A NEW APPROACH TO SPARSE IMAGE REPRESENTATION USING COMPRESSED SENSING

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ABSTRACT

Image representation is important for efficient image processing, data compression and pattern recognition. The development of pursuit algorithms from *compressed sensing* [1], with the capability to find a sparse representation, has offered new approaches for tackling the aforementioned problem. Hereafter, consider an $n \times m$ image Y and a unknown dictionary $D \in \mathbb{R}^{n \times k}$, the problem of image representation can be addressed as a sparse decomposition over a learned dictionary by solving the following system of linear equations:

$$\left(\widehat{D}, \widehat{X}\right) = \underset{D,X}{\operatorname{argmin}} \{S_m(X) + \|Y - DX\|_F^2\}, \quad (1)$$

where $S_m(X)$ is a sparsity measure of X and $\|.\|_F^2$ denotes the Frobenius norm.

To date, K-SVD [2] is the state-of-the-art method for solving this problem. However, K-SVD depends heavily on a pursuit algorithm to calculate the sparse coefficients. Also, it updates the dictionary atom-by-atom during each iteration. Furthermore, the K-SVD requires large storage because the computed non-zero coefficients reside in different locations.

To overcome the K-SVD disadvantages, we propose a new approach [3] for dictionary-based learning for image representation, which offer a better trade-off between computational accuracy and storage requirement. The proposed method uses an enhanced MMV pursuit algorithm (EOMP) to find a minimal-$S_m(X)$ solution and the multi-singular value decomposition to accelerate processing. Consequently, the proposed method requires significantly less storage compared to the traditional K-SVD method. Furthermore, it allows the simultaneous update of several atoms, which leads to faster convergence and better reconstruction accuracy.

The new method is applied to a simulated data with white Gaussian noise and the problem of image representation and its performance is assessed in terms of reconstruction accuracy and convergence speed. Experimental results indicated that the new method runs 3.6 to 6.9 times faster, and has lower reconstruction error, compared to the existing K-SVD algorithm. The comparisons are shown in Table. 1 and Fig. 1, respectively.

Table 1. Comparison of K-SVD and IK-SVD on simulated signals with white Gaussian noise.

(K_{max}, k, m)	**PSNR (db)**		
$(\mathbf{12}, \mathbf{50}, \mathbf{1000})$	SNR=10	SNR=20	SNR=30
K-SVD	64.11	65.47	65.74
IK-SVD (proposed)	67.16	69.60	70.36
$(\mathbf{12}, \mathbf{70}, \mathbf{2000})$	SNR=10	SNR=20	SNR=30
K-SVD	63.69	64.91	65.25
IK-SVD (proposed)	65.18	66.36	66.91

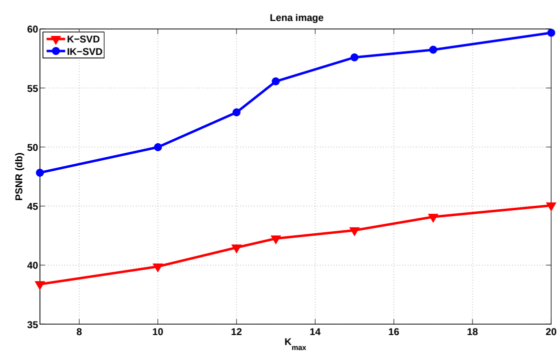

Fig. 1. Comparison of K-SVD and IK-SVD in image representation task: PSNR of reconstructed images.

1. REFERENCES

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