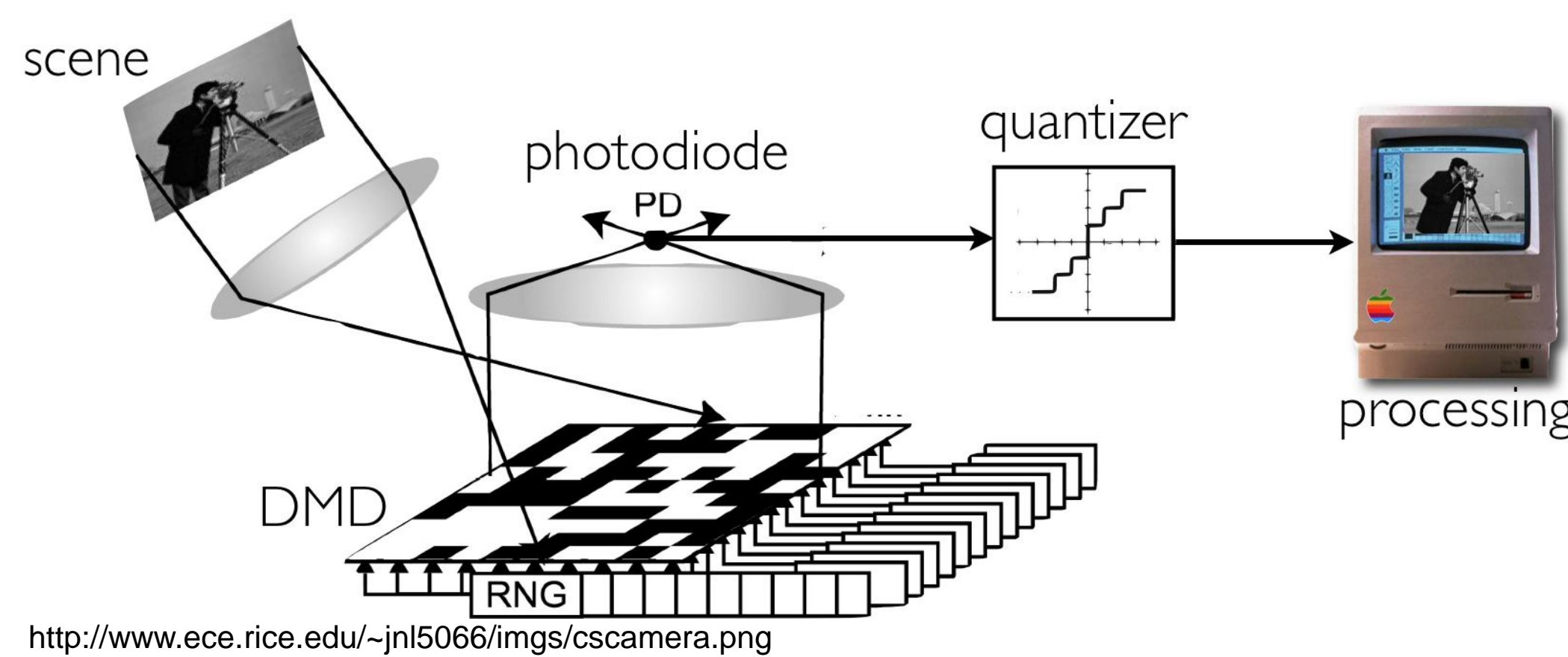




Object Tracking and Image Reconstruction from Compressive Sensing Cameras

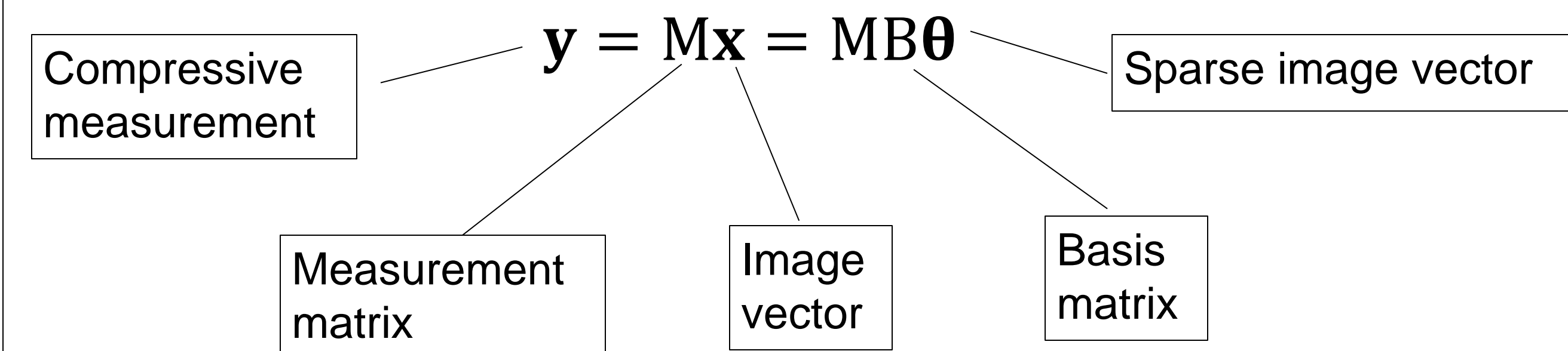


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Compressive Sensing Camera Architecture

- Rather than sensing a grid of m small pixels, take a series of linear measurements y over the whole image using n different pseudorandom masks.
 - $n \ll m$, hence the signal is *compressively sensed*.
- The original image is known to be sparse (i.e. compressible) using some basis B , for example a wavelet basis:

