Chapter 13

Distributed Adaptive Parametric Power Spectral Estimation Using Wireless Sensor Networks

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ABSTRACT

Spectrum analysis is one of the momentous fields in signal processing. It has a large variety of applications in radar, sonar, speech and image processing. Parametric methods have been proposed and employed for spectrum analysis including power spectral density (PSD) estimation. These methods estimate the parameters of a statistical model and compute the PSD, afterwards. In some circumstances one is obliged to deal with observations of numerous geographically dispersed sensors, to either increase the precision or based on application demands. Having a set of sensors linked together to take the advantages of cooperation and network topology, one obtains a more comprehensive estimation. In this chapter, the authors propose and study four different algorithms capable of facing spatio-temporal variations for parametric modeling and PSD estimation using wireless sensor networks (WSNs). For this purpose, the authors first validate the proposed algorithms using theoretical and mathematical formulations. Thereafter, performing simulation tasks demonstrates and supports the theoretical achievements. The next section of the chapter illustrates the concepts to a greater degree, the authors analyze and compare the performance of these algorithms with each other, as well as with the simple PSD estimation using individual sensors, wherein there is no cooperation among the nodes.

INTRODUCTION

The researches involved in WSNs paradigm are typically divided into three main fields. The first is the circuit and hardware, which predominantly emphasizes on optimal design of the sensor nodes based on two fundamental criteria: having more functionality as well as less resource consumption (Hou & Bergmann, 2012; Papotto, Carrara, Finocchiaro, & Palmisano, 2014; Somov, Baranov, Spirjakin, & Passerone, 2014; Stojcev, Kosanovic, & Golubovic, 2009). Furthermore, the topics related to the processors, proper communication links, and sensors are categorized in this branch.
Distributed Adaptive Parametric Power Spectral Estimation

(Sizov, Gashinova, Zakaria, & Cherniakov, 2013; Sung & Hsu, 2011; Tolentino, Juson, Tan, & Talampas, 2010). The second field is the network and communications, which investigates the WSNs from topology, data packet, coding, and security points of view (Huang, Xiao, Soltani, Mutka, & Xi, 2013; Liu, Gong, & Zheng, 2014; Ma, Xu, Hempel, Peng, & Sharif, 2014; Naderi, Nintanavongsa, & Chowdhury, 2014). Eventually, the third category is signal processing. Notwithstanding the previous fields which mainly concentrate on data, the signal processing division proposes various algorithms to convert data into information. To extract meaningful information from the raw data, the statistical signal processing employs estimation, classification, and recognition methods (Agarwal & Jagannatham, 2014; Chaudhari & Serpedin, 2008; Koutsopoulos & Halkidi, 2014; Msechu & Giannakis, 2012; Soltanmohammadi, Orooji, & Naraghi-Pour, 2013; Wang & Su, 2013). In this chapter, we study WSNs under the third field, and intend to extract the model parameters and power spectral density from raw data in a sensor network.

One of the key issues in signal processing is to estimate the power spectrum of a time series, for the purpose of so many applications. Various approaches have been proposed for PSD estimation over the past few decades. These methods could generally be divided into two main categories. In classical methods, in the first instance, Autocorrelation Function (ACF) is aimed to be estimated for a time series, and afterwards, the power spectrum is obtained by transforming the estimated autocorrelation function into the frequency domain using Fourier transform. Periodogram (Welch, 1967) and Blackman-Tukey (Blackman & Tukey, 1959) approaches can be noted as examples of these methods. This relation between spectral density and autocorrelation function is considered as a nonparametric description of a second-order statistics of a random process. In the second category, parametric description of second-order statistics is achievable by considering the time-series model in a random process. In this designation, spectral density is a function of the model parameters instead of autocorrelation function (Marple Jr, 1987). The Autoregressive (AR), Moving Average (MA) and Autoregressive-Moving Average (ARMA) models well thought-out as some of these models. The fundamental reason for parametric modeling of a random process is to achieve a more comprehensive spectral density than in classical methods. In other words, using the classical methods leads to obtaining the spectral density from a windowed data or an autocorrelation function estimation, while both the unavailable data or unestimated ACFs are considered to be zero. This unrealistic assumption leads to distortions in spectral estimation, nevertheless, model parameters provide more realistic assumptions about the data outside the window rather than assigning zero values for them (Kay, 1988).

Among the aforementioned models, the autoregressive model has received more attentions. Attractiveness of the AR model arises from the fact that the calculation of the model parameters is possible by solving linear equations while, parameters in other models are computed using nonlinear equations. Yule initially introduced the modeling idea of a time series with a \( p \) order autoregressive model (AR\( (p) \)). In this method, the autocorrelation lag, i.e. \( p \), is calculated based on the available data, in which the known Yule-Walker equation is then solved. Burg (Burg, 1967) reached a similar conclusion by maximizing the process entropy.

The methods for calculating the autoregressive model parameters are divided into two categories. The first group includes the algorithms for calculating the coefficients of a fixed-size block of accumulated data, while in the second category, coefficients are calculated from sequential data. The methods based on data blocks are called recursive-in-order, as they operate on a block of time samples and recursively achieve higher-order parameters based on lower-order estimates of the AR parameter. This method could be beneficial