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Research article

A new computing approach for power signal modeling using fractional adaptive algorithms

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ABSTRACT

Estimating the harmonic parameters is fundamental requirement for signal modelling in a power supply system. In this study, exploration and exploitation in fractional adaptive signal processing (FrASP) is carried out for identification of parameters in power signals. We design FrASP algorithms based on recently introduced variants of generalized least mean square (LMS) adaptive strategies for parameter estimation of the model. The performance of the proposed fractional adaptive schemes is evaluated for number of scenarios based on step size and noise variations. Results of the simulated system for sufficient large number of independent runs validated the reliability and effectiveness of the given methods through different performance measures in terms of mean square error, variance account for, and Nash Sutcliffe efficiency.

1. Introduction

Signal modeling expresses a signal in terms of a model parameters and is applied in many applications of engineering, science and technology such as speech recognition, control systems, wireless sensor networks and power systems [1–4]. Power signal modeling estimates power line sinusoidal signal parameters to analyze power systems [5,6]. Many identification algorithms have been proposed to estimate the model parameters. For instance, Cao used the hierarchical identification approach for parameter estimation of power signals [7], Li proposed gradient and recursive least squares based algorithms for power signals modeling [8,9]. Recently, modified normalized least mean square and multi-innovation stochastic gradient based parameter estimation methods are developed for harmonic modeling of power signals [10–12].

Normally stochastic gradient and least squares based parameter estimation methods are used for system identification [13–17]. A number of variants of these standard identification approaches have been introduced for efficient parameter estimation; for example, hierarchical identification method [18,19], the multi-innovation estimation approach [20,21], the maximum likelihood technique [22] and modified least mean square algorithm based on fractional calculus concepts [23].

Fractional calculus is as old as integer order calculus but its main utilization is limited to the field of mathematics only. Recently, its applications in the domain of engineering and applied sciences are explored. For instance, fractional order system identification [24], filter design [25], failure prediction for predictive maintenance [26], biomedical problems [27] and control theory [28–31]. Ortigueira and Machado explored the applications of fractional calculus in the domain of signal processing and hosted many special issues based on fractional signal processing and its applications [32–35]. Recently, new adaptive identification strategies have been proposed based on fractional signal processing. For example, fractional least mean square (FLMS) identification algorithm is developed by exploiting the theories and concepts of fractional calculus in weight update mechanism of standard LMS [23].

Fractional adaptive identification algorithms have been applied for parameter estimation of input nonlinear control autoregressive systems [36,37], linear and nonlinear control autoregressive moving average model [38–40], Box-Jenkins (BJ) and input nonlinear BJ systems [41–43], active noise control [44,45], channel equalization [46], speech enhancement [47] and chaotic time series prediction [48]. It is observed in all these illustrative applications that fractional based identification algorithms outperform standard estimation methods in terms of accuracy and convergence. These facts motivate the authors to explore in designing an alternate, accurate, reliable and robust computing mechanism

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based on fractional signal processing for effective parameter estimation of power signals.

This study aims to develop fractional identification algorithms to estimate the parameters of power signals and compare the results of proposed fractional estimation techniques in terms of convergence, accuracy and complexity. The design methodology is evaluated for different step size strategies and signal to noise ratios (SNRs). In order to draw reliable inferences, statistical analysis based on hundred independent runs of the proposed schemes are performed. The salient features of the proposed methodology are:

- The potential of fractional adaptive algorithms is exploited for parameter identification of power signals.
- The effectiveness of the given methods is established through accurate power signal estimation for number of scenarios based on noise and fractional order variations.
- The results of Monte Carlo simulations verified and validated the consistent accuracy of the design scheme.
- Reliability and effectiveness of the given methods is proven through different performance measures in terms of mean square error, variance account for, and Nash Sutcliffe efficiency.

Rest of the paper is organized as follows; in Section 2, a brief description of the identification model based on power signals is presented. Design of fractional adaptive estimation algorithms for power signal identification model is given in Section 3. Simulation results of each scenario of the proposed method are presented in Section 4. The comparison based on results of statistical analysis is also given here. Conclusions are listed in the last section, along with a few future research directions.

