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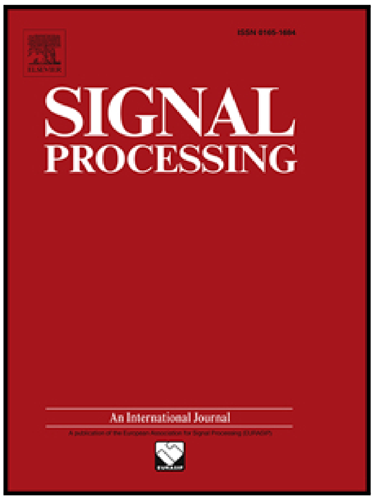

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Distributed Low-Rank Adaptive Estimation Algorithms Based on Alternating Optimization

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***Abstract*—This paper presents a novel distributed low-rank scheme and adaptive algorithms for distributed estimation over wireless networks. The proposed distributed scheme is based on a transformation that performs dimensionality reduction at each agent of the network followed by transmission of a reduced set of parameters to other agents and reduced-dimension parameter estimation. Distributed low-rank joint iterative estimation algorithms based on alternating optimization strategies are developed, which can achieve significantly reduced communication overhead and improved performance when compared with existing techniques. A computational complexity analysis of the proposed and existing low-rank algorithms is presented along with an analysis of the convergence of the proposed techniques. Simulations illustrate the performance of the proposed strategies in applications of wireless sensor networks and smart grids.**

***Index Terms*—Dimensionality reduction, distributed estimation techniques, low-rank algorithms, wireless sensor networks, smart grids.**

I. Introduction

DISTRIBUTED strategies have become fundamental for parameter estimation in wireless networks and applications such as sensor networks [1], [2], [3] and smart grids [4], [5]. Distributed techniques deal with the extraction of information from data collected at nodes that are distributed over a geographic area [1]. In this context, a specific sensor node or agent in the network collects processed data from its neighbors and combines them with its local information to generate improved estimates. However, when the unknown parameter vector to be estimated has a large number of parameters, the network requires a large communication bandwidth between neighboring nodes to transmit their local estimates. This problem limits the usefulness of existing algorithms in applications with large data sets as the convergence speed is dependent on the number of parameters [2], [6], [7]. Hence, distributed dimensionality reduction has become an important tool for distributed inference problems with large data sets.

In order to perform dimensionality reduction or compression, several algorithms have been proposed in the literature in the context of distributed quantized Kalman filtering [8], [9], quantized consensus algorithms [10], distributed principal subspace estimation [11], the single bit strategy [12] and Krylov subspace optimization techniques [13]. However, these distributed algorithms [8]-[13] have drawbacks such as high computational complexity, unsatisfactory performance and implementation issues. Available distributed approaches for dimensionality reduction or compression [8]-[13] have trade-offs between the amount of cooperation, communication and system performance. This calls for the development of cost-effective techniques that can approach the performance of theoretical bounds for parameter estimation, have flexibility and high-compression capability, and exhibit low computational complexity. In this context, low-rank techniques are powerful tools to perform dimensionality reduction, which have been applied to spread-spectrum systems [14], [15], [16], [17], [18], [19], multi-input-multi-output (MIMO) systems [20], [21] and beamforming [22], [23], [24]. However, limited research has been carried out on distributed low-rank estimation, in which the distributed principal subspace estimation [11] and the Krylov subspace optimization [13] techniques are recent contributions. Related approaches to low–rank techniques include compressive sensing-based strategies [25],[26], which exploit sparsity to reduce the number of parameters for estimation, distributed dictionary learning [27], [28], [29], [30], which employs a bilinear dimensionality-reduction factorization scheme similar to some low-rank schemes but assumes no regression vectors, and attribute-distributed learning [31], which employs agents and a fusion center to meet communication constraints. Another important tool in recent related work is the principle of alternating optimization [32], [33], which consists of fixing a set of parameters, adjusting the remaining parameters and then proceeding in cycles [18], [21], [34], [35], [36], [37]. Ling and Ribeiro have studied dynamic decentralized optimization using the alternating direction method of multipliers [34]. Bai *et al.* have examined alternating optimization procedures to design sensing matrices and dictionaries for compressive sensing. Yan *et al.* have developed an alternating optimization for multigraph matching, whereas Magnusson *et al.* [37] have studied convergence of nonconvex optimization problems.

In this paper, we propose a scheme for distributed signal processing and distributed low–rank algorithms for parameter estimation. In particular, the proposed algorithms are based on an alternating optimization strategy [32], [33], [18], [21] and are called the distributed reduced-rank joint iterative optimization normalized least mean squares (DRJIO–NLMS) algorithm and the distributed reduced-rank joint iterative optimization recursive least squares (DRJIO–RLS) algorithm. In contrast to prior work on low-rank techniques [18]-[24] and distributed methods [8]-[13], distributed adaptive techniques based on the alternating optimization strategy are investigated. The proposed low-rank strategies are distributed and perform dimensionality reduction without costly decompositions at each agent. The proposed DRJIO–NLMS and DRJIO–RLS al-

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