www.elsevier.com/locate/image

Compressive Sensing Reconstruction via Decomposition

Thuong Nguyen Canh, Khanh Quoc Dinh, Byeungwoo Jeon

PII: S0923-5965(16)30152-7
DOI: http://dx.doi.org/10.1016/j.image.2016.10.001
Reference: IMAGE15138

To appear in: *Signal Processing : Image Communication*

Received date: 26 March 2016
Revised date: 17 October 2016
Accepted date: 17 October 2016

Cite this article as: Thuong Nguyen Canh, Khanh Quoc Dinh and Byeungwo Jeon, Compressive Sensing Reconstruction via Decomposition, *Signa Processing : Image Communicatior* http://dx.doi.org/10.1016/j.image.2016.10.001

Compressive Sensing Reconstruction via Decomposition

Thuong Nguyen Canh, Khanh Quoc Dinh, Byeungwoo Jeon*

College of Information and Computer Engineering, Sungkyunkwan University

---

Abstract

When recovering images from a small number of Compressive Sensing (CS) measurements, a problem arises whereby image features (e.g., smoothness, edges, textures) cannot be preserved well in reconstruction, especially textures at small-scale. Since the missing information still remains in the residual measurement, we propose a novel Decomposition-based CS-recovery framework (DCR) which utilizes residual reconstruction and state-of-the-art filters. The proposed method iteratively refines residual measurement which is closely related to the denoise-boosting techniques. DCR is further incorporated with a weighted total variation and nonlocal structures in the gradient domain as priors to form the proposed DEcomposition based TExture preserving Reconstruction (DETER). We subsequently demonstrate robustness of the proposed framework to noise and its superiority over the other state-of-the-art methods, especially at low subrates. Its fast implementation based on the split Bregman technique is also presented.

Keywords: compressive sensing, image decomposition, total variation, nonlocal structure, Split Bregman

---

1. Introduction

COMPRESSIVE sensing (CS) has increasingly received interest from researchers in a variety of areas due to its capability of simultaneous sampling and compression [1–11]. For a compressible signal $f \in \mathbb{R}^{n\times 1}$, CS can dramatically reduce the sensing cost by employing a far lower sampling rate than the Nyquist rate. It captures a much smaller number of measurements $y \in \mathbb{R}^{m\times 1}, m \ll n$, as

$$y = \Phi f + \eta, \tag{1}$$

where $\Phi \in \mathbb{R}^{m\times n}$ is a sensing matrix that satisfies the restricted isometry property [1, 2] and η is the additive Gaussian noise. Since its reconstruction takes time, CS can be said to shift complexity from the signal-capturing to the signal-reconstruction stage. For multi-dimensional signals, CS burdens the encoder due to by the very large size of the sensing matrix. With respect to this problem, a Block-based CS (BCS) [3–5] and Kronecker CS (KCS) [6, 7] have been investigated. While BCS can reduces the sensing matrix complexity by sensing each block independently, KCS reduces the complexity by sampling each signal separately. The sensing matrix under the KCS scheme is the Kronecker product of each dimension-sensing matrix; that is, $\Phi = R \otimes G^T$ with $R, G^T \in \mathbb{R}^{\sqrt{m}\times\sqrt{n}}$ and its corresponding measurement $Y = RFG$, $Y \in \mathbb{R}^{\sqrt{m}\times\sqrt{m}}$, and a 2-D image $F \in \mathbb{R}^{\sqrt{n}\times\sqrt{n}}$.

CS recovery shares the same problem with image restoration (e.g., image denoising, image inpainting, image super-resolution, etc.) which all belong to a very ill-posed problem, so its exact

---

[*] Corresponding author
Email address: `bjeon@skku.edu` (Byeungwoo Jeon)