Electric Power Systems Research 114 (2014) 28–38

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Adaptive tracking of system oscillatory modes using an extended RLS algorithm

I. Moreno*, A.R. Messina

Department of Electrical Engineering, The Centre for Research and Advanced Studies (Cinvestav), Guadalajara, Mexico

ARTICLE INFO

Article history:
Received 31 May 2013
Received in revised form 24 March 2014
Accepted 30 March 2014
Available online 26 April 2014

Keywords:
Kalman filtering
Power phasor measurement
RLS algorithms
WAMS

ABSTRACT

The study of low-frequency electromechanical modes in power systems has experienced much progress in the past few years. In this research, a nonstationary recursive least-squares (RLS) algorithm with variable forgetting factor is combined with a Kalman filter to simultaneously estimate low-frequency electromechanical modes from measured ambient power system data. Extensions and generalizations to current adaptive filtering algorithms to account for nonstationarity are implemented and tested and the correspondence between the Kalman and RLS variables is examined.

Applications of the proposed nonstationary RLS algorithm to track the evolving dynamics of critical power system electromechanical modes in both, simulated and measured data, are presented. Comparison with other RLS and least-mean squares algorithms demonstrate the accuracy of the proposed framework in tracking changes in modal parameters over time. The issues of computational efficiency and memory requirements are discussed in detail.

1. Introduction

There has been increasing recent interest in developing truly adaptive techniques for tracking the time evolution of power system's electromechanical modes from ambient data [1–7]. Because of the random nature of the observed oscillations, much of the recent literature on modal identification has been based on stochastic formulations [1,4–7].

Ambient oscillations are the result of complex random variations and interactions between many system components. Measured power system ambient noise data, are known to exhibit noisy, nonstationary fluctuations and are highly time varying due to measurement noise, system topology changes and small magnitude, random changes in loads, wind and other variable generation [3–5,8]. Ambient data, in general, are difficult to interpret and characterize because of their inherent random characteristics. A challenging task is to find ways to extract and characterize power system's electromechanical modes from highly nonstationary conditions.

Many techniques have been developed to analyze ambient system oscillations based on a variety of different criteria. These approaches may generally be categorized as parametric and nonparametric [8,9]. Parametric methods include least-squares estimation techniques [6], robust RLS and regularized robust RLS methods [2,3], least-mean squares adaptive filtering techniques [4,5], canonical variate algorithms [7], sub-space system identification (N4SID) [10], Yule-Walker algorithms [10] and Kalman filtering [9].

A common assumption to many procedures is that ambient noise is statistically stationary at least for a block of data [4,6,10]. Also, the parameters are assumed to be slowly time varying [11]. Standard estimation techniques, however, may fail to consider the effects of nonstationarity on system behavior and may result in numerical problems and considerable error in the frequency and damping estimates. Recently, least-mean squares (LMS) adaptive filtering techniques have been used to track the frequency and damping associated with low-frequency electromechanical modes [4,5].

A new generation of truly adaptive filtering algorithms is envisioned that may be used to improve the convergence behavior of the standard LMS filter. As discussed in [5], further research is needed to reduce the variability of the mode estimates. Accounting for stochastic and time-varying features can provide a better description of the observed data and result in improved modal estimation algorithms.

In this paper, a fully nonstationary RLS algorithm with variable forgetting factor is combined with a Kalman filter to deal with ambient system oscillations that are nonstationary in time. In contrast to existing nonstationary RLS algorithms using constant forgetting

* Corresponding author. Tel.: +52 3338425341.
E-mail addresses: imoreno@gdl.cinvestav.mx (I. Moreno), aroman@gdl.cinvestav.mx (A.R. Messina).

http://dx.doi.org/10.1016/j.epsr.2014.03.034
0378-7796/

factor [12], the proposed technique adaptively adjusts the size of the forgetting factor to improve the tracking capability in time varying parameter estimation.

