
EE6221 Robotics and Intelligent Sensors (Part 3)

Lecture 2: Vision Sensors and Systems

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Outline

- Introduction
- Application scenarios
- Cameras
- Pinhole camera model
- Camera calibration
- For reference reading:
 - Color space representations
 - Useful image processing methods

Application Scenarios of Camera Sensors

- Vision-based control
- Vision-based estimation
- Vision-based navigation
-

Academic Examples



Vision-guided tracking examples



Vision-guided robot navigation

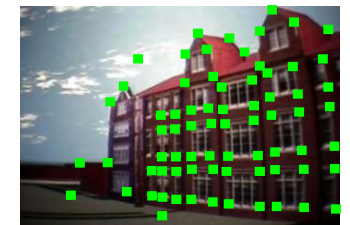
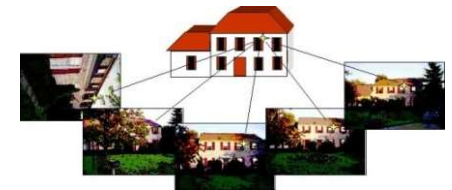
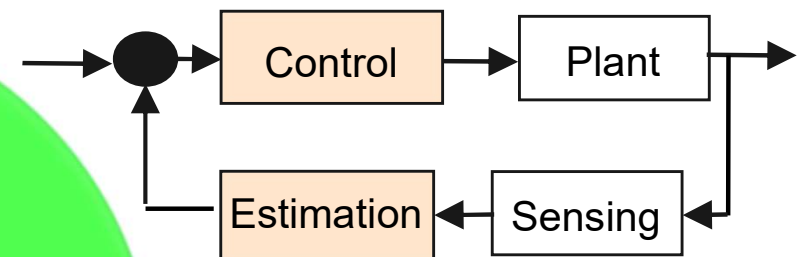
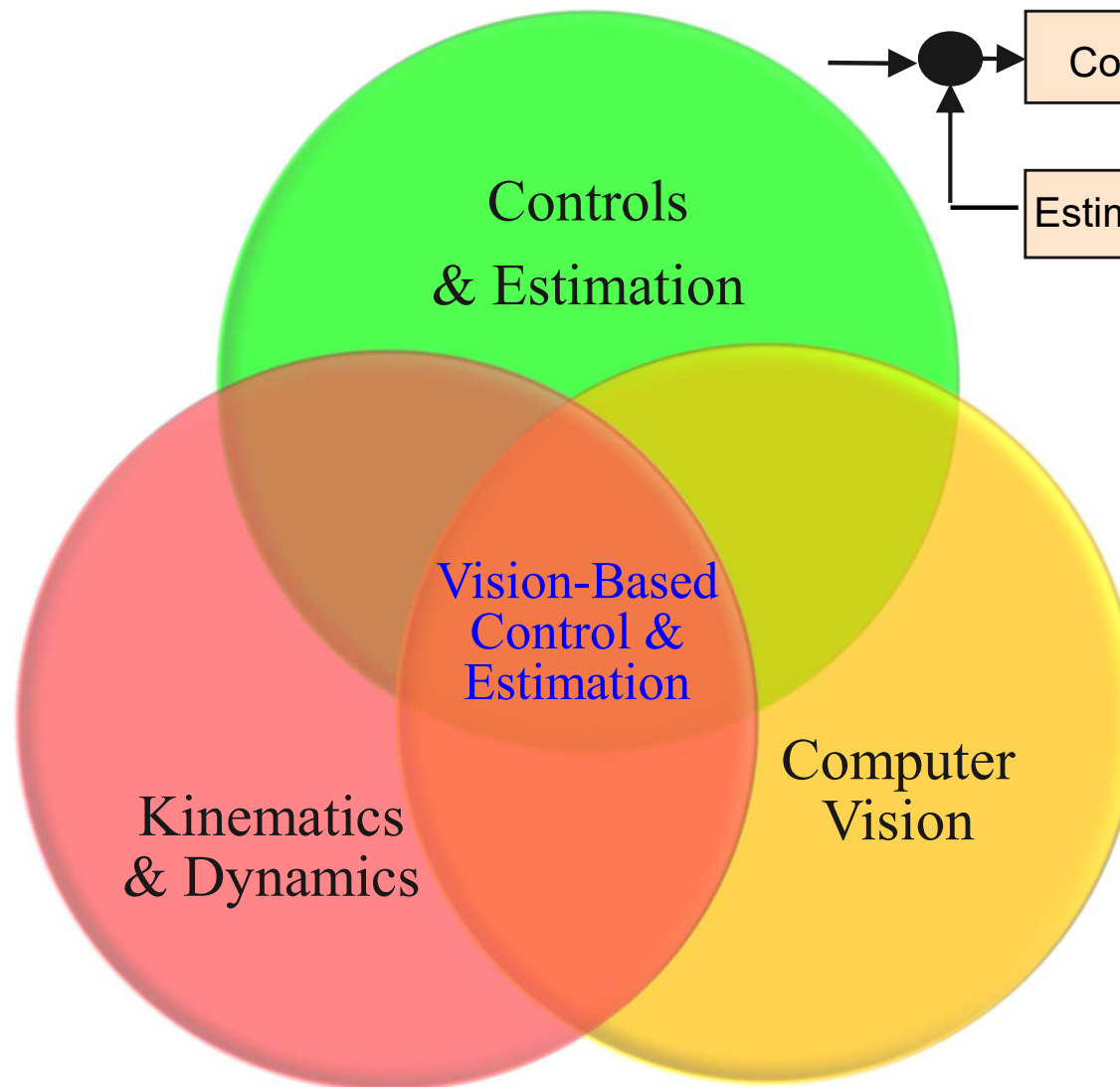
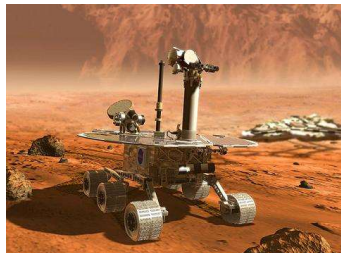
Recent Examples



