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Multi-Frame Super-Resolution Imaging

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Adaptive Computational Sensing

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Outline

- Motivation
- Imaging and Sampling Theory
- Super-Resolution via Drizzle
- Super-Resolution via Nonlinear Optimization
- Trends in Super-Resolution Research
- Summary

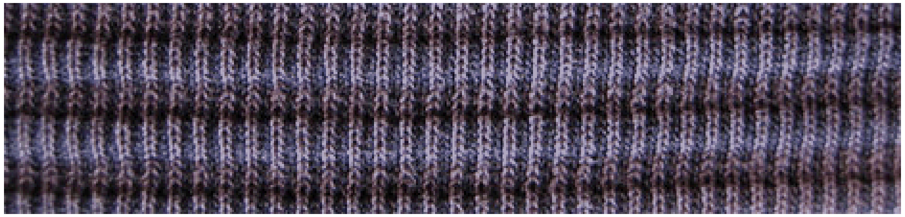
Motivation

- **Why can't we see infinitely fine detail with an imaging system?**
- **Because the resolution is limited by some component of the system.**
- **Common limitations for resolution include:**
  - Optics: The laws of physics control how small a spot can be formed.
  - Focal plane pixels: Shannon sampling theory and the finite size of the pixels limits what details can be accurately sensed.
  - Jitter: If the image is moving relative to the focal plane during the time light is collected, then the image is blurred.
    - For the purposes of this presentation we will neglect jitter.
    - Integration times are assumed to be short enough such that jitter blur does not occur.
    - For most visible imaging systems used during the day (and not held by a person), this is a good assumption.

Motivation

- **For reasons to be discussed later, the resolution of the system is usually limited by the finite size of the pixels.**
- **Rather than discuss the abstract concept of "fine details", we will discuss resolution in terms of "spatial frequency."**
  - Spatial frequency is completely analogous to temporal frequency.
  - The dimensionality of spatial frequency is reciprocal length.
  - Imaging fine details such as sharp edges or point objects requires accurately measuring high spatial frequencies.
- **When the resolution of the imaging system is limited by the size of the pixels, there are high spatial frequencies transmitted accurately by the optics but sensed incorrectly by the focal plane.**
  - The high spatial frequencies are "aliased", i.e., sensed as lower spatial frequencies.
- **Techniques exist for using multiple, aliased images and reconstructing a properly-sampled image.**
  - These techniques are known as multi-frame super-resolution techniques.

Motivation



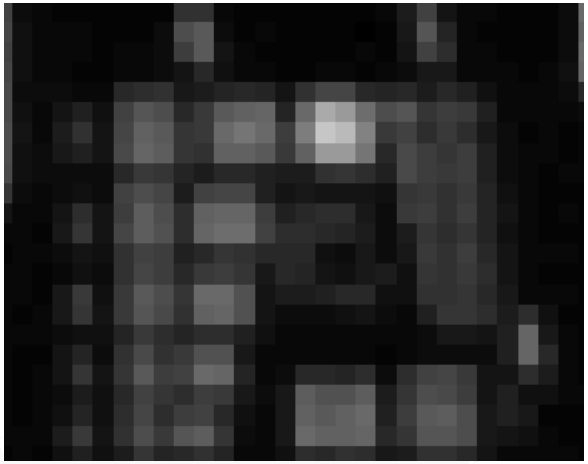
From:
http://www.hookedongolfblog.com/2006/05/13/firethorn-golf-apparel

From http://people.cs.clemson.edu/~tadavis/cs809/aa.html

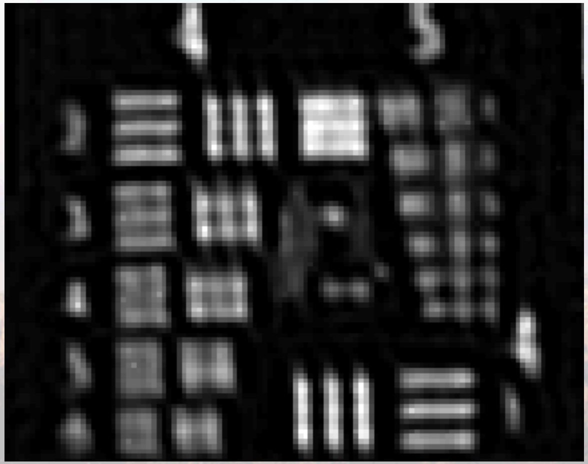
These images show extreme cases of aliasing.

Motivation – The Bottom Line

- **We can take a system whose native imagery looks like:**



- **and turn it into a system that outputs imagery like:**



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Sampling Theory

- **For an incoherent imaging system, the highest spatial frequency that the optical system can transmit is**

  $$\nu_{opt} = \frac{1}{\lambda f^{\#}}$$ **where** λ: Optical wavelength

  $f^{\#}$: f/number of the optical system (focal length divided by aperture diameter)

  - Spatial frequencies above ν_{opt} are not transmitted by the optical system.

- **The highest spatial frequency that can be sensed accurately by the detector is**

  $$\nu_{det} = \frac{1}{2p}$$ **where** p: Detector pixel pitch

  - Spatial frequencies above ν_{det} are aliased back to lower frequencies.

