). These expressions are used for the frequency estimation through the DTFT in (11),

$$\hat{\varphi}_j(t) = \angle\hat{\xi} \qquad (9)$$

$$\widehat{\dot{\varphi}}(t) = \frac{Im\{\widehat{\dot{\xi}}\boldsymbol{e}^{-i\hat{\varphi}_j(t)}\}}{\hat{\boldsymbol{a}}(t)} \qquad (10)$$

$$\hat{f}_j(t) = f_j + \frac{\widehat{\dot{\varphi}}(t)}{2\pi} \qquad (11)$$

The instantaneous damping for the jth mode is computed taking into account [22–24]. It is defined as the change of the amplitude over time. If the instantaneous damping value is negative, it means that its amplitude is growing,

$$\hat{\sigma}_j(t) \approx -\frac{\hat{\dot{a}}_j(t)}{\hat{a}_j(t)}, \qquad (12)$$

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