Information Sciences 382–383 (2017) 115–134

Contents lists available at ScienceDirect

Information Sciences

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

Communication-reducing diffusion LMS algorithm over multitask networks

Wei Huang, Xi Yang, Guojiang Shen*

College of Computer Science and Technology, Zhejiang University of Technology, Hangzhou, 310023, China

ARTICLE INFO

Article history:
Received 13 July 2016
Revised 17 October 2016
Accepted 6 December 2016
Available online 7 December 2016

Keywords:
Distributed estimation
Diffusion LMS
Multi-task
Mean square deviation
Communication cost

ABSTRACT

Many practical problems in the filed of distributed estimation happen to be multi-task oriented. Without prior knowledge of clustering structure, i.e. nodes do not know which clusters they belong to beforehand, distributed algorithms for parameter estimation have received great attention in recent years. In most previous work, each node collaborates with all its neighboring nodes at each iteration, which introduces unnecessary communication assumption when any node cooperates with neighboring nodes from different clusters. In this paper, we propose a novel communication-reducing diffusion LMS (Least-Mean-Square) algorithm, called the CR-dLMS algorithm, for estimating true parameters in multi-task environment. Under the CR-dLMS algorithm, we control the probabilities of data fusion from neighboring nodes by minimizing mean-square-deviation (MSD) to reduce communication cost among nodes. Theoretical analysis for the learning behavior of the CR-dLMS algorithm is performed, and simulation results show that the CR-dLMS algorithm can indeed achieve the same estimation performance as several other previous algorithms while great reducing the communication cost among nodes.

1. Introduction

In recent years, the problem of distributed estimation over sensor networks has received great concerns in theoretical studies and has a broad variety of practical applications such as environment monitoring [4], target localization [44], routing protocol design [42] and cognitive radio [20]. This is mainly because the fusion center does not necessarily exist in the network and the parameter of interest can be estimated by all nodes in cooperative way. Compared to centralized estimation, communication cost among nodes can be great reduced by using distributed strategies for parameter estimation [5,14,31,45,50].

In distributed estimation over networks, the diffusion strategy is widely adopted due to its stronger robustness to node or link failures when compared to other strategies such as the incremental strategy [31]. To date, a number of diffusion-type distributed estimation algorithms have been proposed including the diffusion Least-Mean-Square (dLMS), the diffusion Recursive-Least-Square (dRLS) [5] and the diffusion Total-Least-Square (dTLS) [26,45]. Due to the inherently simple process of LMS algorithm [13,19,48], the dLMS algorithm has been more extensively studied in a variety of scenarios, such as exploring the performances of dLMS in the presence of noisy links [22,23,53], variable step-size dLMS algorithm [21,25,39], variable component-wise step-sized LMS algorithm [18], generalized cost function and data model [9,11,15], the impact of

* Corresponding author.
E-mail address: gjshen1975@zjut.edu.cn (G. Shen).

http://dx.doi.org/10.1016/j.ins.2016.12.010

network topology on the performance of dLMS algorithm [28,30], dLMS algorithm under non-Gaussian noise environment [27] and dLMS algorithm for sparse vector estimation by incorporating additional regularizers [10,29,33].

In most previous studies on the dLMS algorithm, it was assumed that all nodes share a common estimation interest. Usually, problem of this type is referred to as single-task problem. In many practical applications such as multi-target tracking [44] or spectrum estimation with multi-antenna devices [34], however, the estimation interest on different nodes may not be identical. Problem of this type is therefore referred to as multi-task problem, which can be regarded as generalization of single-task problem. In this study, we focus on multi-task problem in the context of the dLMS algorithm over adaptive networks.