- **When these two frequencies are equal we have**

$$\frac{\lambda f^{\#}}{p} = 2$$

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Sampling Theory

- **Define the sampling ratio Q as $Q \equiv \dfrac{\lambda f^{\#}}{p}$.**
- **When $Q \geq 2$ the system is properly sampled.**
  - The pixel pitch is small enough that all of the spatial frequencies up to the optical cutoff frequency are sensed without aliasing.
  - For a diffraction-limited Airy disk, there are at least 2.44 pixels across the first-null diameter.
  - The resolution of the system is limited by diffraction.

- **When $Q < 2$ the system is undersampled.**
  - The pixel pitch is relatively large compared to the optical spot. Spatial frequencies below the optical cutoff frequency and above the detector cutoff frequency are aliased.
  - The resolution of the system is limited by the pixel pitch.
  - We can increase the resolution up to the point where the optics become the limiting factor.

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Undersampled Systems

- **Why not always design a system such that it is Nyquist sampled?**
- **Q depends on the focal length, aperture diameter, and pixel pitch. These parameters affect many other decisions in a design trade study.**
- **For example, the pixel pitch directly impacts the field-of-view (FOV).**
  - Using smaller pixels but maintaining the same FOV requires more pixels.
    - Data processing needs will increase.
    - Power consumption will go up.
    - Data bandwidth needs will increase.
  - Using smaller pixels but maintaining the number of pixels reduces FOV.
- **Smaller Q values produce more energy on a single pixel.**
  - Increases signal-to-noise ratio.
  - Increases integration time and hence motion-blur.
- **Smaller Q values often produce higher quality images despite the effects of aliasing[†].**

[†] R. D. Fiete, "Image quality and $\lambda FN/p$ for remote sensing systems," Opt Eng **38**, 1229-1240 (1999).

Examples of Undersampled Systems

- **Consider the following systems at a wavelength of 0.5 microns.**

Name	f/#	Pixel Pitch (μm)	Q
Ikonos 2	14.3	12	0.60
Quickbird 2	14.7	12	0.61
SkySat-1 (Skybox Imaging)	10.4	6.5	0.8
iPhone 6 or 6 Plus	2.2	1.5	0.73
Canon EOS Rebel T3i (18-55 mm lens)	3.5-5.6	4.3	0.41-0.65

- **These systems are all considerably undersampled and would have improved resolution if Q were increased to 2. Other system trades impact the decision.**
- **There may be times when improved resolution is desired.**

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Super-Resolution Imaging

- **Super-resolution techniques allow the sampling ratio Q to be effectively increased.**
- **Super-resolution refers to using a number of low-resolution images to create a single high-resolution image.**
  - The low-resolution images are usually laterally displaced by sub-pixel amounts.
  - Super-resolution algorithms have been implemented which use precise axial shifts.
    - Such algorithms are generally impractical in deployed systems due to vibrations and variations in the line-of-sight pointing angle.
- **Excellent overview articles on super-resolution techniques exist[1,2].**

[1]S. C. Park, M. K. Park, and M. G. Kang, "Super-resolution image reconstruction: A technical overview," IEEE Signal Proc Mag **20**, 21-36 (2003).
[2]J. Tian and K. K. Ma, "A survey on super-resolution imaging," Signal, Image and Video Processing **5** (3), 329-342 (2011).

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Drizzle

- One commonly used super-resolution algorithm is Drizzle†.
- It was developed by Fruchter and Hook for use with the Hubble Space Telescope.