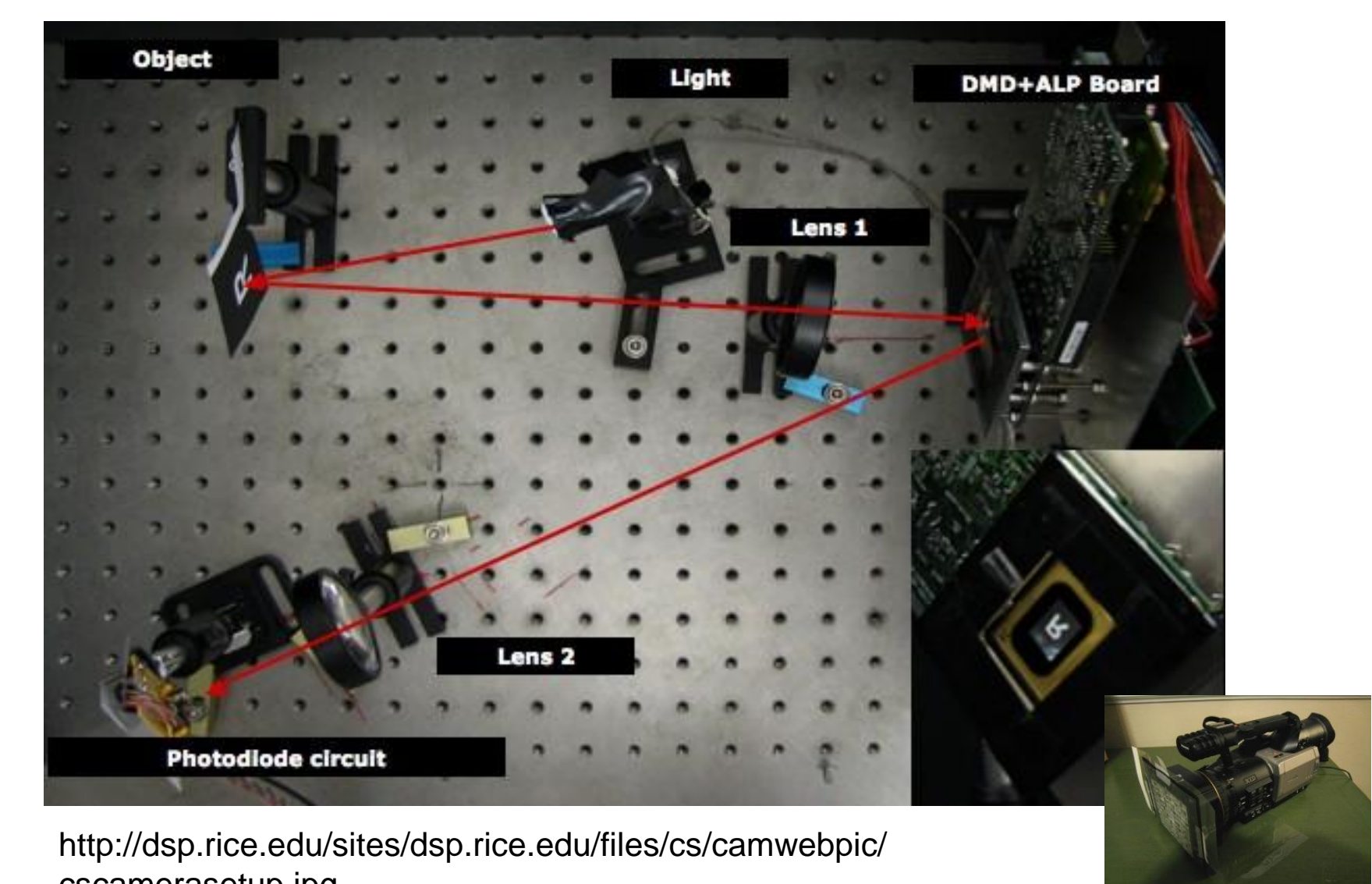


Video Reconstruction Incorporating Optical Flow

- Modern video codecs exploit correlations between neighboring frames when encoding video from conventional cameras – how can we do the same when reconstructing compressively sensed video sequences?
- If we know the optical flow vectors u and v between two frames, we can reconstruct by solving the following optimization problem:

$$\hat{\theta}, \hat{\eta} = \underset{\theta, \eta}{\operatorname{argmin}} \left\| \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} - \begin{bmatrix} MB & 0 \\ MF_{u,v} & M \end{bmatrix} \begin{bmatrix} \theta \\ \eta \end{bmatrix} \right\|_2 + \tau \left\| \begin{bmatrix} \theta \\ \eta \end{bmatrix} \right\|_1$$

- If optical flow is known to be constant across the image, we can perform single-frame reconstruction to estimate the shift between frames, and use this shift as before to perform 2-frame reconstruction.



<http://dsp.rice.edu/sites/dsp.rice.edu/files/cs/camwebpic/cscamerasetup.jpg>
http://cs.uky.edu/~jacobs/projects/integral-pixel-motion/camera_with_arrays_small.jpg

