Signal Processing 113 (2015) 211–217

Contents lists available at ScienceDirect

Signal Processing

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

Fast communication

Data-selective diffusion LMS for reducing communication overhead ☆

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ARTICLE INFO

Article history:
Received 28 September 2014
Received in revised form
27 January 2015
Accepted 28 January 2015
Available online 7 February 2015

Keywords:
Adaptive networks
Distributed estimation
Dynamic update
Selective communication
Diffusion adaptation

ABSTRACT

The diffusion strategies have been widely studied for distributed estimation over adaptive networks. In the structure, communication resources are assigned to every node in order to share its processed data with predefined neighbors. Although the performance improves through the information exchange, it entails a communication cost. We present a dynamic diffusion method that shares only reliable information with neighbors. Each node has the ability to evaluate its updated estimate by the contribution of the new measurements to minimizing mean-square deviation (MSD). In only case of decrease of MSD, the node is allowed to transmit its estimate to neighbors. Accordingly, the proposed algorithm has a reduced amount of communication while keeping the performance as much as possible. Experimental results show that the proposed algorithm achieves more efficient reduction of communication and better performance compared to the other related algorithms.

1. Introduction

We study the problem of distributed estimation over adaptive networks, in which every node uses local interaction and cooperation with each other for estimation. Consider N nodes distributed in space (Fig. 1). The set of nodes that are connected to node k (including k itself) is called the neighborhood of node k which is denoted by $\mathcal{N}_k$. Each node k is assumed to receive desired response $\boldsymbol{d}_k(i)$ and $1 \times M$ regression vector $\boldsymbol{u}_{k,i}$ at successive time instant i. Each node k would like to use these data to estimate an unknown $M \times 1$ parameter vector w^o in a distributed and adaptive manner by sharing information only within $\mathcal{N}_k$.

For the solution of such distributed estimation problems, several variations have been proposed, such as incremental least-mean-square (LMS) algorithms [1–3], diffusion LMS algorithms [4–11], and algorithms based on consensus strategies [12–16]. Since each node has an ability to estimate an unknown system and shares data with its neighbors, refined information diffuses all nodes over the network, by which estimation performance improves greatly. In the structure, the diffusion LMS algorithms consist of adaptation and combination steps. According to the order of two steps, the combine-then-adapt (CTA) and the adapt-then-combine (ATC) diffusion LMS algorithms have been proposed [4]. In the sense of steady-state error, the ATC structure always outperforms the CTA structure. It implies that the combination step contributes to improve estimation accuracy.

Although the various diffusion techniques achieve faster convergence speed and lower steady-state error than no

☆ This work was supported in part by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (2012R1A2A2A01011112), in part by the MSIP (Ministry of Science, ICT&Future Planning), Korea, under the C-ITRC (Convergence Information Technology Research Center) support program (NIPA-2014-H0401-14-1001) supervised by the NIPA (National IT Industry Promotion Agency).

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http://dx.doi.org/10.1016/j.sigpro.2015.01.019
0165-1684/

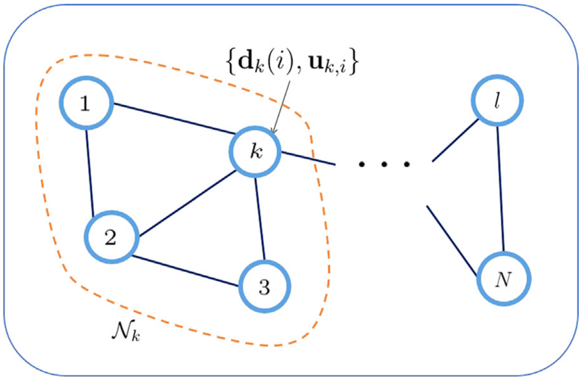

Fig. 1. A distributed network with N nodes. At time i, each node k gets a measurement $\{\boldsymbol{d}_k(i), \boldsymbol{u}_{k,i}\}$ and communicates only with its neighborhood $\mathcal{N}_k$.

