COMPRESSIVE SENSING RECONSTRUCTION BASED ON STANDARDIZED GROUP SPARSE REPRESENTATION

Zhirong Gao[1], Lixin Din[1], Chengyi Xiong[2], Zhongyi Gong[2], Qiming Xiong[3]

[1] School of Computer Science, Wuhan University, Wuhan, China

[2] College of Electronic and Information Engineering, South-Central University for Nationalities, Wuhan, China

[3] School of Mathematics and Computer Science, Wuhan Textile University, Wuhan, China

HIGHLIGHTS

- A new method for image compressive sensing reconstruction (ICSR) is proposed based on the z-scores standardized group sparse representation (ZSGSR).
- Reconstruction model: firstly, extracts the similar patch groups of the image, decomposed by adaptive PCA dictionary; then, normalize the resulting coefficients using z-score standardization in component-wise, and using L1 norm regularize recovery.
- Solved by splitting Bregman iteration and soft threshold shrinking algorithm.
- ZSGSR improve the sparse representation ability of the image and better restore the edges and texture details

PROPOSED METHOD

- Mathematical model of proposed ZSGSR based method

$$\min_x \frac{1}{2}\|\Phi x - y\|_2^2 + \lambda \sum_k \left\| \frac{\psi_k G_{x_k} - \mu_k}{\sigma_k} \right\|_1$$

- Where y is measure, x is the reconstructed image, and μ and σ are the estimated mean and covariance vectors

- Iterative solution of model using SBI algorithm

$$f^{(t+1)} = \arg\min_f \lambda \sum_k \left\| \frac{\Psi_k G_{f_k} - \mu_k}{\sigma_k} \right\|_1 + \frac{\eta}{2}\left\| x^{(t)} - f - b^{(t)} \right\|_2^2,$$

$$x^{(t+1)} = \arg\min_x \frac{1}{2}\|\Phi x - y\|_2^2 + \frac{\eta}{2}\left\| x - f^{(t+1)} - b^{(t)} \right\|_2^2,$$

$$b^{(t+1)} = b^{(t)} - (x^{(t+1)} - f^{(t+1)})$$

ALGORITHM SUMMARY

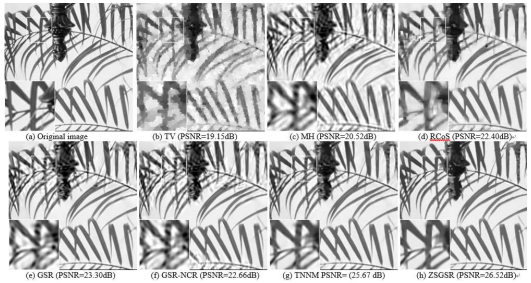
- Initially reconstruct image $X^{(0)}$ by MH method
- Iteratively update image By the ZSGSR based method, through repeating the following steps:
  - S1: Divide the image into many overlapping blocks
  - S2: Form the similar patches group, and perform filtering by an adaptive soft threshold shrinking method
  - S3: Obtain an updated image by solving a quadratic function minimum
  - S4: Determine whether to terminate the iteration
- Output the final reconstructed image X

OBJECTIVE EVALUATION

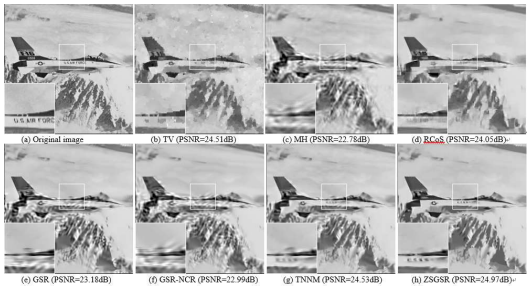
- Average PSNR(DB)/SSIM COMPARISON OF SEVERAL RECONSTRUCTION ALGORITHMS

SR	Algorithms						
	TV	MH	RCoS	GSR[1]	GSR-NCR[2]	TNNM[3]	Ours
0.1	24.64/ 0.7247	24.40/ 0.7451	25.71/ 0.8006	26.15/ 0.8456	25.53/ 0.8112	27.21/ 0.8548	27.52/ 0.8562
0.2	27.28/ 0.8401	26.83/ 0.8473	30.42/ 0.8864	30.99/ 0.9158	30.09/ 0.9034	31.76/ 0.9232	32.01/ 0.9234
0.3	31.04/ 0.8961	30.13/ 0.9040	32.15/ 0.9272	34.10/ 0.9466	34.18/ 0.9476	34.65/ 0.9494	34.97/ 0.9512
0.4	33.86/ 0.9320	32.28/ 0.9218	34.21/ 0.9485	35.56/ 0.9639	36.87/ 0.9650	37.07/ 0.9656	37.35/ 0.9662

SUBJECTIVE EVALUATION



- Fig. 1: visual comparison of the reconstructed Leaves at SR=0.1



- Fig. 2: visual comparison of the reconstructed Plane at SR=0.1

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