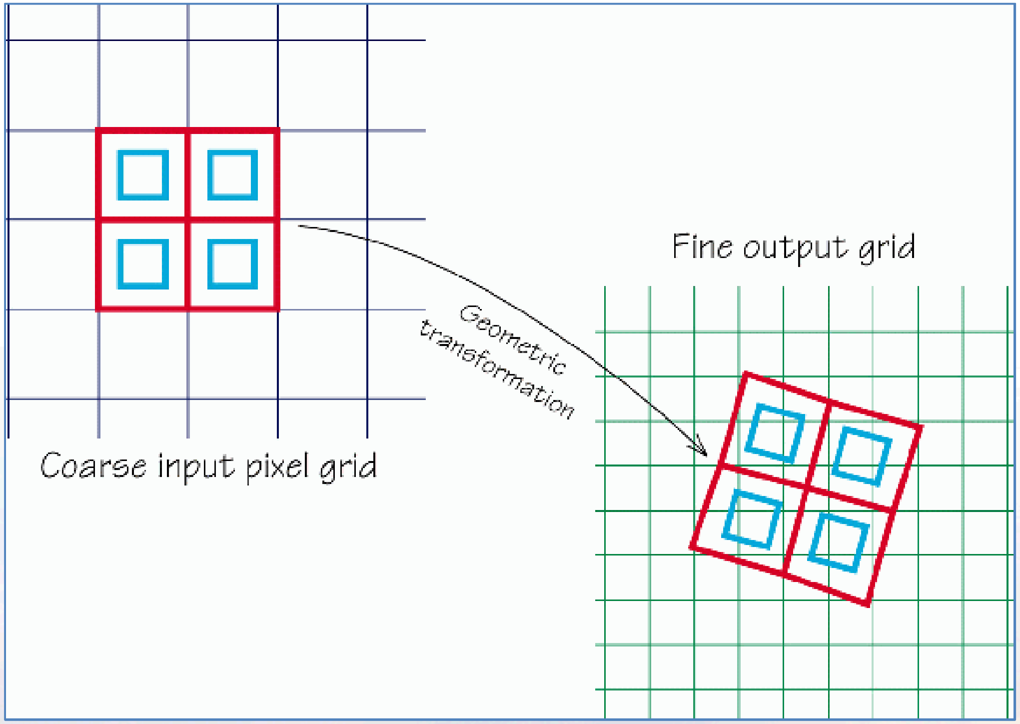
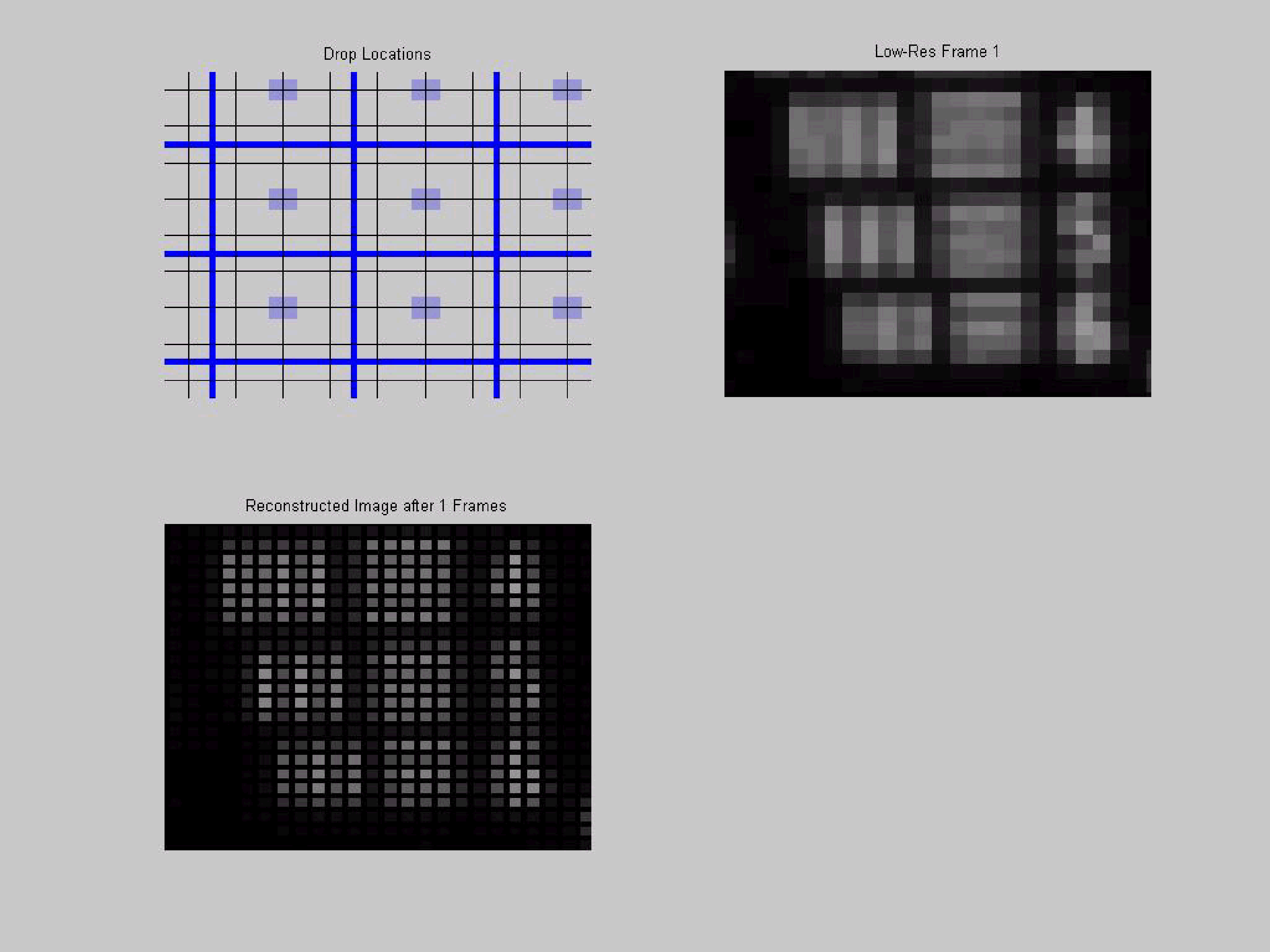


