# Multiple View Image Denoising

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**Goal:** Given multiple noisy images of a scene taken from different viewpoints, compute the underlying noiseless images.

**Motivation:** Low-Power Surveillance Networks, Micro/Mini Mobile Robots, Multi-Camera Laparoscopy, Portable Camera Arrays → Miniaturized Cameras, Simple Optics → Insufficient Light, Noisy Image Capture

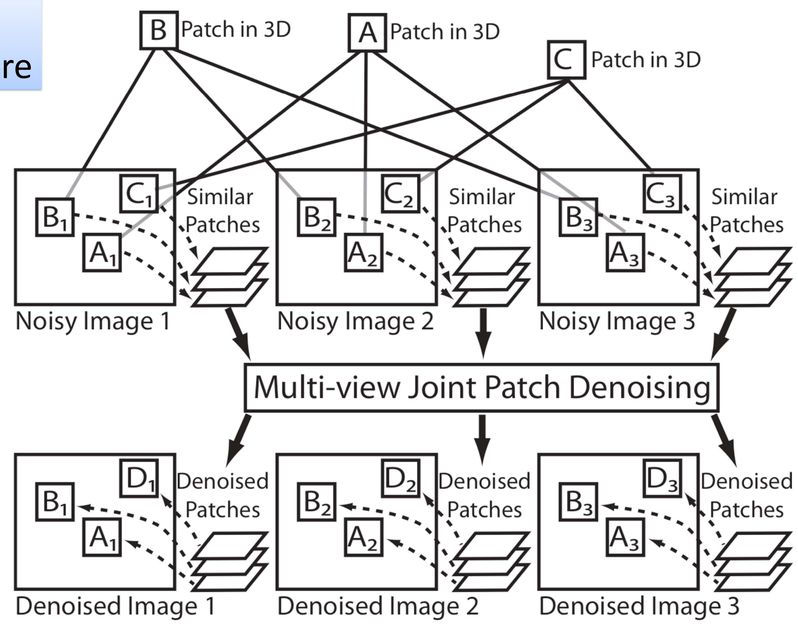
**Problem Statement:** Input Noisy Images of the same scene: $\{I_m\}_{m=1...M}$, $I_m=G_m+n_m$
Independent per-pixel noise n with intensity-dependent variance: $\sigma^2=\tau^2+k^2G$
Output Images: $\{G_m\}_{m=1...M}$

**Existing Approaches:**

Single Image Denoising: not using data redundancy across views
Video Denoising: not using scene geometry constraint
Synthetic Aperture Denoising: not using redundancy within each individual image
Computational Cameras: requiring customized sensors

**Our Approach:**

Exploiting data redundancy both across views and within each individual image using a depth-based constraint

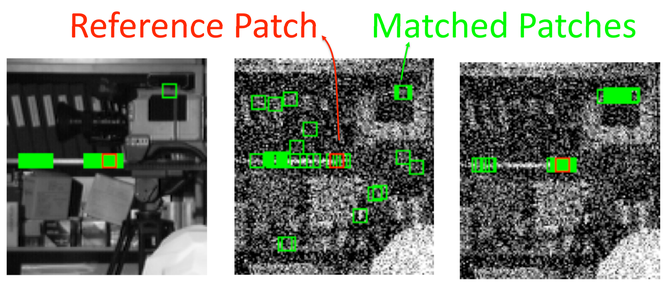



**The Outline of Our Algorithm**

**Technical Details:**

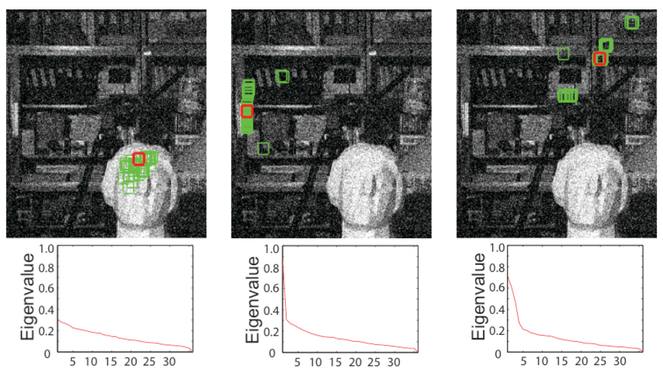
**0. Multi-View Stereo for Depth Estimation:** using the standard SSD with winner-take-all technique for depth estimation.

**1. Depth-Guided Patch Matching:** if two patches are similar in one view, their corresponding patches in other views usually look similar as well.




Using depths to verify patch similarity improves patch grouping accuracy in the presence of large noise. (a) The green patches are the closest K=35 patches to the red reference patch in a clean image. (b) After the image is corrupted by noise with standard deviation τ=65, for the same reference patch, the closest K=35 patches are scattered around, and do not correspond to the closest patches that would be found in the clean image. (c) Using 25 noisy images from multiple viewpoints (only one shown here), the K=35 closest patches to the same reference better resemble those in (a).

