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Distributed acoustic signature identification using incremental adaptive networks

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ABSTRACT

Considerable amount of information about objects is obtained from their acoustic signature. Since the acoustic signal is physically propagated over a geographical region, any fixed point observer records data with a limited quality. Moving sources also decreases the generality of single point modeling. In this paper, we propose employing distributed incremental adaptive networks for the aim of acoustic signature identification, as a time-varying autoregressive (TVAR) stochastic process. The distributed adaptive sensor network considers spatial and temporal challenges simultaneously and provides real-time estimations. By formulating the problem under non-stationary conditions, we proceed to show the superiority of the proposed incremental adaptive algorithm compared to the classical single point observations methods. To practically prove this merit, the proposed algorithms were implemented on and evaluated using a real sensor network dataset recorded from moving vehicles for the first time in the adaptive networks field; this is a substantial real-world validation test. The experimental results well support the claim and demonstrate the excellence and competence of distributed incremental adaptive networks for this case.

1. Introduction

Acoustic signatures contain notable information about its source. This information can be used for a variety of applications including source classification, detection, and tracking [1,2]. Moreover, source localisation and motion parameter estimations are also possible using acoustic sensors [3,4]. Being passive and deployable, as well as low power and generally low cost, makes the acoustic sensors an unsurpassed choice for surveillance applications for both ground and air vehicles. Autoregressive (AR) modeling, as a parametric method, is a well-known solution for extracting acoustic signature. Although the AR model is appropriate for stationary signals, practical real-world acoustic signals are always seen to be of non-stationary nature. The non-stationarity usually arises from source and environment spatio-temporal variations. In order to add to the accuracy and reliability of this estimation, the non-stationary characteristics are considered by defining a time-varying autoregressive model [5]. TVAR parameter modeling is divided into three main categories. The first is the basis function method, wherein a TVAR system is assumed to be a linear combination of a set of basis functions [5]. The second class are adaptive methods in which a dynamic model is regraded for the time-varying parameter [6]. Monte Carlo is the last category, in which the time-varying parameters are considered to be random variables, and a large number of samples of each parameter are drawn with respect to the corresponding probability distributions. Following this, the sample means are evaluated as the approximations for the desired parameters [7,8]. TVAR modeling is performed using maximum-a-posteriori (MAP) estimation in which the identification problem is formulated in a Bayesian inference framework [9]. Generally speaking, although the basis functions and Monte Carlo methods outperform adaptive techniques in some cases when either rapid time changing is observed, or signal to noise ratio (SNR) is considerably low, they do not have a developed theoretical foundation. Given this fact, their advantages or drawbacks cannot be accurately predicted in different circumstances. Furthermore, they are more complicated and computationally expensive. Moreover, the basis functions and Monte Carlo algorithms are generally incompetent in estimating unknown parameters in a real-time (online) fashion. Since the acoustic signal propagates over a geographical region physically, every fixed point observes the process with a limited quality. Source movements also add more complexity to this problem. To deal with these challenges multiple observations should be employed in the modeling procedure. If a more comprehensive estimation is to be obtained by merging multiple observations, a sensor network should be implemented, in which some of the

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nodes are linked together. Nodes are allowed to cooperate with each other to estimate the unknown parameter, mostly through wireless links. Adaptive networks which were first introduced in [10] are a general model that is capable of being fitted to sensor networks. Adaptive networks consist of a set of adaptive filters cooperating with each other to solve an optimization problem using a pre-defined cost function. In general, adaptive networks work in two different manners, centralized and distributed. In the centralised method, the observations from all nodes are gathered in a single point and the optimisation step occurs in the fusion centre, while in the distributed manner it is fully distributed throughout the network. Omitting the fusion centre as a potential critical point, distributed schemes optimise the cost function in some inaccuracy expenses. From the topology point of view, adaptive networks could be classified into two main categories: incremental and diffusion. Incremental adaptive networks cycle the network in a Hamiltonian path, wherein each adaptation step needs a full cycle [11]. A full cycle at each adaptation step gives an overall result which is clearly desirable. In diffusion topology, every node prepares a local estimation consulting with its adjacent nodes only [12]. Acoustic signature identification using a diffusion version of adaptive networks has been proposed in [13]. In this paper, after reconsidering incremental adaptive networks, we propose employing them for the aim of acoustic signature identification. By considering a TVAR model for the acoustic signal, the proposed adaptive network solves the spatio-temporal problem simultaneously i.e., under non-stationary conditions, and provide real-time (online) estimations. We initiate incremental version of adaptive networks for this aim, and then, a classical algorithm based on individual estimations is regarded. The performance of the proposed method is compared in terms of the network steady-state mean-square deviation (MSD) and excess mean-square error (EMSE) under non-stationary conditions. For evaluation and validation purpose, we implement the proposed algorithm on a real sensor network data acquired from moving vehicles. It is worth noting that while adaptive networks have been suggested for a decade, they have not been implemented on any raw data to date. Consequently, the experimental section of our paper adds another appreciable contribution to the field by examining the proposed algorithms on a real-world gathered dataset. It thus maximises the test's validity, and allows greater comparison of the performance with classical methods. We use the data collected in situational experiment (SITEX02), organised by DARPA/IXOs SensIT (Sensor Information Technology) program [14]. The rest of the paper is organised as follows. Incremental adaptive networks are reviewed in Section 2. The TVAR model for acoustic signature identification is expressed in Section 3. In Section 4 employing incremental adaptive networks for TVAR problem is proposed under non-stationary conditions, and eventually in Section 5, the proposed algorithms are implemented on the real recorded acoustic data from moving vehicles and are compared with classical techniques. Shorter version of this work was presented in [29].

