Multi-scale/Multi-resolution Kronecker Compressive Imaging

Idea Presentation
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Motivation

- Image prior improve CS performance [4, 5, 6]
  - Most focus to improve CS reconstruction: time, image quality
- CS is universal sampling - all sample are equally important [7]
  - Not for image/video [8]: HVS is more sensitive to low frequency
  - Multi-scale sampling is proof as optimal sampling [9],
- Recovery complexity direct proportional to spatial resolution [10]
  - Multi-resolution sensing is a solution [10], [11], [12]

[4]F. Krahmer and R. Ward, "Stable and robust sampling strategies for compressive imaging," IEEE Trans. Image Process., 2014.
[5] C. Chen, E. W. Tramel, and J. E. Fowler, "Compressed-Sensing Recovery of Images and Video Using Multihypothesis Predictions," in Proc. Asilomar Conf. on Signals, Systems, and Comp, 2011.
[6] T. N. Canh et.al. , "Detail-preserving compressive sensing recovery based on cartoon texture image decomposition," in IEEE Inter. Conf. Image Process.(ICIP), 2014.
[7] M. A. Davenport, J. N. Laska, P. T. Boufounos, and R. G. Barani-uk, A simple proof that random matrices are democratic, Available at Arxiv.org (arXiv:0911.0736v1), 2009.
[8]]. Li, A. C. Sankaranarayanan, L. Xu, R. Baraniuk, and K. F. Kelly, "Realization of hybrid compressive imaging strategies," J. Opt. Soc. Am. A,, 2014.
[9] B. Adcock, A. Hansen, C. Poon, and B. Roman, Breaking the co-herence barrier: A new theory for compressed sensing, Available at arxiv.org (arXiv:1302.0561), 2014.
10] T. Goldstein et al, "The STONE transform: multi-resolution image enhancement and real-time compressive video," Arxiv.org, 2013
[11] A. Sankaranarayanan, C. Studer, and R. Baraniuk, "CS-MUVI: Video compressive sensing for spatial-multiplexing cameras," in IEEE Inter. Conf. Computational Photography (ICCP), pp. 1-10, 2012.
[12]. J. E. Folwer, S. Mun, and E. W. Tramel, "Multiscale block com-pressed sensing with smoothed projected Landweber reconstruc-tion," IEEE European Sig. Process. Conf., pp. 564-568, 2011.

Related Work

- MH[16]: different subrate at each wavelet decomposition
    - *Costly assumption*: wavelet coefficient is available at the encoder
    - *No-longer block-based sensing*: wavelet transform is frame based
    - Lost some level of details

Subrate 0.1

Original

MH-MS-SPL

Our method

[16] J. E. Folwer, S. Mun, and E. W. Tramel, "Multiscale block com-pressed sensing with smoothed projected Landweber reconstruc-tion," IEEE European Sig. Process. Conf., pp. 564-568, 2011.

Proposed Sensing Matrix

- Block-based Kronecker CS

$$\boldsymbol{\Phi}_K^i = \begin{bmatrix} \boldsymbol{\Phi}_0^i & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Phi}_1^i & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \boldsymbol{\Phi}_K^i \end{bmatrix}, \boldsymbol{i} = \mathbf{1}, \mathbf{2}$$

- Separatable Wavelet at level k

$$F_k = \mathcal{W}_K^n F (\mathcal{W}_K^n)^T$$

$$\mathcal{W}_K^n = \widehat{\mathcal{W}}_K^n \widehat{\mathcal{W}}_{K-1}^n \ldots \widehat{\mathcal{W}}_1^n = \bigcup_{j=1}^{K} \widehat{\mathcal{W}}_i^n;$$

$$\widehat{\mathcal{W}}_i^n = blkdiag\left(\widehat{\mathcal{W}}_{i-1}^{n/2}, I^{n/2}\right), i = 1, \ldots, K$$

$\mathcal{W}^{n,L}, \mathcal{W}^{n,H} \in \mathbb{R}^{(n/2)\times n}$: low pass & high pass filter

- KCS measurement

$$Y = \Phi_K^1 (\mathcal{W}_K^n F (\mathcal{W}_K^n)^T)(\Phi_K^2)^T$$

$$= \underline{(\Phi_K^1 \mathcal{W}_K^n)} F \underline{(\Phi_K^2 \mathcal{W}_K^n)}^T$$