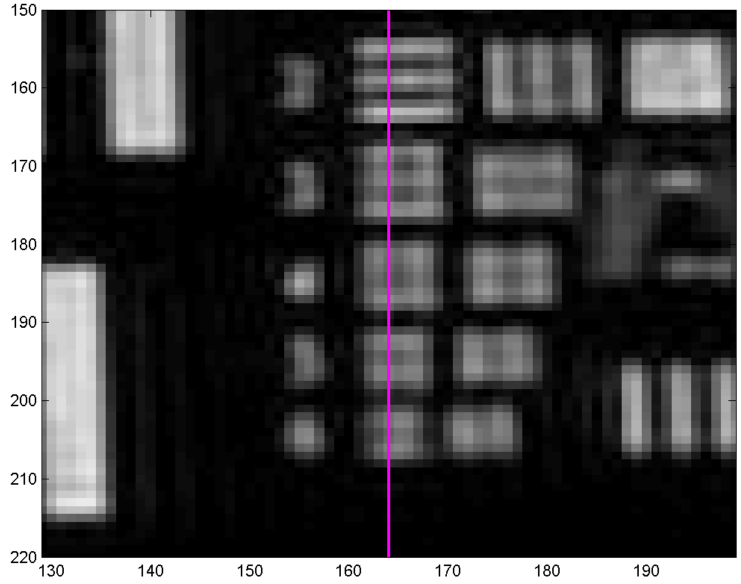
Image from http://www.stsci.edu/~fruchter/dither/drizzle.html

† A. S. Fruchter and R. N. Hook, "A novel image reconstruction method applied to deep Hubble Space Telescope images," Proc SPIE **3164**, 120-125 (1997).