**2. Patch Denoising using PCA/Tensor Analysis on Patch collections:** denoising by discarding small coefficient components using an adaptive threshold.




Different collection of patches have different eigenvalue distribution. (a) Since this collection of patches is on the bust, the residual patches after mean removal approximately correspond to noise. The eigenvalues therefore correspond to noise power along the components. (b) The reference patch contains an intensity edge. The top component captures the subtle variation of these edge patches. The rest of the small eigenvalues correspond to noise power along these components. (c) The reference patch has an irregular intensity pattern and more components are needed to capture patch variation within the collection. We automatically determine the number of discarded components such that their total energy roughly equals to the known noise power.

**3. Removing Intensity-Dependent Noise:** Scale down each pixel in noisy patches using its noise std (approximated by its mean) before SVD or tensor SVD.

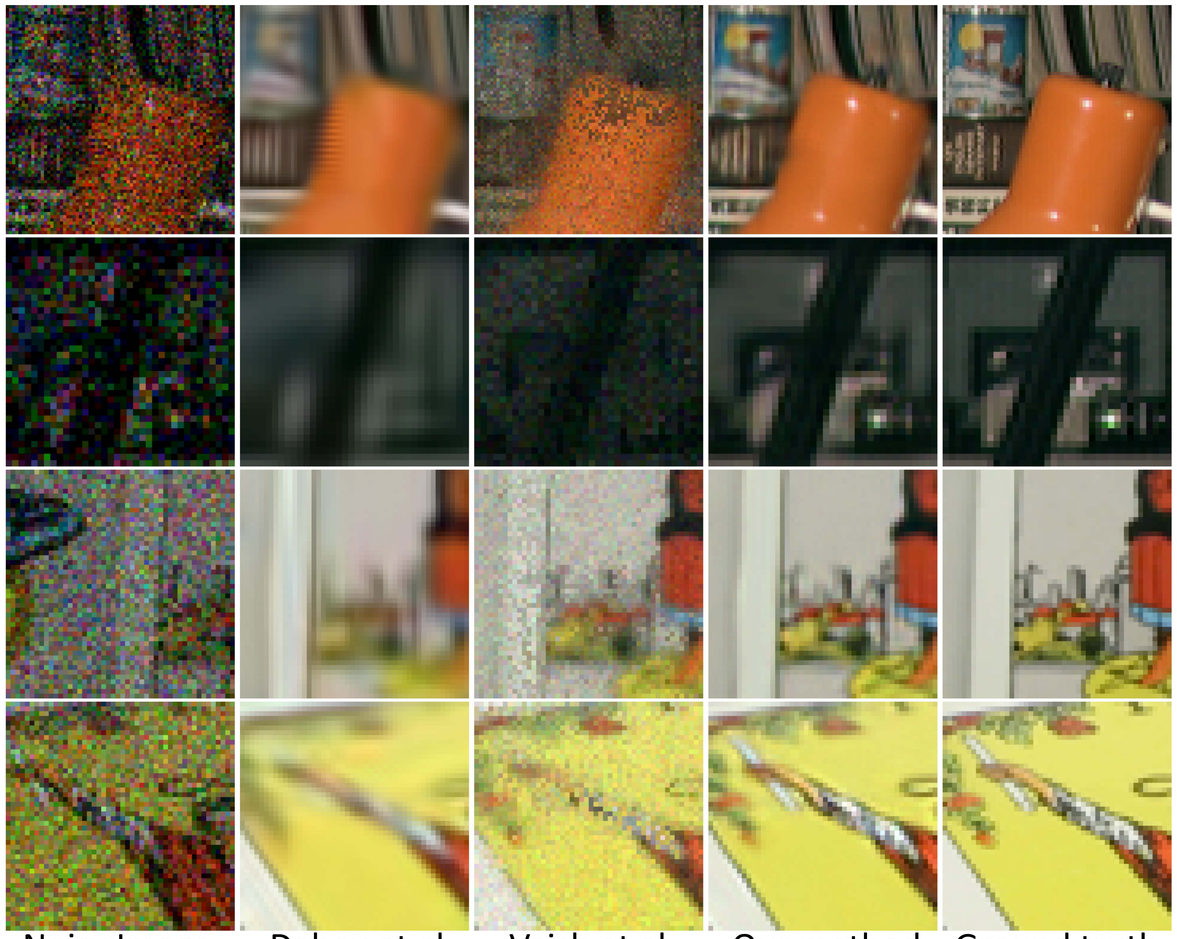
**4. Combining Overlapping Denoised Patches to Form an Output:**

Weighted combination that favors denoised patches from compact patch groups
Using 1/(# of kept components) as weights
Helps to reduce artifacts near occlusion boundaries