Comparison with other RLS algorithms and least-mean squares algorithms demonstrate the accuracy of the proposed procedure on both, synthetic and measured data.

2. Recursive least-squares adaptive filtering

Ambient-based mode estimation aims at estimating low-frequency electromechanical modes when the primary sources of excitations to the system are random load changes of small magnitude [4,5]. Fig. 1 shows a conceptual representation of the identification problem using an RLS adaptive filtering algorithm. The underlying assumption for system identification is that the discrete-time input signal u_k to the power system, can be characterized by a zero-mean white noise (WN) process with variance σ_u^2 [4–6,13]. Further, it is assumed that only the output y_k is available for identification purposes [14].

The vectors $\bar{y}_k$ and $\hat{y}_k$ represent the measured outputs from the power system, contaminated by additive (measurement/observation) noise or uncertainty, v_k, which is assumed to be white noise, and the estimate of the desired (noise free) response, respectively; subscript k refers to time. The estimation error is given by $\tilde{u}_k = y_k - \hat{y}_k$, and is also assumed to be white noise with variance $\sigma_{\tilde{u}}^2$.

The central goal of such analysis is to track the evolving dynamics of critical electromechanical modes present in the measured data, y_k, using a fully adaptive filtering technique. This problem has been previously addressed using least-mean squares (LMS) adaptive filtering techniques [4] and ARMA models [10].

To better understand the role of the adaptive filtering technique, assume that the unknown power system model can be adequately characterized by an all-pole model with transfer function $H_k(z) = 1/W_k(z)$, such that $\bar{Y}(z) = H_k(z)U(z)$ [15], where $W_k(z)$ is the characteristic polynomial of the system, $H_k(z)$. Following [13], let the convolution summation between the input sequence u_k and the impulse response of the system, h_n, be given by $\bar{y}_k = \sum_{n=-\infty}^{\infty} h_n u_{k-n}$. Denoting $H_{Ik}(z) = 1/H_k(z)$ and assuming that the system is causal and stable, the observed data can be expressed recursively in terms of previous measurements as

$$\bar{y}_k = -\sum_{n=1}^{\infty} hI_n \bar{y}_{k-n} + u_k, \quad \text{with } hI_o = 1 \tag{1}$$

On the basis of Eq. (1), it is possible to use a forward linear predictor to form an estimate, $\hat{y}_k$, of the present measurement y_k as a linear combination of M past measurements as suggested in Fig. 1. Let $\boldsymbol{w}_k = [\,-w_k^1 \quad -w_k^2 \quad \cdots \quad -w_k^M\,]^T$ be a vector that represents the impulse response coefficients hI's up to an order M of the inverse system $H_{Ik}(z)$. The unknown coefficients w_k^n's of the linear predictor can be adaptively adjusted to estimate the inverse system $H_{Ik}(z)$ for blocks of M samples. Once the hI's are determined, the poles of $H_k(z)$ can be obtained from the polynomial of the inverse system $H_{Ik}(z)$, $W_k(z) = [\,1 \quad z^{-1} \quad \cdots \quad z^{-M}\,][1 \quad \boldsymbol{w}_{k-1}^T]^T$ [4,13].

Clearly, $H_k(z)$ is rational such that the power spectral density of the resulting process is also rational, and its shape is completely determined by the weights $\boldsymbol{w}_k$. In this case, the z-transform of the autocorrelation of $H_k(z)$ is given by $R(z) = H_k(z)H_k^*(1/z^*)$ and, its frequency spectrum is given by $R(e^{j\omega}) = \left|H_k(e^{j\omega})\right|^2 = 1/\left|W_k(e^{j\omega})\right|^2$. This result shows that the frequency spectrum of the data y_k can be calculated from $W_k(e^{j\omega})$ by taking the Fourier transform of the polynomial $W_k(z) = 1 - w_k^1 z^{-1} \ldots - w_k^M z^{-M}$. Therefore, M frequencies are obtained from the weights in $\boldsymbol{w}_k$ and tracked at each time instant k.