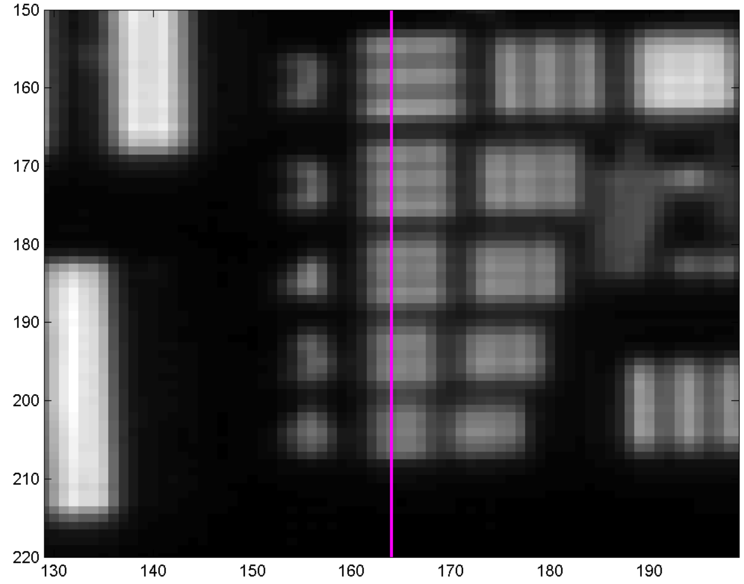
Drizzle Simulation



Drizzle Simulation

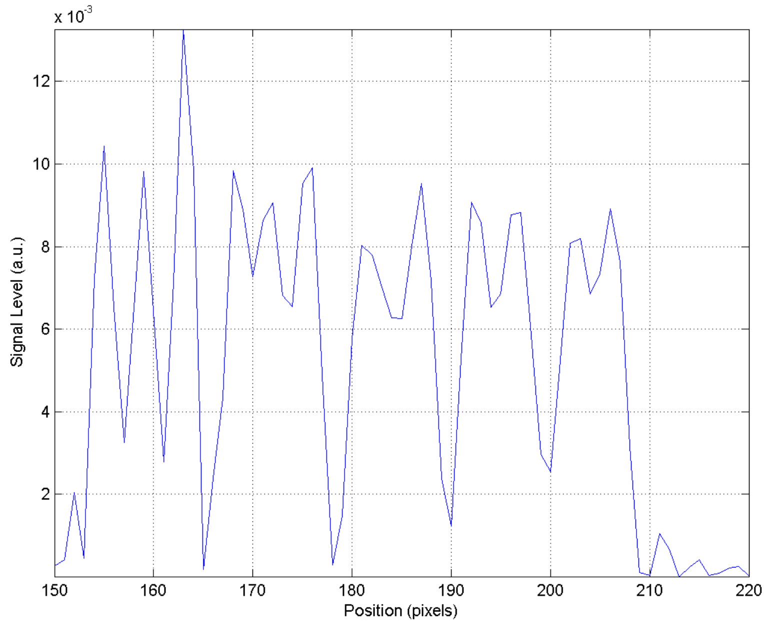


Reconstructed Image

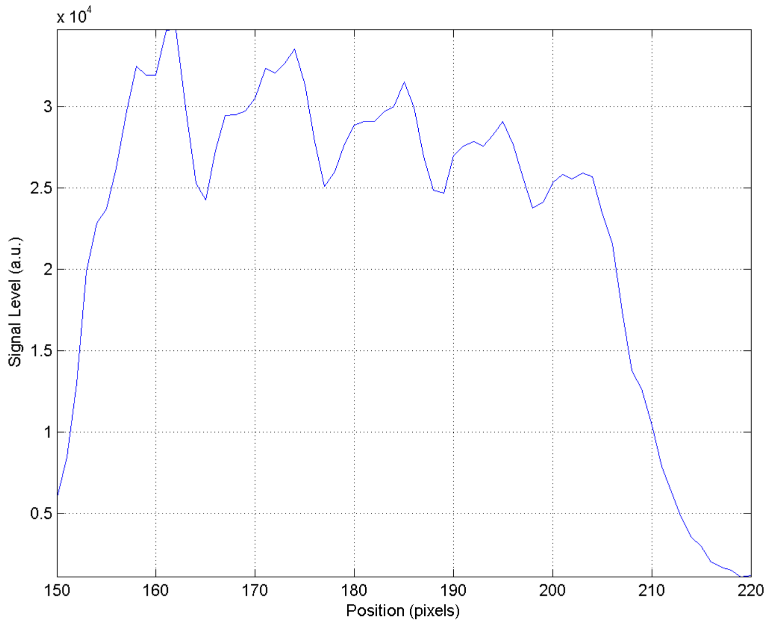


Best Focus Measurement

Drizzle Simulation – Slices



Reconstructed Image



Best Focus Measurement

- The three-bar pattern is not visible for any of the groups for the best focus measurement.
- The three-bar pattern is discernible for two of the groups in the reconstructed image.
  - Higher-spatial frequencies are present in the reconstructed image.

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Drizzle Limitations

- **The Drizzle algorithm only corrects for the effects due to the undersampled nature of the system.**
- **Blurring due to the optics remains.**
- **If we know the optical point-spread function (i.e., how the optics blurs an image), we can correct for that as well.**
  - Phase-diverse phase retrieval techniques can be used to determine the optical point-spread function for undersampled systems[1-3].
- **Similar effects such as focal plane charge diffusion can be corrected in post-processing as well.**

[1] E. A. Shields, *Opt Lett* **37**, 2463-2465 (2012).
[2] E. A. Shields, *Computational Optical Sensing and Imaging*, OSA Technical Digest (online) paper CTu2B.4 (2012).
[3] E. A. Shields, *Proc. of SPIE,* **8499** *(2012).*

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Super-Resolution via Nonlinear Optimization

- **While the Drizzle algorithm is fast and simple, it is not necessarily the most accurate algorithm.**
- **A commonly-used technique that potentially provides better results uses non-linear optimization techniques to estimate the high-resolution image.**
- **An objective function is defined and minimized. This objective function provides a metric for the difference between:**
  - 1) the estimated high-resolution image blurred by the system imaging model and then downsampled to the focal plane pixel pitch
  - 2) the measured undersampled images
- **If relatively few frames of data are available, the super-resolution problem is ill-posed and regularization terms are used to constrain the solution.**

Super-Resolution via Nonlinear Optimization

- **Mathematically, we represent the objective function via:**

$$J(z) \equiv \sum_{k=1}^{K} \mathrm{N}\left(\mathbf{DC}(\theta_k) z - d_k\right) + \mathrm{R}(z)$$

where

z denotes the high-resolution image estimate

k enumerates the K undersampled images

d_k denotes the measured, undersampled images

θ_k denotes the lateral shifts for the k$^{\text{th}}$ undersampled image

$\mathbf{DC}(\theta_k)$ converts a high-resolution image into an undersampled image via translation, convolution, and downsampling

N is commonly chosen to be either the ℓ^1 or ℓ^2-norm function

$\mathrm{R}(z)$ is an image regularization function

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Super-Resolution via Nonlinear Optimization

$$J(z) \triangleq \sum_{k=1}^{K} \mathrm{N}\left(\mathbf{DC}(\theta_k) z - d_k\right) + \mathrm{R}(z)$$

- **The goal is to find the high-resolution image z that minimizes J.**
- **The number of variables is equal to the number of pixels in the high-resolution image.**
  - Reconstructing a 1024x1024 image requires optimizing over 1 million variables.
- **To efficiently perform this minimization, the gradient of J with respect to z is necessary.**
  - Techniques that do not use gradient information are much too slow.
  - Techniques that use first-order derivative information (e.g., conjugate gradient optimization) can efficiently handle this problem.

Super-Resolution via Nonlinear Optimization

- **The traditional super-resolution technique assumes that the imaging model is known precisely.**
  - This usually means that an image registration step is performed to determine the θ_k parameters.
- **If the image registration algorithms fails, the super-resolution reconstruction is quite poor.**
- **Recently, Drew Kouri (1441) and I extended this technique to include simultaneous optimization of the lateral shifts†.**
- **New analytic derivative terms were calculated.**
  - $\frac{\partial J}{\partial z}$ already existed in the literature.
  - We calculated $\frac{\partial^2 J}{\partial z^2}, \frac{\partial J}{\partial \theta}, \frac{\partial^2 J}{\partial \theta^2}, \frac{\partial J^2}{\partial z \partial \theta}$, and $\frac{\partial J^2}{\partial \theta \partial z}$.
  - $\frac{\partial^2 J}{\partial z^2}$ is useful for the traditional, image-only problem. If an ℓ^2 norm is used, $J(z)$ is quadratic and Newton-methods can be used for very efficient minimization.

†D. P. Kouri and E. A. Shields, "Efficient multiframe super-resolution for imagery with lateral shifts," Applied Optics **53** (24), F1-F9 (2014).