Generally speaking, it is usually regarded that nodes with the same optimum estimation interest form a cluster in multi-task scenario. In [1], the authors proposed a dLMS strategy under which the nodes cooperate to estimate the true parameters that can vary in both space and time domains. In [7], the authors proposed a cooperative algorithm based diffusion adaptation to solve the multi-task learning problem, with the assumption that the estimation interest on each node consists of an offset component shared by all nodes and a node-specific component in an orthogonal subspace. In [38], under the assumption that clusters are known beforehand, the authors developed an extended dLMS algorithm for application to multi-task learning problems by minimizing mean-square error with l_2-regularization. In [47], the authors developed an optimization algorithm in which inter-cluster cooperation weights are optimized to achieve better estimation performances compared to the use of an average rule for inter-cluster cooperation. In [16], the authors proposed multi-task diffusion strategies based on the Affine Projection Algorithm (APA) to enhance the robustness against correlated input. Another group of work is described by [3,36,37], where incremental-based LMS, incremental-based RLS and diffusion-based LMS strategies are used to solve the problem of distributed estimation in scenarios where all nodes simultaneously estimate both local and global parameters.

In all the work described above, it was assumed that the information of clustering structure is known a prior, i.e. each node knows which of its neighbors share the same estimation interest as itself. Nodes in this case do not need to learn which neighbors they should cooperate with and which other nodes they should choose to ignore. In [51], the authors designed an adaptive strategy to dynamically adjust combination coefficients to endow nodes to identify clustering structure of the whole network. However, estimation performances of the algorithm in [51] are dependent on the initial conditions used by the nodes to launch their adaptation rules. In [8], the authors examined the performances of traditional dLMS algorithm with fixed combination coefficients in multi-task environment and proposed a novel unsupervised clustering method for each node collectively choosing to operate with neighboring nodes addressing the same task. Under the condition that each node does not know which other nodes share the same estimation interests, the authors of [35] studied the problem of distributed node-specific parameter estimation, i.e. scenarios in which nodes perform simultaneous estimation for both local and global unknown parameters.

Although [8] and [51] can identify clustering structure with satisfying performances via adaptively learning way, much communication cost is consumed for fusing data from neighboring nodes. In strategies proposed in [8] and [51], each node can adaptively learn to assign large combination coefficients to neighboring nodes with the same task while assigning small combination coefficients to neighboring nodes with different tasks. This requires each node to cooperate with all its neighboring nodes at each iteration. One way to lower communication cost is to reduce the opportunities of cooperation among nodes with different estimation interests, since cooperation with neighboring nodes with different estimation interest does not benefit estimation performances. In [52], the authors proposed a novel strategy that enables nodes to identify their clusters with probabilities very close to one under sufficiently small step-size, thus saving communication cost among nodes. Besides, the authors of [24] proposed a modified strategy that merges the clustering and inference tasks. Numerical simulations have shown that estimation performance can be enhanced by using the strategy in [24] than that in [52]; however, a predefined threshold for reaching a symmetrical pattern of cooperation is required for implementing these strategies.

In this paper, we propose a novel communication-reducing diffusion LMS (CR-dLMS) algorithm, to control the probabilities of data fusion from neighboring nodes by minimizing mean-square-deviation (MSD). Under the CR-dLMS algorithm, each node learns to select the neighboring nodes with which it cooperates in probabilistic and adaptive manner. The clustering structure then gradually emerges alongside the evolution of iterations. Once the adaptation process reaches the steady-state, the probability of fusing data from neighboring nodes with the same estimation interest is nontrivial - this allows nodes with the same estimation interest to cooperatively perform estimation. In the meanwhile, the probability of fusing data from neighboring nodes with different estimation interests gradually shrinks to zero. In this way, the CR-dLMS algorithm can save communication cost while still achieving satisfying estimation performances. We shall analyze the CR-dLMS algorithm in terms of its mean weight deviation and mean-square deviation in this paper. Results of numerical simulations are then followed after theoretical analysis.

The rest of paper is organized as follows. In Section 2, we introduce the proposed CR-dLMS algorithm after describing the linear data model upon which it was based. In Section 3, we present the analysis of mean-stability and learning behavior of mean-square deviations. In Section 4, we present the results of numerical simulations for comparing the CR-dLMS algorithm with several other existing algorithms. Finally, conclusions are drawn in Section 5.

Notations: In this paper, bold letters and normal letters are used to denote random quantities and deterministic quantities respectively. The superscript notation $(\cdot)^T$ stands for the transposition of a matrix or a vector, and the notation $E[\cdot]$ stands for the expectation operation. Identity matrix with size $N \times N$ is denote by I_N. The notation $\mathcal{N}_k$ denotes the neighbors of