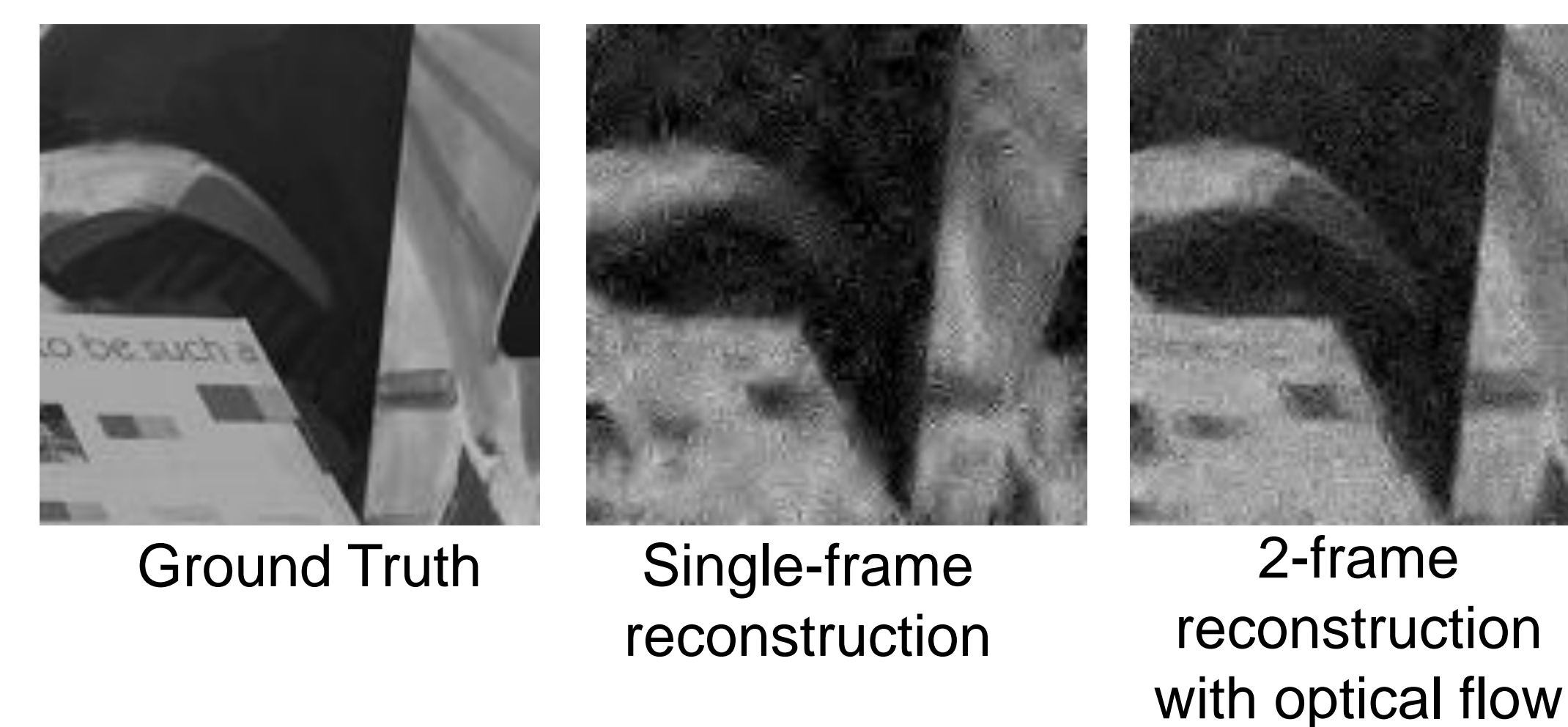
Summary

Compressive imaging is a novel sensing paradigm which promises lower data rates and lower cost sensing hardware, particularly in non-visible wavelengths where per-pixel costs are high. However, current methods for reconstructing compressively sensed videos do not fully exploit prior knowledge of motion and frame-to-frame correlations. We have extended typical l_1 reconstruction to incorporate optical flow information when simultaneously reconstructing multiple frames of video. Although estimating generalized dense optical flow from compressively sensed data is a difficult and unsolved problem, we demonstrate the usefulness of this approach for two special cases: known optical flow and unknown but constant optical flow. In both cases, a clear perceptual improvement in reconstructed frames is evident, as is an increase in Peak Signal-to-Noise Ratio (PSNR).