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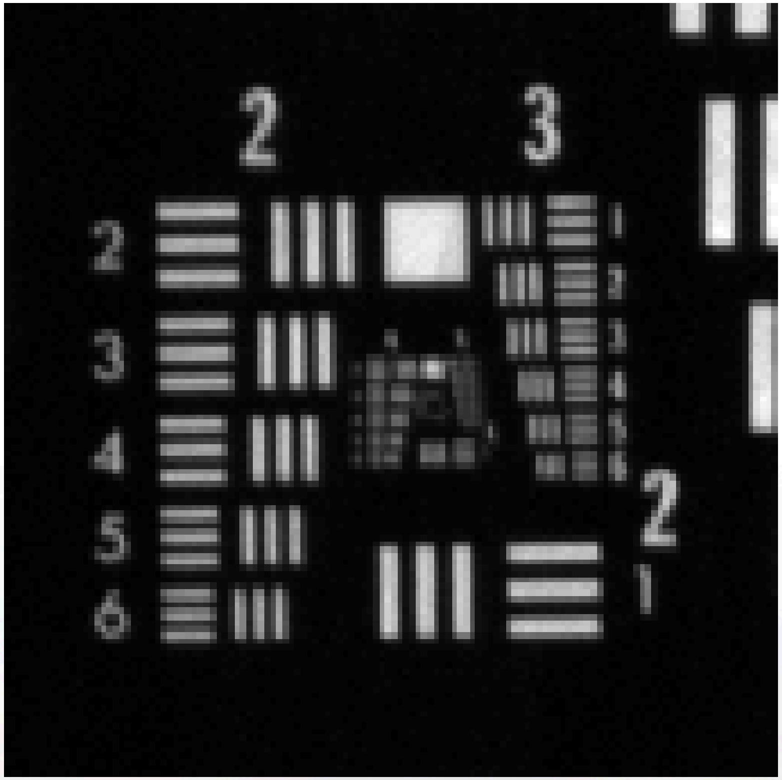
Super-Resolution Results

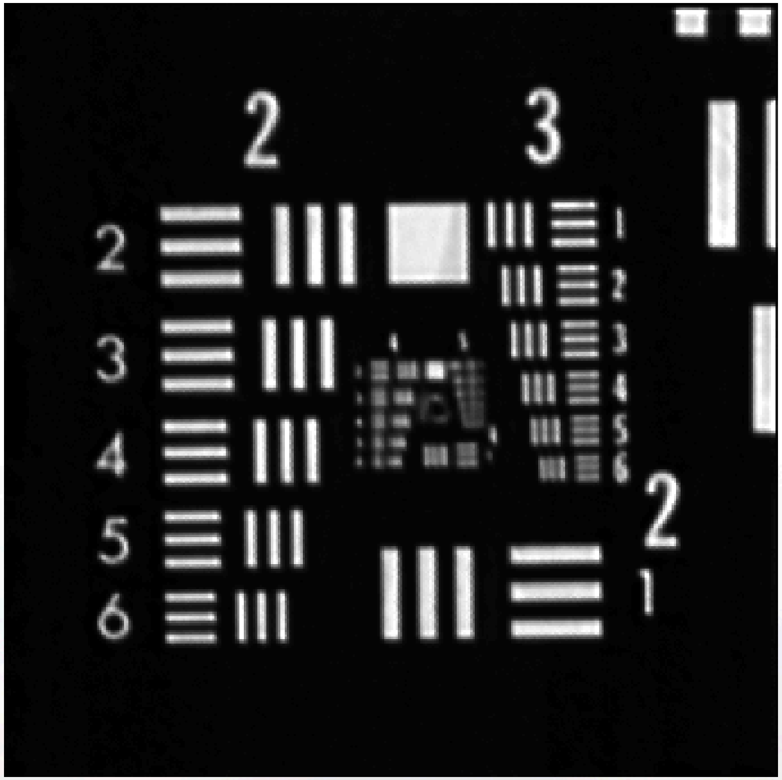
- **Measured data from an unclassified optical testbed system were used.**
  - The optical point-spread function was known from interferometric measurements.
  - 50 frames with a Q of 0.75 were used.
  - 3X super-resolution was performed.
- **The Drizzle algorithm was used in the following manner:**
  - Initial image registration
  - Drizzle super-resolution reconstruction
  - Deconvolution to mitigate the effects of optics and slight blurring terms associated with the Drizzle algorithm itself.
- **The optimization algorithm was used in the following manner:**
  - The initial estimates for the lateral shifts were all zero.
  - The initial estimate for the high-resolution scene was an interpolated version of a single low-resolution scene.
  - Lateral shifts and pixel values were optimized simultaneously.
  - A final optimization over pixel values was performed.

Measured Low-Resolution Image



50 such images, slightly displaced from each other, were used.