Proposed sensing matrix

How to assign measurement

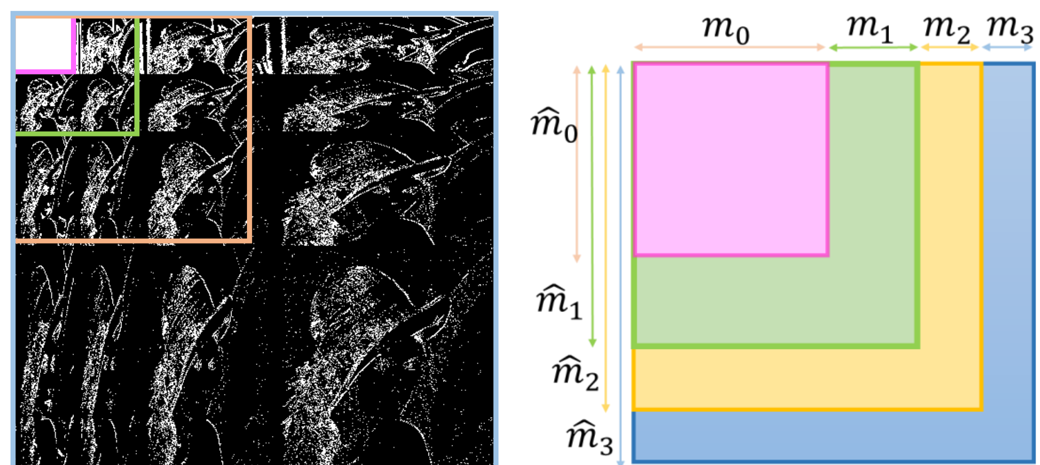


Fig. 1. Binary image of SWT and proposed multi-scale measurement at decomposition level 3

Proposed Subrate Allocation

- (MRK) Require no information about the to be sampled images
  - More measurement for lower SWT level

$$m = m_0 + \sum_{i=1}^{K} m_i = \sum_{i=1}^{K} \tilde{m}\omega_i \frac{1}{2^{K-j+1}}$$

$m_j = \tilde{m}\,\omega_j / 2^{K-j+1}$, $m_0 = n/2^K$, $\tilde{m}$ is intermediate value.

$\omega_j = a^{K-j}$ stands for weight ratio, a is a constant.

→ *preserve low frequency better but still lost some level of high frequency*

- (MRKa) Require information of wavelet coefficients (adaptive)
  - Thresholding the wavelet coefficients

$$\tau = \lambda\sigma\sqrt{2\log Q}, \text{ where } \sigma = \frac{median(|F_K|)}{0.6745}$$

λ is a constant,
Q number of coefficient of F_K

  - Relative sparsity $s_j = \left\|(F_K)_j\right\|_0 / Q_K$
  - KCS measurement $m_j = \tilde{m}\,\omega_j s_j / 2^{K-j+1}$

Expected to preserve high frequency better

[1] S. Shishkin, H.Wang and G. Hagen, "Total variation minimization with separable sensing operator," Conf. on Image and Signal Process., pp. 86–93, 2010.

Experiments

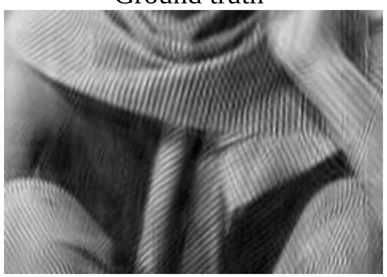
- Visual comparision of various CS methods

Ground truth

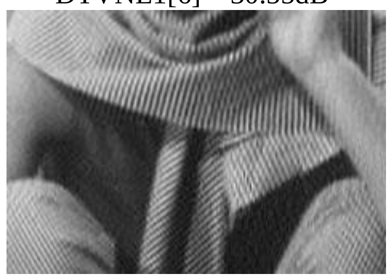
DTVNL1[6] – 30.55dB

ALSB[20] – 32.02dB

TVHybrid[2] 24.95dB



TGVSH$^{\#}$[21] – 29.10dB



MH-MS$^{\#}$ [16] – 26.78dB

MRK3$^{\#*}$ - 30.05dB

MRK3a$^{\#*}$ - 30.90dB

Multi-scale sensing (#), Support multi-resolution recovery (*)

MRK3: the proposed matrix with separable wavelet level 3

- Require no costly assumption of wavelet transform
- An efficient subrate allocation
- Support up to K resolution reconstruction