cooperation LMS, they are compromised by communication cost. In practical wireless sensor networks, each node often has limited power resources for communication. To reduce the communication cost without significant degradation of the estimation, various techniques have been applied to diffusion LMS, such as choosing a subset of the nodes [17–20], selecting a subset of the entries of the estimates [21,22], and reducing the dimension of the estimates [23–25]. Among these methods, we focus on the first method in which only a subset of nodes are participated in communications. Probability diffusion LMS [17] considered the changing network topology where each link between two nodes is connected with a probability. Takahashi and Yamada [18] proposed a method varying the probability on link connection by minimizing the MSD, in order to improve the estimation performance of [17]. In [19] and [20], each node is allowed to select a subset of $\mathcal{N}_k$ to combine the data based on the additional information that represents the quality of the nodes. In [19], a scaled product of the noise variance and the regression variance was used as a measure for selection criterion; each node selects one node with the minimum measure value. In [20], each node tries to estimate the current MSD value and exchanges it with the neighbors. Then, by some procedure with the transmitted data from the neighbors, each node calculates the cost values for the neighbor nodes to select one node. Namely, the previous algorithms [19,20] require the additional communication to transmit scalar values for selecting one node to *receive* the data. In contrast to the previous work, our purpose is to endow each node with ability to conclude whether it will *transmit* the data or not. Since each node is able to implement this determination process with only its own information, the additional communication is not required anymore.

In this paper, we introduce a novel method for communication reduction, in which each node is allowed to dynamically update its estimate and transmit only when it is updated. To do so, we first derive a criterion that uses the mean-square deviation (MSD) to determine whether the updated estimate is worth sharing. Each node updates the estimate and transmits the updated data to its neighbors only when the MSD decreases by the adaptation. Because non-updated nodes do not send those estimates to their neighbors, some data are missing during the combination step. So we also present a method that uses previously-saved data to replace the missing data. In simulations, the proposed algorithm efficiently reduced the communication cost with less performance degradation compared to the related node selection algorithms.

Notation: We use boldface letters for random variables and normal letters for deterministic quantities.

2. Conventional diffusion LMS

At every node k and time instant i, we assume that the desired response $\boldsymbol{d}_k(i)$ is related to the regression vector $\boldsymbol{u}_{k,i}$ as a following linear model:

$$\boldsymbol{d}_k(i) = \boldsymbol{u}_{k,i} w^o + \boldsymbol{v}_k(i) \tag{1}$$

where $\boldsymbol{v}_k(i)$ corresponds to zero-mean measurement noise with variance $\sigma^2_{v,k}$, which is assumed to be white over time and independent over space. $\boldsymbol{v}_k(i)$ and $\boldsymbol{u}_{l,j}$ are assumed to be independent of each other for all k, l, i, j. All data are assumed to be complex values.

The diffusion strategies [4] consist of two operations: adaptation and combination. In the adaptation stage, each node updates its estimator using observed data $\{d_k(i), u_{k,i}\}$ and collects the estimators from its neighbors in the combination stage. We focus on the adapt-then-combine (ATC) diffusion LMS algorithm that is described by

$$\psi_{k,i} = w_{k,i-1} + \mu_k u^*_{k,i} e_k(i) \tag{2}$$

$$w_{k,i} = \sum_{l \in \mathcal{N}_k} a_{l,k} \psi_{l,i} \tag{3}$$

where $e_k(i) = d_k(i) - u_{k,i} w_{k,i-1}$, and $a_{l,k}$ is a nonnegative combination weight that node k assigns to data arriving from its neighboring node l. The coefficients $a_{l,k}$ is designed to satisfy the following conditions:

$$a_{l,k} = 0 \quad \text{if } l \notin \mathcal{N}_k \quad \text{and} \quad \sum_{l=1}^{N} a_{l,k} = 1. \tag{4}$$

The combination step (3) allows information to diffuse through the network and each node to achieve spatial diversity. Accordingly, the diffusion LMS algorithm has much better performance compared to no cooperation LMS that performs only adaptation step (2).

3. Dynamic diffusion LMS

Although the combination step (3) improves estimation performance, it is compromised by the communication cost. To decrease the amount of communication, we first derive a criterion to decide whether the current measurements contribute to the decrease of MSD, and propose a novel diffusion LMS algorithm in which each node shares the updated estimate with its neighbors only if the criterion is satisfied. Moreover, the combination step is modified to recover unsent estimates from neighbor nodes that do not satisfy the criterion.

3.1. Dynamic update in adaptation

We first introduce the weight error vectors:

$$\tilde{\boldsymbol{w}}_{k,i} = w^o - \boldsymbol{w}_{k,i}, \quad \tilde{\boldsymbol{\psi}}_{k,i} = w^o - \boldsymbol{\psi}_{k,i}. \tag{5}$$