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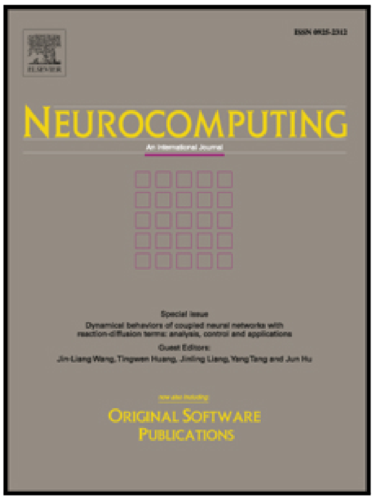

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A New Greedy Algorithm for Sparse Recovery

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Abstract

Compressed sensing (CS) has been one of the great successes of applied mathematics in the last decade. This paper proposes a new method, combining the advantage of the Compressive Sampling Matching Pursuit (CoSaMP) algorithm and the Quasi-Newton Iteration Projection (QNIP) algorithm, for the recovery of sparse signal from underdetermined linear systems. To get the new algorithm, Quasi-Newton Projection Pursuit (QNPP), the least-squares technique in CoSaMP is used to accelerate convergence speed and QNIP is modified slightly. The convergence rate of QNPP is studied, under a certain condition on the restricted isometry constant of the measurement matrix, which is smaller than that of QNIP. The fast version of QNPP is also proposed which uses the Richardson's iteration to reduce computation time. The numerical results show that the proposed algorithms have higher recovery rate and faster convergence speed than existing techniques.

Keywords: Sparse Signal; Compressed Sensing; Restricted Isometry Property; Signal Processing; Greedy Algorithm

1. Introduction

Compressed sensing (CS), established a decade ago [1, 2, 3, 4], allows one to sample a signal using far fewer measurements than those required by the Nyquist-Shannon sampling theorem. The basic premise of CS is that a signal $x \in \mathbb{R}^N$ can be recovered from underdetermined sampling

$$y = Ax \in \mathbb{R}^m, \tag{1}$$

as long as the signal to be reconstructed is sparse. A signal $x \in \mathbb{R}^N$ is called s-sparse, if x satisfies $||x||_0 \le s << N$, where $||x||_0$, 0-norm, means the number of non-zero elements of x. Sparse recovery techniques have been widely applied in lots of machine learning and pattern recognition problems [5, 6, 7, 8, 9]. Since most signals of interest are indeed sparse through some orthogonal transforms, CS has been applied in many areas, including medical imaging [10], radar [11], camera design [12], information extraction [13], face recognition [14] and sensor networks [15].

The main principle of CS is well formulated as solving a ℓ_0-minimization problem with constraint equation (1). Because it is NP-hard and hence not practical, one natural approach is to solve it via the convex ℓ_1-minimization [2] based on Linear Programming (LP) techniques. LP plays an important role in CS algorithms, but it still has high complexity. So several classes of faster algorithms are put forward, cf. [16, 17].

Another interesting line is greedy search approach which has low computational complexity and simple geometric interpretation. They include Orthogonal Matching Pursuit (OMP) [18], Compressive Sampling Matching Pursuit (CoSaMP) [19], Subspace Pursuit (SP) [20], Iterative Hard Thresholding Pursuit (IHT) [21], the Regularized OMP (ROMP) [22], and the Stagewise OMP (StOMP) [23] algorithms. The basic idea behind these methods is to find the support of the unknown signal sequentially. At each iteration of these algorithms, one or several coordinates of the vector x are selected into the candidate of support for testing based on negative gradient, then one finds a vector on this candidate minimizing the residual. Recently, a new algorithm called Quasi-Newton Iterative Projection (QNIP) [24], which uses a new search direction rather than negative gradient, is proposed. QNIP is inspired by Newton iteration method which can yield superlinear convergence.

This paper combines the merits of QNIP and CoSaMP to get a new approach. The new algorithm, called Quasi-Newton Projection Pursuit (QNPP), at

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