Image Compression Performance Using Total Variation Minimization and Noiselet Transform

Machine Vision Project
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Outline

- sparse coding for compression
  - 3 methods used in this experiment
- experimental setup
- results
- conclusions

Introduction

- goal: sparse coding for lossy compression
- methods
    - DCT compression, least squares recovery
    - DCT compression, TV min recovery
    - noiselet compression, TV min recovery

Motivation

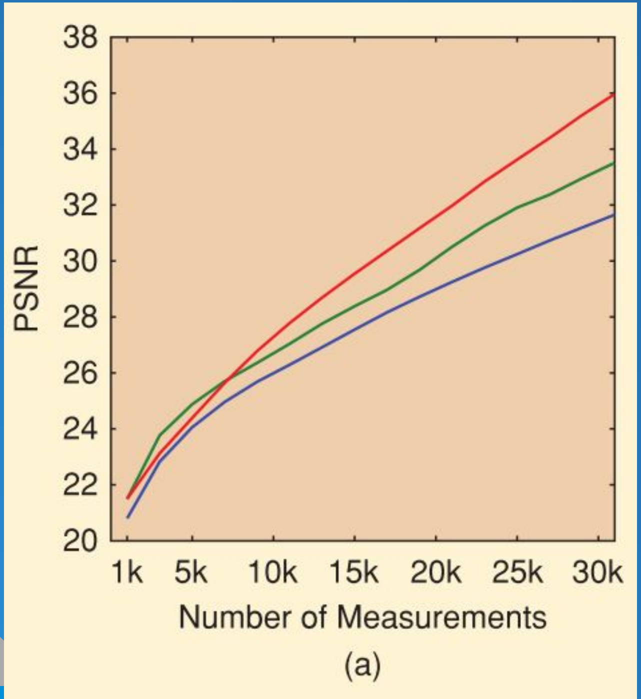


Figure reprint from [2]

Reference: Imaging via Compressive Sampling

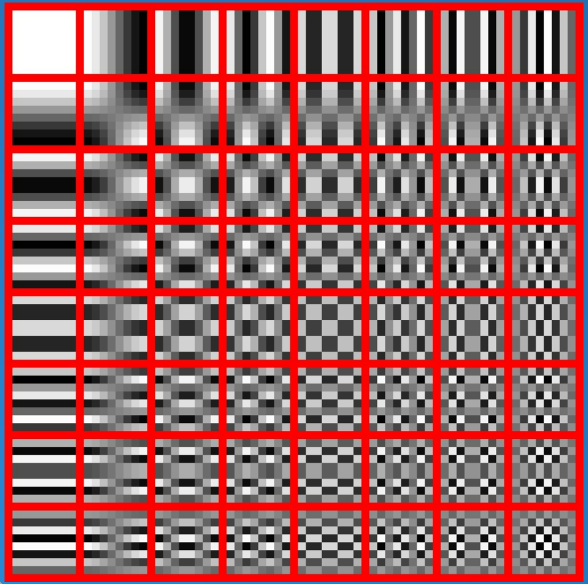
- image quality as a function of compression

Evaluation Metric: PSNR

pseudo signal-to-noise ratio (from [2])

$$PSNR(X, \bar{X}) = 20 \log_{10} \frac{255 * 256}{\|X - \bar{X}\|_{l_2}}$$

Theory:
Discrete Cosine Transform Compression



http://blogs.msdn.com/b/devdev/archive/2006/04/12/575384.aspx

- decompose image into series of cosine waves
  - similar to fourier transform
- inverse DCT gives least squares recovery

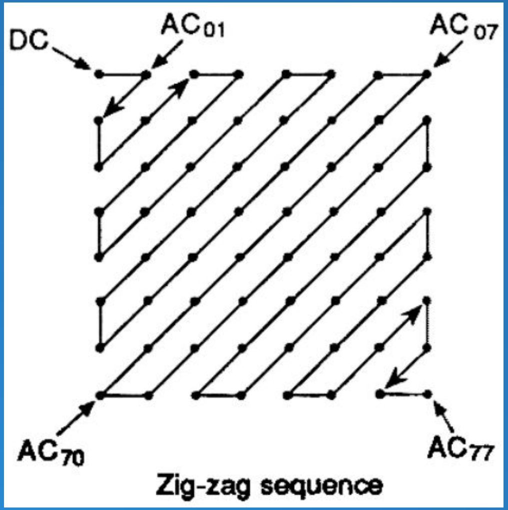
Cameraman DCT

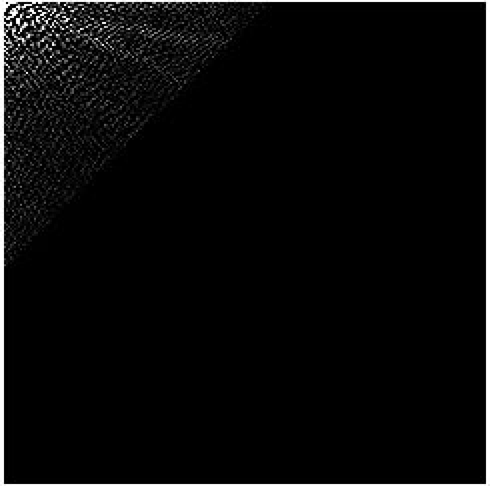
Theory: Least Squares Recovery

- in practice for DCT: inverse DCT of sparse DCT
- in practice for noiselet: solve normal equations