Results

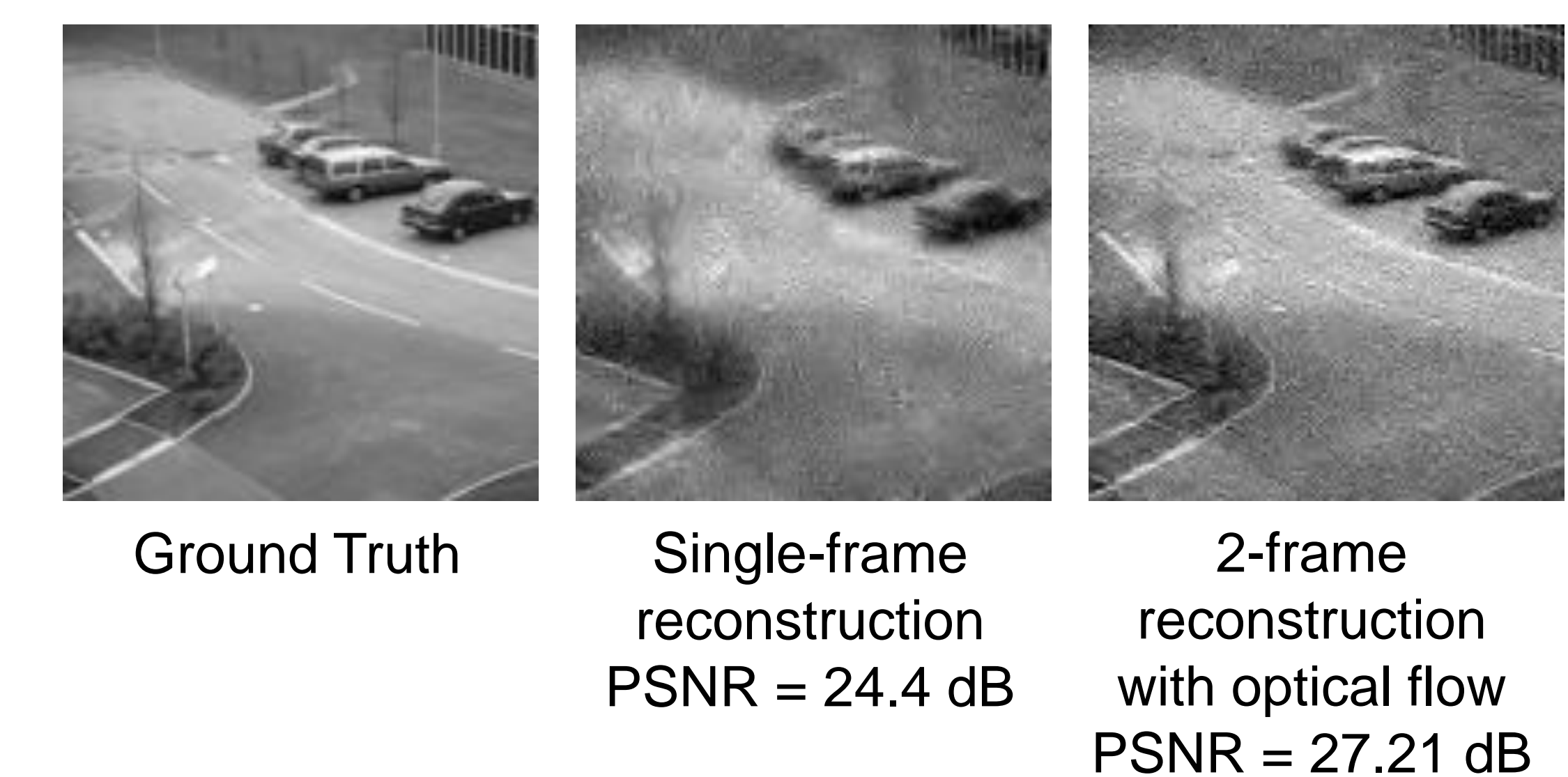
Reconstruction with known motion

- The reconstruction algorithm above was tested using the Middlebury optical flow dataset, which includes known optical flow data.
- Clear improvements in both perceptual quality and PSNR across a wide range of sensing rates.



Reconstruction with constant shift

- The algorithm was tested on a single cropped frame from the PETS2000 dataset, with a shift introduced to simulate a moving camera.



Conclusion

This work is an important first step toward fully incorporating temporal information in compressively sensed video. Relative to single-frame reconstruction, the algorithm described here shows clear benefits in the quality of reconstructed compressively sensed images. This knowledge may speed the commercialization of cost-effective imaging systems in a variety of wavelengths beyond the visible range.

Acknowledgements

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