1.1. Notation

In this paper, lower-case letters are used to denote vectors, upper-case letters for matrices, plain letters for deterministic variables, and bold-face letters for random variables. For instance, $\boldsymbol{d}$ represents a random quantity while d is a realization or measurement of that, R is a deterministic matrix where $\boldsymbol{w}$ denotes a random vector. All the vectors in this paper are column vectors, with the exception to the regression vectors ($\boldsymbol{u}_{k,i}, x_{p,i}$), which are taken to be row vectors. The notation $\mathbb{E}$ denotes the expectation operator, Tr(.) shows the trace of its matrix argument, while $(.)^*$ indicates complex conjugation for scalars, and complex conjugate transposition for matrices.

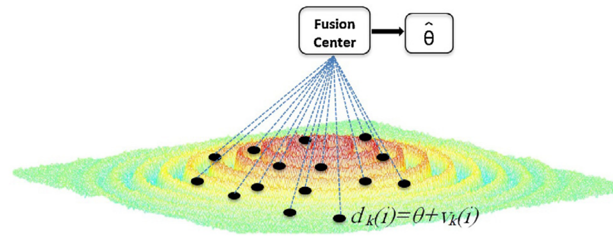

Fig. 1. Centralized system diagram.

2. Incremental adaptive network

This section reconsiders incremental version of adaptive networks to present the readers with the essential fundamentals for next sections. Consider a distributed sensor network comprising N individual sensor nodes and a fusion centre, for observing and estimating an unknown parameter θ (Fig. 1). Each individual sensor node has a single observation at each time instant, which is distorted by additive noise. This observation is described as:

$$\boldsymbol{d}_k(i) = \theta + \boldsymbol{v}_k(i), \quad k = 1, \ldots, N. \tag{1}$$

where k is the node's number, and i represents the time instant. Assume that the noise $v_k(k = 1, \ldots, N)$ has a zero mean and is spatially uncorrelated variable having $f_k(x)$ and σ_k^2 as its probability density function (PDF) and variance, respectively. Using this model we can estimate the unknown parameter θ in different ways. In centralised estimation method, which is the most basic and simplest way of solving this estimation problem, each individual sensor node can transmit the observed raw data, $\boldsymbol{d}_k(i)$, to the fusion centre (FC) wirelessly. In the fusion centre, final estimation will be extracted based on the received data from all nodes. In these situations, if the fusion centre has the noise's characteristics (i.e. variance or PDF), and all the sensors transmit their data to the centre perfectly, it can subsequently estimate the unknown parameter θ using the received data by employing maximum likelihood estimator (MLE) or best linear unbiased estimator (BLUE) [15]. Centralised estimation methods are very much relied upon for the received information from all nodes, and failure of nodes in sending true information to the FC will result in a considerable degradation of performance. As a result, there is a need for the communication channel among the nodes and the fusion centre to have sufficient bandwidth and fine characteristics. However, this is not practically implementable in most cases due to high cost of communication and power consumption, as well as hardware limitations. Therefore, as a consequence of resource limitations and wireless channel noise, this method is practically non-implementable in the worst case, and inefficient in the best case. We are therefore motivated to look for alternatives. To resolve the centralised estimation drawbacks, different methods have been proposed for distributed estimation. Distributed incremental strategy was first introduced as a solution in [16]. Despite the centralised mode, it offers an algorithm considering the incremental collaboration among sensor nodes. In this fashion, information is regularly transmitted from one node to the adjacent as shown in Fig. 2. Requiring a cyclic pattern to create cooperation among the nodes, this method begins the cycle with what is known as node 1, and each node updates its local estimation by receiving local estimation of the previous node. At the end of the cycle, local estimation of the last node is a result of cooperation with all other nodes, which is considered as the network estimation on that iteration. More detailed discussions and performance analysis of adaptive networks under non-stationary conditions can be found in [30].