$$\hat{x} = \Phi^T (\Phi \Phi^T)^{-1} y$$

Cameraman Sparse DCT, LS recovery





Total Variation Minimization

$$\hat{x} = \min_{x'} \|\Psi x'\|_{l_1} \quad subject\ to \quad \Phi x' = y$$

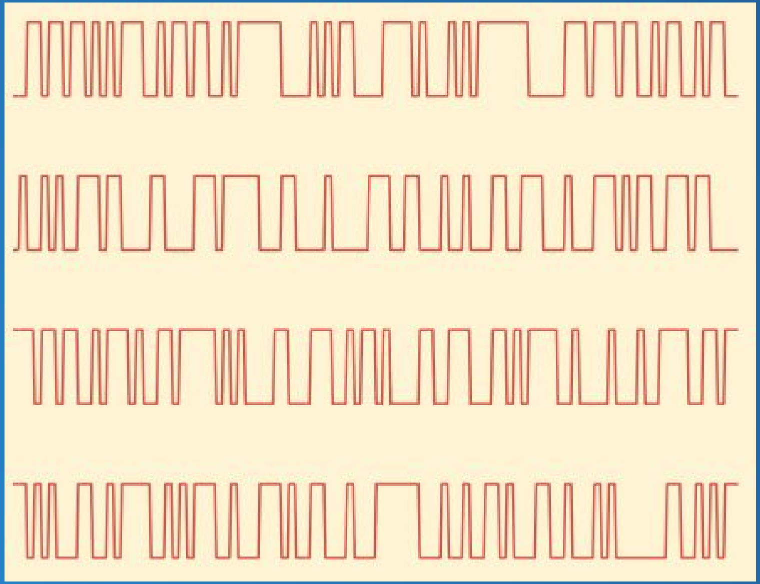
$$\|u\|_{l_1} = \sum_{i=1}^{n} |u_i|, \quad where \quad u = [u_1\ u_2\ \dots\ u_n]^T$$

$$\hat{x} = \min_{x'} \sum_{i}, j|(\nabla X')_{i,j}| \quad subject\ to \quad \Phi x' = y$$

DCT Compression, TV Min Recovery

Theory: Noiselet Compression

- compression with random basis

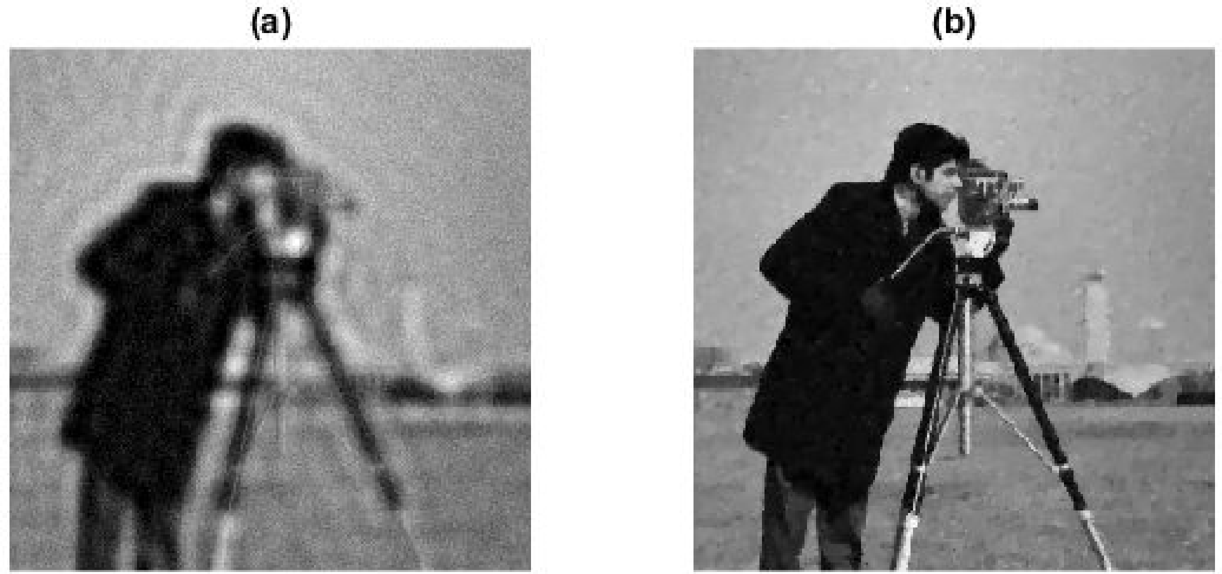


reprint from [2]