(U) Drizzle Algorithm Reconstruction



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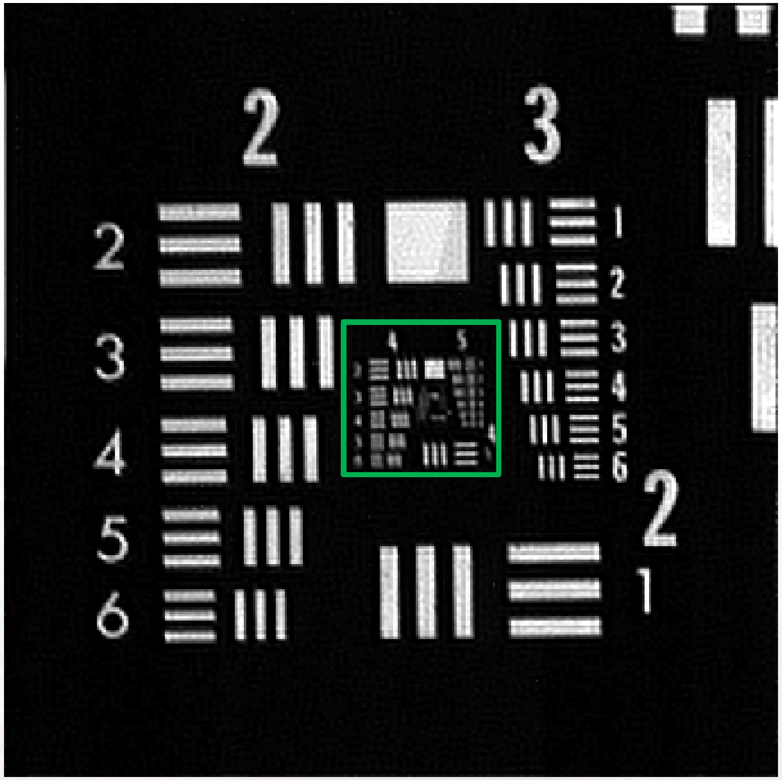
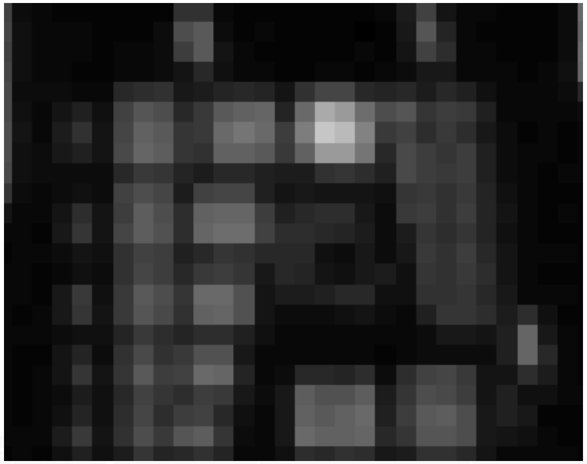
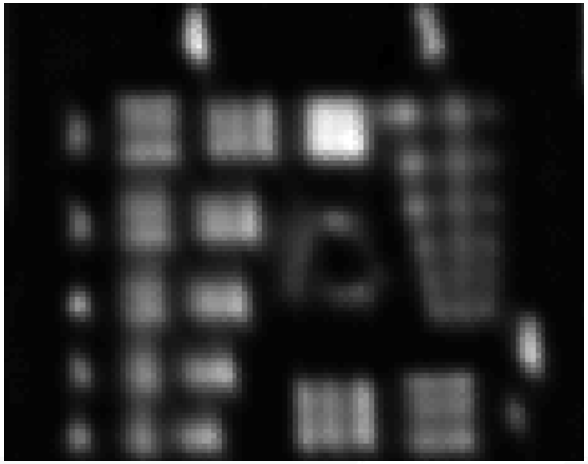
(U) Optimization Algorithm Reconstruction



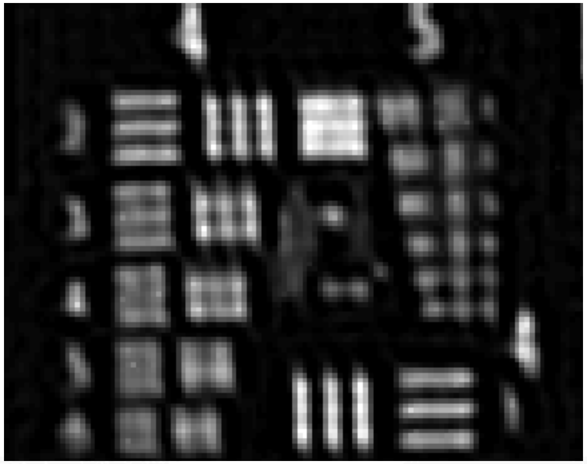
Reconstructions



Low-Resolution Image



Drizzle Reconstruction



Optimization Reconstruction

- **The optimization reconstruction clearly does a better job reconstructing high-spatial frequency content.**
- **Re-running the Drizzle algorithm with registration parameters obtained via the optimization algorithm does not noticeably change the Drizzle result.**

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Ongoing Super-Resolution Research

- **Bryan Arguello (5773) is continuing our super-resolution research while obtaining his PhD.**
- **Currently we are investigating adding image rotation to our simultaneous minimization of pixel values and lateral shifts.**
  - Can we analytically calculate the derivative of the objective function with respect to image rotations?
- **We would also like to investigate utilization of Automatic Differentiation (AD) techniques for super-resolution.**
  - AD allows specialized software analysis tools to perform gradient calculations analytically without analytic derivations.
  - This could potentially allow for efficient optimization of the objective function for much more complex motion models.
- **The underlying formulation of the super-resolution problem assumes Gaussian noise.**
  - For imaging systems, Poisson-distributed noise may be more appropriate.
  - How do we efficiently model Poisson-distributed noise systems?

