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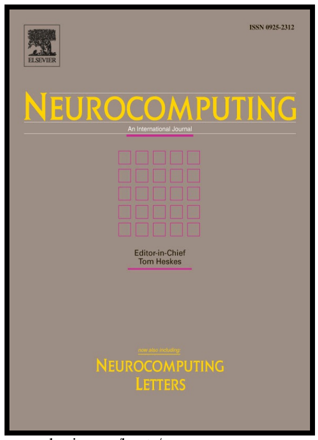

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Compressive Sensing via Nonlocal Low-Rank Tensor Regularization

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Abstract

The aim of Compressive Sensing (CS) is to acquire an original signal, when it is sampled at a lower rate than Nyquist rate previously. In the framework of CS, the original signal is often assumed to be sparse and correlated in some domain. Recently, nonlocal low-rank regularization (NLR) approach has obtained the state-of-the-art results in CS recovery which exploits both structured sparsity of similar patches and nonconvexity of rank minimization. However, it still suffers from two problems. First, the NLR approach cannot preserve the original geometrical structure of image patches and ignores the relationship between pixels because it deals with the vector form of image patches and the matrix form of patch groups for simplicity. Second, logdet $(\cdot)$ which is used as a surrogate function for the rank cannot well approximate the rank, because it is a fixed function and the optimization results by this function essentially deviate from the real solution of original minimization problem. In this paper, we propose a nonlocal low-rank tensor regularization (NLRT) approach toward exploiting the original structural information of image patches and structured sparsity of similar patches. We also exploit Schatten p-norm as a nonconvex relaxation for the tensor rank. To further improve the computational efficiency of the proposed algorithm, we have developed a fast implementation utilizing the alternative direction multiplier method technique. Experimental results have demonstrated that the proposed NLRT approach significantly outperforms the existing state-of-the-art CS algorithms for image recovery.

Keywords: compressive sensing, low-rank tensor approximation, structured sparsity, schatten p-norm, alternative direction multiplier method

1. Introduction

Digital images or signals are conventionally acquired by Nyquist/Shannon sampling. That requires, to incur no loss, the underlying analog signal must be sampled at Nyquist rate which is at least twice of its highest analog frequency. The resulting raw digital data is too large to sense, transmit or store in many applications such as infrared imaging, magnetic resonance imaging (MRI) and wireless sensor networks.

Recently, Compressive Sensing [1], [2] has been developed to help reduce the sampling rate to a frequency that is lower than the Nyquist rate. The main idea of Compressive sensing is that a signal can be decoded from incomplete compressive measurements by seeking its sparsity in some domain. The resulting sampling rate (defined as the ratio of the sample count to the signal size) is roughly to the signal sparsity.

Owing to the fact that image prior knowledge plays a critical role in the performance of image recovery algorithms, designing effective regularization terms to reflect the priors is crucial to image recovery. Standard CS methods exploit the sparsity nature of natural image in some domains, such as DCT [3], wavelets [4], gradient domain utilized by total variation (TV) [5], [6], [7], [8], [9], [10] and learned dictionary [11]. More recently, the concept of sparsity has evolved into various sophisticated forms including Bayesian [12], nonlocal sparisty [13], [14], [15], [16] and structured/group sparsity [17], [18], [19], [20], where exploiting higher-order dependency among sparse coefficients has shown beneficial to CS theory.

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