Algorithm: Noiselet Compression

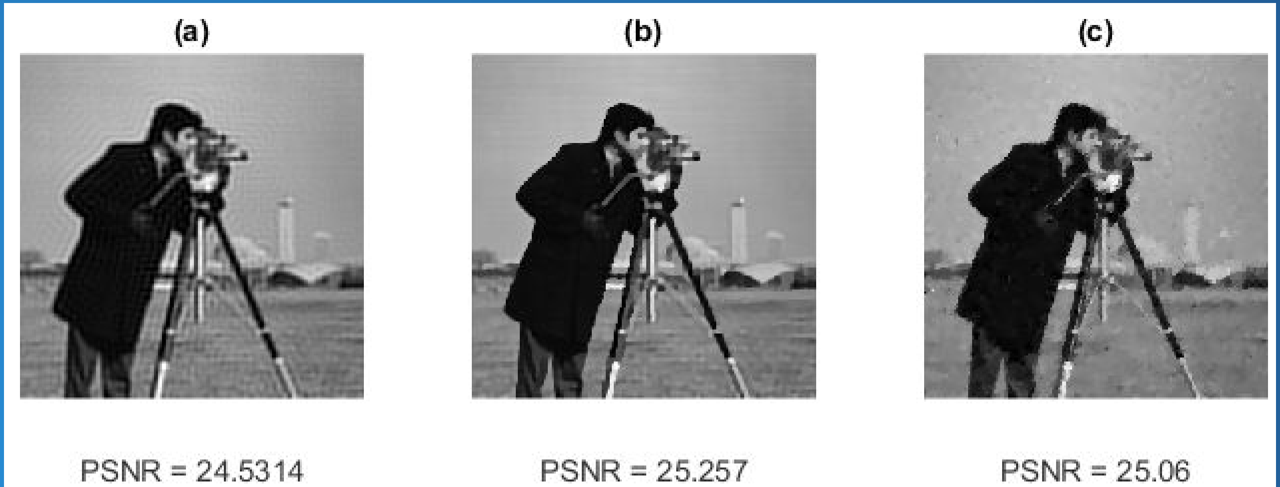
- perform DCT and Noiselet transforms
- remove coefficients from both bases
- solve normal equations for initial point
- use logbarrier algorithm from [2] to solve total variation minimization

Demo:
Noiselet Compression, TV Min Recovery



Results:
Image Appearance Comparison

(a): dct compression, LS recovery
(b): dct compression, TV min recovery
(c): noiselet compression, TV min recovery



