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ScienceDirect

Procedia Computer Science 125 (2018) 228–233

Procedia Computer Science

www.elsevier.com/locate/procedia

6th International Conference on Smart Computing and Communications, ICSCC 2017, 7-8 December 2017, Kurukshetra, India

Subspace Pursuit for Sparse Signal Reconstruction in Wireless Sensor Networks

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Abstract

Subspace pursuit (SP) algorithm provides the two most important features of greedy algorithms. It has lowest computational complexity in comparison to other greedy algorithms such as OMP and ROMP. It provides the reconstruction quality of same order as that of linear programming techniques for very sparse signals. SP algorithm estimates the sparse signal step by step, in an iterative fashion. The presented analysis shows that SP exactly recovers the sparse signals for temporally correlated data collected during real-time experimentation using NI WSN platform. The efficacy of recovered signal is analyzed using the parameters of peak signal to noise ratio and root mean square error.

Peer-review under responsibility of the scientific committee of the 6th International Conference on Smart Computing and Communications.

Keywords: wireless sensor networks; compressed sensing; subspace pursuit; compression ratio; peak signal to noise ratio.

1. Introduction

Wireless sensor networks (WSNs) are resource confined networks with limited processing potential, memory space, power supply and bandwidth. Energy consumption is the primary issue due to the limited power supply. The

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1877-0509 © 2018 The Authors. Published by Elsevier B.V.
Peer-review under responsibility of the scientific committee of the 6th International Conference on Smart Computing and Communications
10.1016/j.procs.2017.12.031

principal source of energy consumption is the radio communication which is directly proportional to the number of data bits, transmitted within the network. Reducing the number of bits to be transmitted using compression, reduces the energy consumption, hence, increases network lifetime [1]. Compressive sensing (CS) refers to the idea that for sparse signals; having their amplitude in the decaying order, a few data bits carry sufficient information to approximate the sparse signal considerably.

CS transforms a discrete time signal x of size N i.e. $x \in \mathbb{R}^N$ into K sparse signal using discrete cosine transform (DCT) matrix, Ψ, ($\Psi \in \mathbb{R}^{N\times N}$) according to the equation (1).

$$x = \Psi\alpha \tag{1}$$

where α is a column vector of transform coefficients. If $\alpha \in \mathbb{R}^N$ has K elements of significant values such that rest of $(N-K)$ elements can be rejected without any substantial loss and $K \ll N$ then, α is known as K sparse representation of the original signal x in DCT domain. The matrix Ψ is referred as the basis matrix. CS encodes K sparse signal, by computing a measurement vector y of dimension M, where $K < M < N$. As x has sparse representation with respect to basis Ψ, y is expressed as

$$y = \Phi x = \mathrm{A}\alpha \tag{2}$$

where Φ is known as measurement matrix $\Phi \in \mathbb{R}^{M\times N}$ [2], [3]. The measurement vector y is decoded into the original signal x by determining the transform coefficient vector using $y = \mathrm{A}\alpha$ where A is a rectangular matrix $\mathrm{A} \in \mathbb{R}^{M\times N} = \Phi\Psi$ and Φ, Ψ matrices are known in advance. The reconstruction of the original signal x from a few random projections is an ill-posed problem, therefore, signal sparsity must be known in prior to recover x using $M \ll N$ projections only. In CS theory, various sparse recovery algorithms have been presented to reconstruct the sparse signal from a small set of measurements. One of such algorithms is l_0 minimization as expressed in equation (3).

$$\min_{\tilde{\alpha}} \|\tilde{\alpha}\|_0 \quad \text{s.t.} \quad A\tilde{\alpha} = y \tag{3}$$

l_0 minimization algorithm requires only $2K$ measurements to accurately recover a noise-free signal. Unfortunately, this algorithm is very difficult in practice and is NP-hard in general [4] hence, replaced by l_1 minimization approach as shown in equation (4). l_1 minimization algorithm is based on linear programming (LP) techniques and imposes the condition of restricted isometry property (RIP) on the measurement matrix to obtain a unique sparsest solution [5].

$$\min_{\tilde{\alpha}} \|\tilde{\alpha}\|_1 \quad \text{s.t.} \quad A\tilde{\alpha} = y \tag{4}$$

Although, l_1 minimization approach provides the strong guarantees of recovered signal yet infeasible for many applications due to its computational complexity and requirement of large simulation time. Therefore, the need of decoding algorithms with strong signal recovery having less simulation time become of critical importance. To solve this problem, a family of greedy iterative algorithms have been proposed e.g. matching pursuit (MP), orthogonal matching pursuit (OMP), stagewise OMP (StOMP), regularized OMP (ROMP), subspace pursuit (SP)etc. [6]. These algorithms work on the principle of selection of one or more column from the measurement matrix which is found to be strongly correlated with residual vector, in each iteration. The selected column is then added to the set of previously selected columns. In this way, support of sparse signal is estimated iteratively along with the residual update. To achieve the efficacy using pursuit algorithms same as that of LP methods, more restrictive constraints are imposed on pursuit algorithms in comparison to LP algorithms. To solve this problem, an algorithm namely, subspace pursuit (SP) was developed by Wei Dai and Olgica Milenkovic in [7]. SP has the lowest computational complexity of greedy pursuit algorithms and provides the reconstruction quality in comparison to LP methods. It recovers K sparse signals in the presence or absence of noise leading to approximate or accurate signal recovery, respectively.