**Future work:**

Better occlusion modeling
Modeling patch deformation across views
Explaining and/or improve performance curve
Better theoretical justification of our method

## Denoising Synthetic Noise

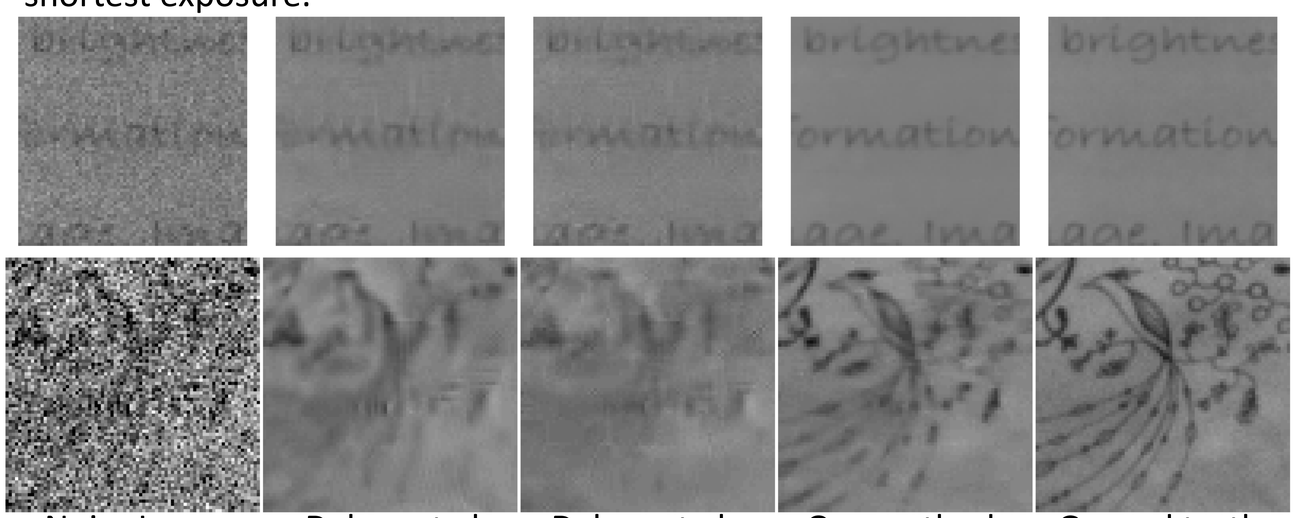


Noisy Image | Dabov et al (BM3D) | Vaish et al (S-Aperture) | Our method (PCA) | Ground truth

Comparison between our 25-view denoising and a state-of-the-art image denoising (BM3D applied on one image) and an existing multi-view denoising (Synthetic Aperture denoising applied on all 25 images). The improvement of our approach over single image denoising is substantial, much more dramatic than the performance difference between various state-of-the-art denoising methods evaluated on a single image. This gain is due to more data for noise cancelation and more accurate patch grouping.

## Denoising Real Noise

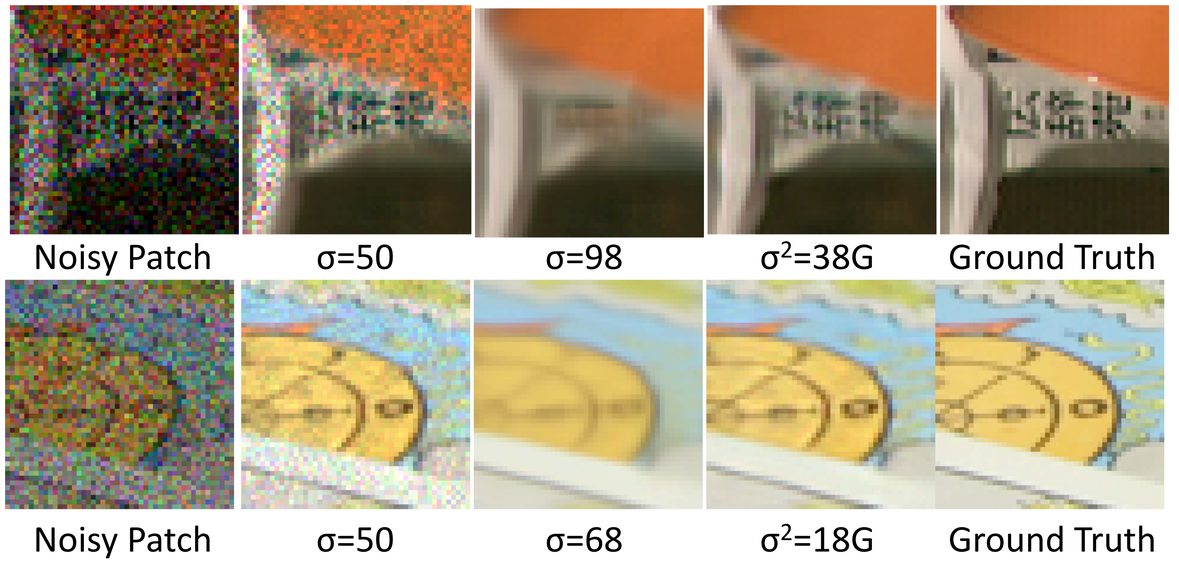
Images are captured using PointGrey DragonFly Express with its largest gain and shortest exposure.