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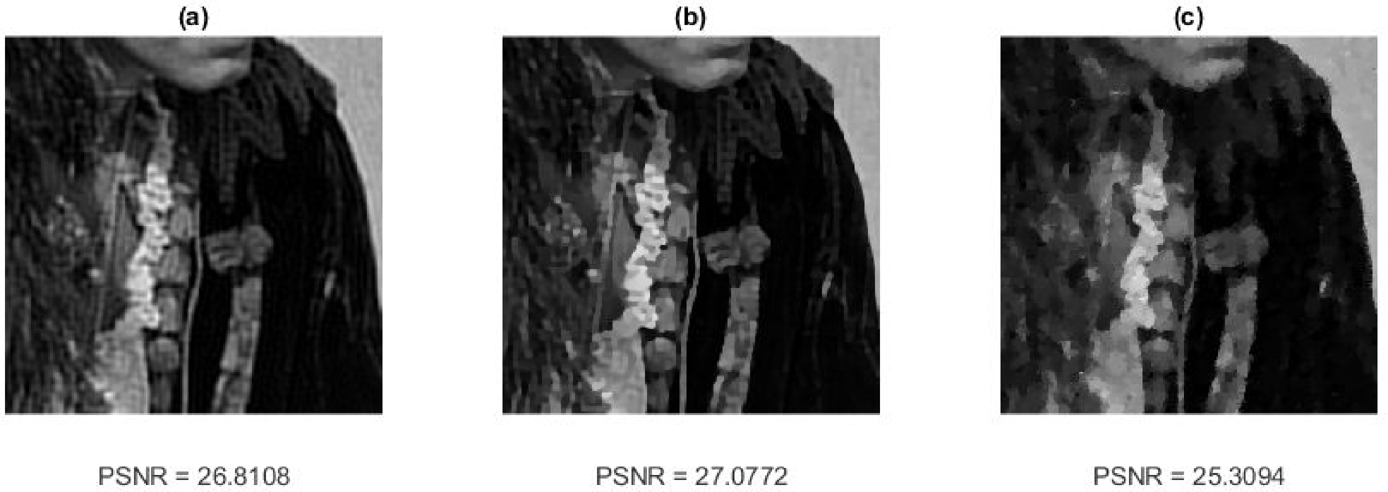
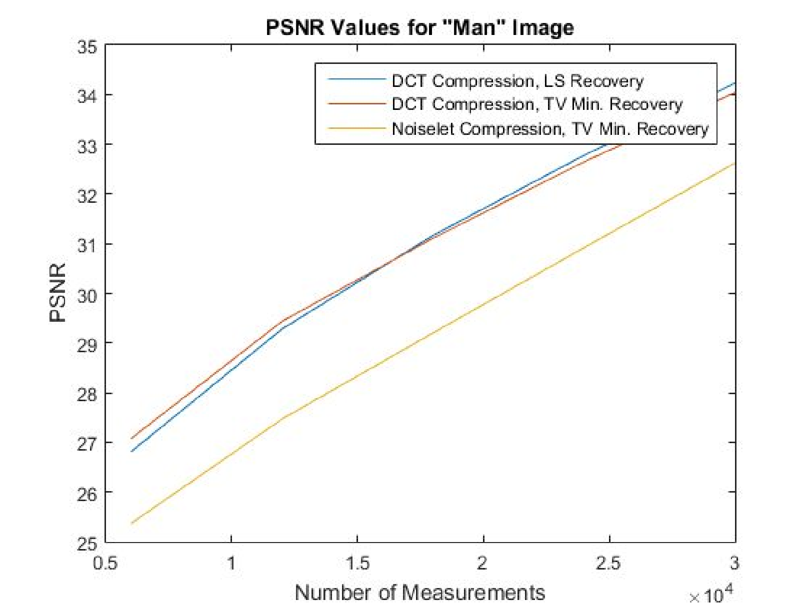
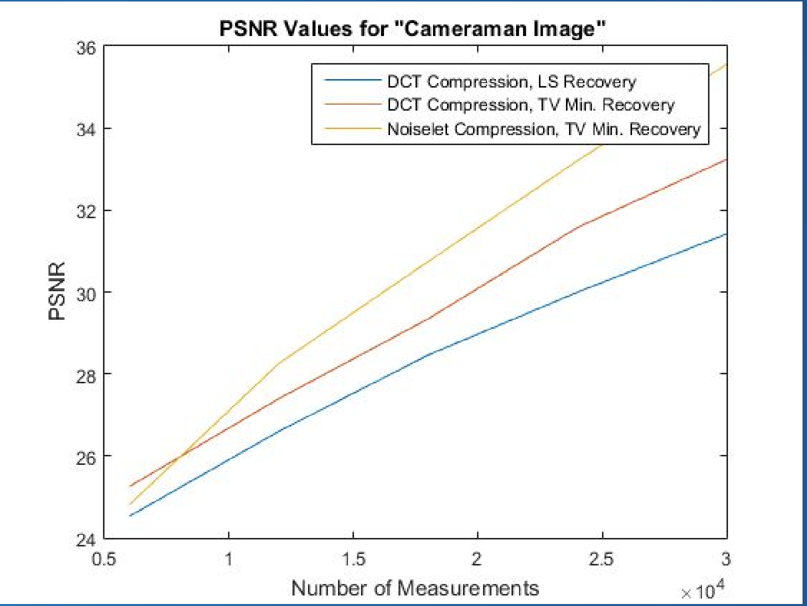


Results: PSNR Performance

"Man" Image PSNR



"Cameraman" Image PSNR



Conclusions

- TV min is very slow
- DCT introduces “ringing” effects, noiselet introduces random noise
- DCT compression with TV min recovery performed best across images
- noiselet transform only worked well for some images

References

1. Wallace, G. K. (1992). The JPEG still picture compression standard. IEEE Transactions on Consumer Electronics, 38(1). doi:10.1109/30.125072
2. Romberg, J. (2008). Imaging via Compressive Sampling. IEEE Signal Processing Magazine, 25(2), 14–20. doi:10.1109/MSP.2007.914729
3. Coifman, R., Geshwind, F., \& Meyer, Y. (2001). Noiselets. Applied and Computational Harmonic Analysis, 10(1), 27–44. doi:10.1006/acha.2000.0313
4. Rombert, J. (2008, January 1). Compressive Imaging Code. Retrieved April 29, 2015, from http://users.ece.gatech.edu/~justin/spmag/