Chapter 3

Distributed Parameter Estimation Using Incremental and Diffusion Differential Evolution

Usha Manasi Mohapatra  
Siksha ‘O’ Anusandhan University, India

Babita Majhi  
Guru Ghasidas Vishwavidyalaya Central University, India

ABSTRACT

Recently the distributed sensor network has achieved more attention than its centralized counterpart. There are a number of literature that used different evolutionary computing techniques in a distributed way for the task of optimization in several problems of wireless sensor network. Particularly, parameter estimation of FIR filter is carried out using numerous sensor nodes through distributed particle swarm optimization. Differential Evolution (DE) is an evolutionary technique and has been applied in various fields due to its simplicity and faster convergence property in comparison to other algorithms. In this chapter differential evolution is used in two different approaches, namely Incremental DE (IDE) and Diffusion DE (DDE) to estimate the parameters of FIR filter in a distributed manner. The performance is compared with other population based algorithms.

INTRODUCTION

Wireless Sensor Network (WSN) provides a platform for the researchers to carry out extensive research work. It has become the integral part of today’s lives due to its wide range of applications in different areas. The application areas of WSN include home, health, agriculture, environmental monitoring, weather forecasting and military (Akyildiz et al., 2002) etc. In a sensor network, the tiny sensors are distributed densely in the geographical area. They have potentially limited capability due to low power, short battery life span, small size, low scale processor. These sensors measure the parameters individu-
Distributed Parameter Estimation Using Incremental and Diffusion Differential Evolution

Individually estimated parameter values are transmitted to a central processing unit to compute the final estimated value. This process invites transmission delay and probably the loss of individual node’s data before reaching the destination node. Nevertheless, the central processor needs noticeable processing speed to process the accumulated data collected from distributed sensors. But there are some optimization problems like motion planning in multi agent systems [Johansson et al., 2008], acoustic source localization (Blatt et al., 2006; Williams et al., 2005; Qiu et al., 2009), and distributed adaptive filtering (Cavalcante et al., 2009; Lopes et al., 2007; Cattivelli et al., 2010) in which the centralized approach is not advantageous. There are two important reasons not to follow centralized approach. One is, the central processor may not access directly the data of all other nodes and the second is, the system may collapse if the central processor fails. Moreover the centralized computing needs an extensive communication between the nodes and the central processor that leads to communication overhead. In the distributed computing, each node computes its own sensed data and communicates with its neighbor to compute the optimized solution. The computation in distributed scenario is the contribution of all the sensor nodes. Hence, the distributed computing significantly minimizes the communication overhead resulted in centralized computing. It also employs a distributed strategy to lead the system to an optimized solution which is uninfluenced from the local observed data of an individual node. By the collaboration of the sensor nodes various complex tasks may be performed like distributed estimation (Xiao et al., 2005), distributed detection, target localization and tracking (Rabbat et al., 2004) etc.

In a sensor network, sensors may be employed to estimate the parameters of an unknown existing system. The examples include sensing the physical properties like humidity, temperature of the climate to predict the weather in the future. Parameter estimation of both linear and non linear systems is considered as one of the important engineering problem. Parameter estimation is otherwise termed as system identification. System identification is a standard phenomenon in the area of digital signal processing. The technique guides to develop a model that characterizes the system for which there is no prior knowledge of its structure. It deals with the identification of an existing unknown system by an approximated model. The system may be a physical system or a technical system. The fundamental concept is demonstrated in Figure 1.

In general, the estimation of the parameters of the original system is achieved by implementing an approximated model and continuous analysis of the input and output, such that the residual error between the desired output and the estimated output (Error) will be sufficiently reduced. In practice the output of the unknown system cannot be observed directly but is impaired by background noise and/or local interferers. These additional signals hamper the identification and are usually modeled as additive noise.

Figure 1. Conceptual model of system identification
Related Content

Applications for Wireless Visual Sensor Networks: The Digital Zoo
www.igi-global.com/chapter/applications-wireless-visual-sensor-networks/59764?camid=4v1a

Wavelet Filters Evaluation in Power Constrained Visual Sensor Networks
www.igi-global.com/chapter/wavelet-filters-evaluation-power-constrained/59753?camid=4v1a

Wireless Sensor Network: Challenges in Underground Coal Mines
www.igi-global.com/chapter/wireless-sensor-network/162381?camid=4v1a

Video-Based Motion Capture for Measuring Human Movement
Chee Kwang Quah, Michael Koh, Alex Ong, Hock Soon Seah and Andre Gagalowicz (2010). Movement-Aware Applications for Sustainable Mobility: Technologies and Approaches (pp. 209-228).
www.igi-global.com/chapter/video-based-motion-capture-measuring/42399?camid=4v1a