In this research we are interested in identifying inter-area modes, which are in the range of 0.1–1 Hz. The order M plays an important role in the frequency estimation. It determines the number of weights in $\boldsymbol{w}_k$ to be estimated and hence the computational complexity of the proposed algorithm. But more importantly, it affects the quality of the spectrum estimates. If a much lower order is selected, then the resulting spectrum will be smooth and will find poor frequency estimate. If a much larger order is used, then the spectrum may contain spurious peaks or spectrum splitting [13]. The order of the system is then selected to obtain good frequency resolution within inter-area frequency range.

Although this approach has been successfully implemented for a wide range of applications, there are several sources of variability in the estimation. In what follows, a novel adaptive weight-control mechanism based on the Kalman filter is proposed. First, the standard adaptive control mechanism based on LS theory is reviewed.

2.1. Linear least-squares estimation

Referring back to Fig. 1, consider a set of N ($N > M$) noisy measurements, $\left\{y_{k+n}\right\}_{n=1}^{N}$. Assuming that $\{y_{k+n}\}_{n=1}^{N}$ is linearly related to $\boldsymbol{w}_k$, we can write in matrix form, $\boldsymbol{y}_{k+1}^{k+N} = \boldsymbol{Y}_k \boldsymbol{w}_k + \boldsymbol{v}_k$, where $\boldsymbol{y}_{k+1}^{k+N} = [\,y_{k+1} \quad \cdots \quad y_{k+N}\,]^T$, $\boldsymbol{Y}_k = [\,\boldsymbol{y}_{k+1} \quad \ldots \quad \boldsymbol{y}_{k+N}\,]^T$, $\boldsymbol{y}_k = [\,y_{k-1} \quad \ldots \quad y_{k-M}\,]^T$ and $v_k = \left[\,v_{k+1} \quad \cdots \quad v_{k+N}\,\right]^T$; the noise component $\boldsymbol{v}_k$ is assumed to be independent of $\boldsymbol{w}_k$.

As discussed in [14], the vector $\boldsymbol{y}_{k+1}^{k+N}$ is not in the range space of $\boldsymbol{Y}_k$ because of the noise component v_k. The objective is to determine an estimate $\hat{\boldsymbol{w}}_k$ for the parameter vector, $\boldsymbol{w}_k$, such that the estimate minimizes the square of the distance between $\boldsymbol{y}_{k+1}^{k+N}$ and $\boldsymbol{Y}_k \boldsymbol{w}_k$, namely $\min_{\boldsymbol{w}_k} \left\|\boldsymbol{y}_{k+1}^{k+N} - \boldsymbol{Y}_k \boldsymbol{w}_k\right\|_2^2$.

An alternate to this problem is obtained by minimizing a weighted regularized least-squares cost function defined by a

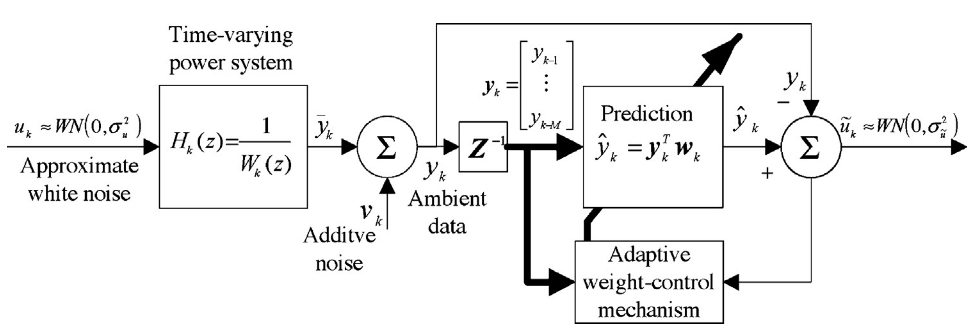

Fig. 1. Stochastic system identification by using adaptive filtering.