2. System model

In this section, the brief description of system based on power signal modeling is presented. An electric signal from an AC power system in the form of Fourier series is written as [7,8]:

$$S(t) = a_0 + \sum_{n=1}^{\infty} \left(a_n \cos nw_0 t + b_n \sin nw_0 t\right), \tag{1}$$

where the fundamental frequency of the AC system is w_0, n represents the harmonic index, and a_n, b_n are the nth harmonic Fourier coefficients; a_0 is the DC component in the system. In case of a typical AC power system, generally there is no DC component *i.e.*, $a_0=0$. In practice, generally infinite harmonics are replaced with finite harmonics. Thus with the finite harmonic assumption having N as the largest harmonic index, Eq. (1) can be written as:

$$S(t) \cong \sum_{n=1}^{N} \left(a_n \cos nw_0 t + b_n \sin nw_0 t\right),$$

or

$$S(t) = \sum_{n=1}^{N} \left(a_n \cos nw_0 t + b_n \sin nw_0 t\right) + v(t). \tag{2}$$

The discrete time expression of (2) according to the samples $S(t_k)$ ($k=0, 1, 2, \ldots$) of $S(t)$, is

$$S(t_k) = \sum_{n=1}^{N} \left(a_n \cos nw_0 t_k + b_n \sin nw_0 t_k\right) + v(t_k). \tag{3}$$

Defining the parameter vector $\boldsymbol{\theta}$ as:

$$\boldsymbol{\theta} = \left[a_1,\ b_1,\ a_2,\ b_2,\ \cdots,\ a_N,\ b_N\right]^T \in R^{2N}, \tag{4}$$

and the corresponding information vector as:

$$\boldsymbol{\varphi} = \left[\cos w_0 t_k,\ \sin w_0 t_k,\ \cos 2w_0 t_k,\ \sin 2w_0 t_k,\ \cdots,\ \cos Nw_0 t_k,\ \sin Nw_0 t_k\right]^T \in R^{2N}, \tag{5}$$

using Eqs. (4) and (5) in (3), the identification model for power signals is given as:

$$S(t_k) = \boldsymbol{\varphi}^T(t_k)\boldsymbol{\theta} + v(t_k). \tag{6}$$

Eq. (6) represents identification model to estimate the parameters of power signals [7,8].

3. Material and method

The research community has shown great interest in newly designed FLMS and proposed its variants. In standard FLMS procedure, first order as well as fractional order derivative of cost function are used to derive the recursive relation for weight adaptation [23]. Naveed and Bilal proposed modified versions of FLMS to improve its performance in terms of accuracy and computational cost [37,48]. In this section, design of these fractional adaptive algorithms are presented for parameter estimation of power signals. Generic workflow of design methodologies for power signals estimation is graphically presented in Fig. 1 while necessary detail of the algorithms are given here.

3.1. Fractional LMS

The objective function for the system is given below:

$$J(t) = E[e^2(t)], \tag{7}$$

where E(.) is an expectation operator, $e(t)$ is the error term, *i.e.*, difference between the desired and estimated response, and is given by:

$$e(t) = d(t) - y(t), \tag{8}$$

where $d(t)$ is the desired response of the system and the estimated output $y(t)$ is written as:

$$y(t) = \widehat{\mathbf{w}}^T(t)\mathbf{u}(t), \tag{9}$$

where $\widehat{\mathbf{w}}$ is the estimated weight vector and $\mathbf{u}$ is the input vector. The recursive weight update relation in case of FLMS algorithm is written as:

$$\widehat{\mathbf{w}}(t+1) = \widehat{\mathbf{w}}(t) - \frac{1}{2}\left[\mu_1 \frac{\partial J(t)}{\partial \widehat{\mathbf{w}}} + \mu_f \frac{\partial^{fr} J(t)}{\partial \widehat{\mathbf{w}}^{fr}}\right]. \tag{10}$$

Taking the first order derivative of cost function (7) with respect to $\widehat{\mathbf{w}}$, given as:

$$\frac{\partial}{\partial \widehat{\mathbf{w}}}\left(J(t)\right) = 2e(t)\frac{\partial}{\partial \widehat{\mathbf{w}}}\left(d(t) - \widehat{\mathbf{w}}^T(t)\mathbf{u}(t)\right), \tag{11}$$

after simplifying (11)

$$\frac{\partial}{\partial \widehat{\mathbf{w}}}\left(J(t)\right) = -2e(t)\mathbf{u}(t). \tag{12}$$

Now, for computing fractional order derivative of a cost function, assume the fractional derivative of a constant is zero, then Eq. (11) is updated as:

$$\frac{\partial^{fr} J(t)}{\partial \widehat{\mathbf{w}}^{fr}} = -2\left(e(t)\mathbf{u}(t)\right)\frac{\partial^{fr}}{\partial \widehat{\mathbf{w}}^{fr}}\widehat{\mathbf{w}}(t). \tag{13}$$

A variety of fractional order derivative definitions are available in the fractional calculus literature including Caputo, Riesz, Riemann-Liouville (RL), Hadamard and Grünwald-Letnikov (GL) [49–