Noisy Image | Dabov et al (BM3D) | Dabov et al (VBM3D) | Our method (Tensor) | Ground truth

Comparison between our 25-view denoising and a state-of-the-art single image denoising (BM3D applied on one image) and its extension to video denoising (VBM3D applied on all 25 images as a video sequence). This comparison suggests that if patches cannot be accurately grouped over time, additional image measurement may not contribute significantly to the denoising performance.

## Importance of Modeling Intensity-Dependent Noise Variance

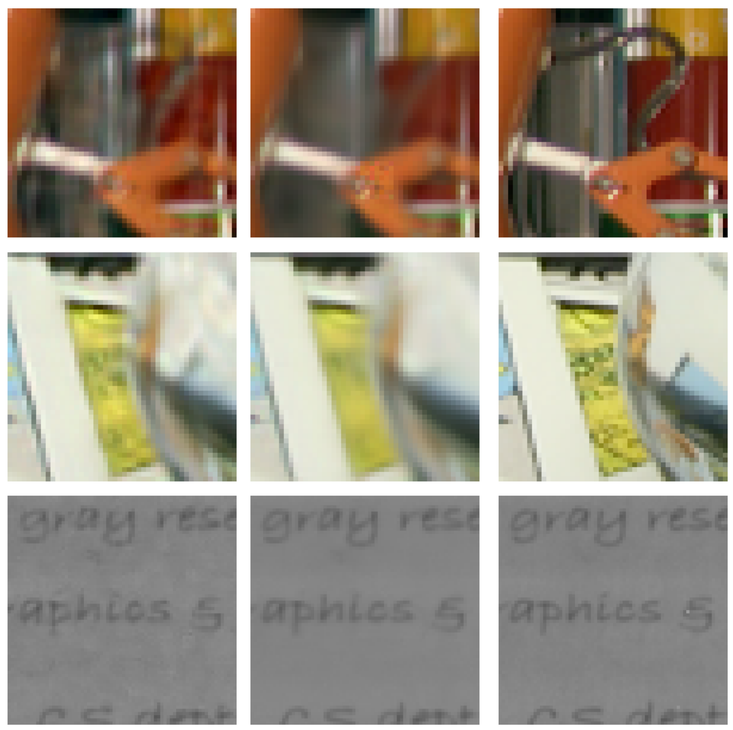


Noisy Patch | σ=50 | σ=98 | $\sigma^2$=38G | Ground Truth

Noisy Patch | σ=50 | σ=68 | $\sigma^2$=18G | Ground Truth

Comparison of multi-view denoising for images with Poisson noise using a fixed variance versus an intensity-dependent variance. Using a small and fixed noise variance keeps image details but is unable to reduces large noise over bright regions. Using a large and fixed noise variance reduces noise in all regions but over-smoothes the details in the dark regions. Using intensity-dependent variance reduces noise in all regions without loosing details in dark regions.

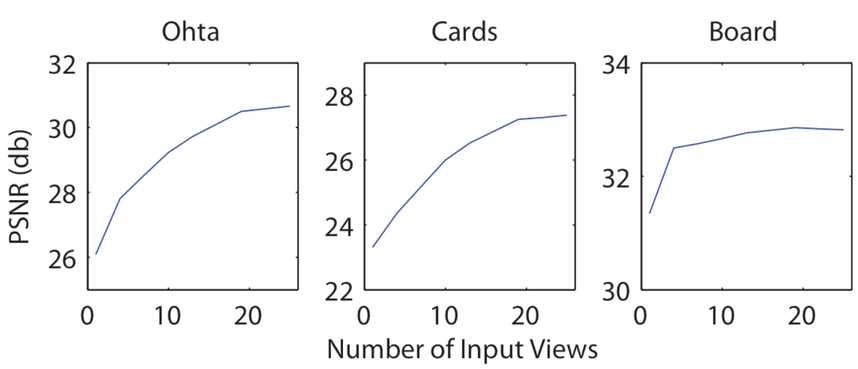
## PCA vs Tensor for Multi-view Denoising



Comparison between patch denoising using PCA versus tensor analysis.

Our method (PCA) | Our Method (Tensor) | Ground Truth

## Denoising Performance w.r.t. the Number of Views.




Intriguingly, the improvement flattens as the number of views passes 20. This phenomena is to be investigated.