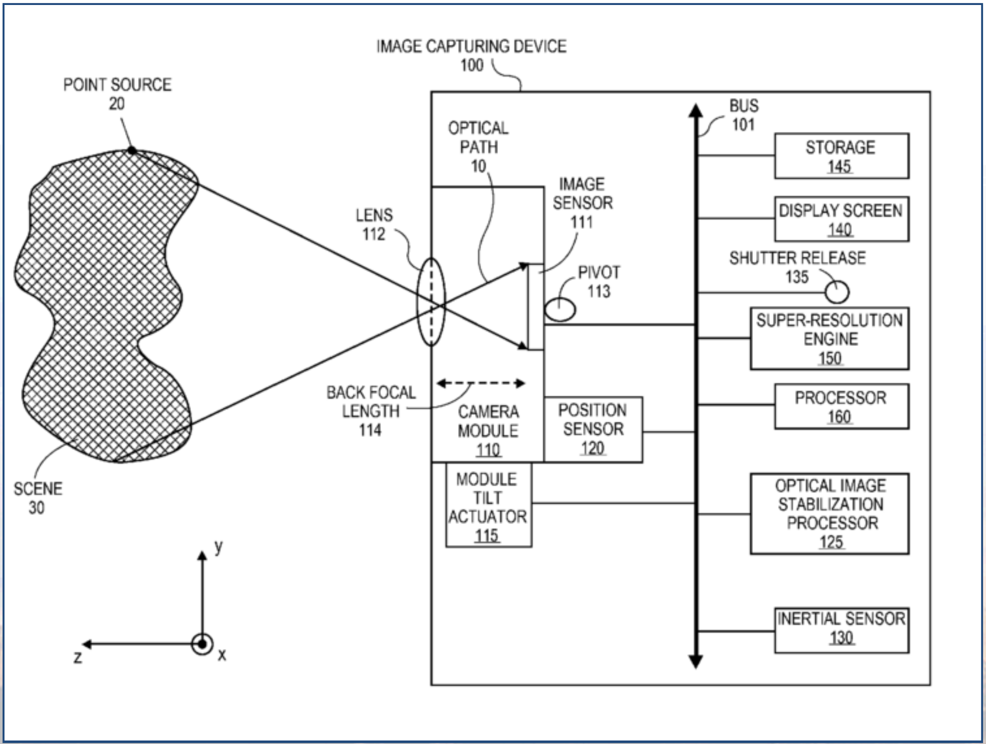
Trends in Super-Resolution Research

- **For the case where relatively few frames of data exist, the super-resolution problem is ill-posed.**
  - Regularization techniques are employed to constrain the solution.
  - Research into appropriate regularization functions is ongoing.
- **Efforts for super-resolution video reconstruction are underway as well.**
  - Traditional techniques simply use a sliding window.
  - A variety of techniques are being studied to either improve calculation speed or reconstruction accuracy.
- **Multi-frame super-resolution has been shown with an array of detectors rather than multiple frames from the same detector[†].**

[†]Charles Guillem, *et al*, "Super-resolution imaging using a camera array," Opt Lett **39**(7), 1889-1892 (2014).

Trends in Super-Resolution Research

- **Apple has apparently been exploring super-resolution imaging for smartphones.**
- **It looks like they are studying using a prism to precisely tilt the image on the focal plane array.**
- **Patent number 20140125825 filed November 8, 2012, published May 8, 2014.**



Trends in Super-Resolution Research

- **Multi-frame super-resolution techniques have been shown to effectively increase the resolution of terahertz imaging systems with pulsed and continuous wave sources[1].**
- **Super-resolution techniques are also being studied for magnetic resonance imaging (MRI)[2].**
  - It is often faster to acquire two-dimensional slice stacks of images rather than true 3D volumes.
  - In such cases super-resolution techniques can be employed.
  - New trades between resolution, signal-to-noise ratio, and acquisition time can be made.

[1] Li-Min Xu, *et al*, "High-resolution reconstruction for terahertz imaging," Appl Opt **53**(33), 7891-7897 (2014).
[2] Esben Plenge, *et al*, "Super-resolution methods in MRI: Can they improve the trade-off between resolution, signal-to-noise ratio, and acquisition time?" Magnetic Resonance in Imaging **68**(6), 1983-1993 (2012).

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Summary

- **Many remote sensing imaging systems are designed such that the pixels are relatively large compared to the size of the optical spot.**
  - Such systems are called undersampled.
  - The resolution of undersampled systems is limited by the pixel size.
  - Aliasing artifacts may be present in undersampled systems since the optical system transmits spatial frequencies that exceed what the detector can measure.
- **Multi-frame super-resolution techniques can be used to improve the spatial sampling.**
  - Increased resolution is not free. Costs include:
    - Considerably more data need to be collected.
    - The image must somehow be moved by small amounts on the detector.
    - Image registration is required.
    - Considerable processing may be necessary for the super-resolution algorithm itself.

Summary

- **What can multi-frame super-resolution do?**
  - Provide a high-resolution reconstruction when multiple, jittered, undersampled frames are available.
  - Provide a high-resolution reconstruction of a moving target when multiple, undersampled frames are available.
    - The motion of the target is used in lieu of motion of the scene.
    - The reconstructed background will be quite blurry.
- **What can multi-frame super-resolution not do?**
  - Improve the resolution of a single frame of data.
  - Improve the resolution of a properly-sampled system.
  - Improve the resolution beyond the point where the system resolution is limited by the optics.