Mobile Aloha (Stanford University and Google)

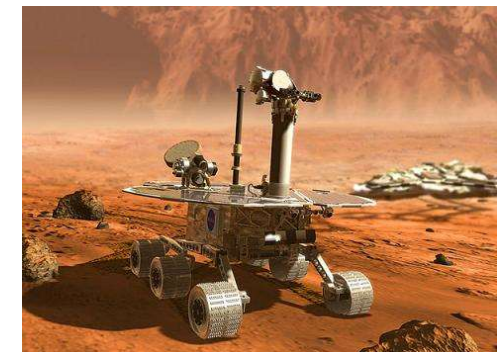
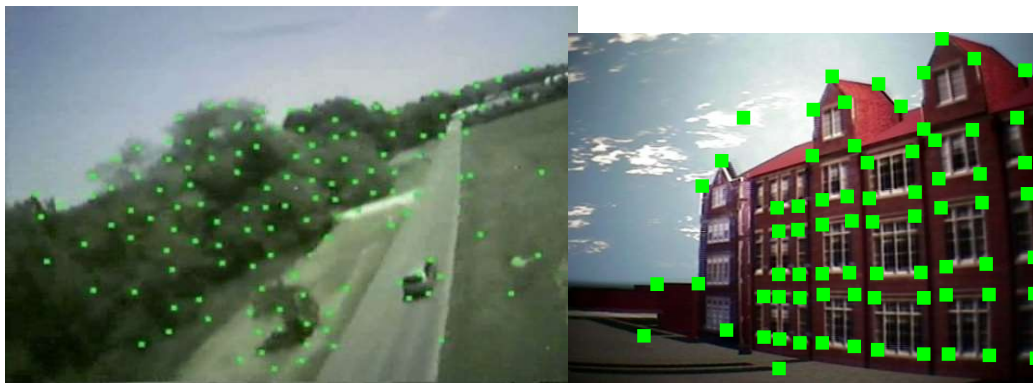
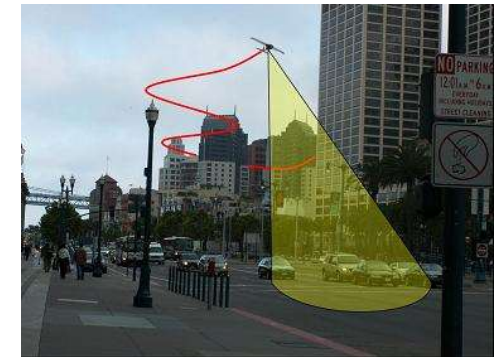
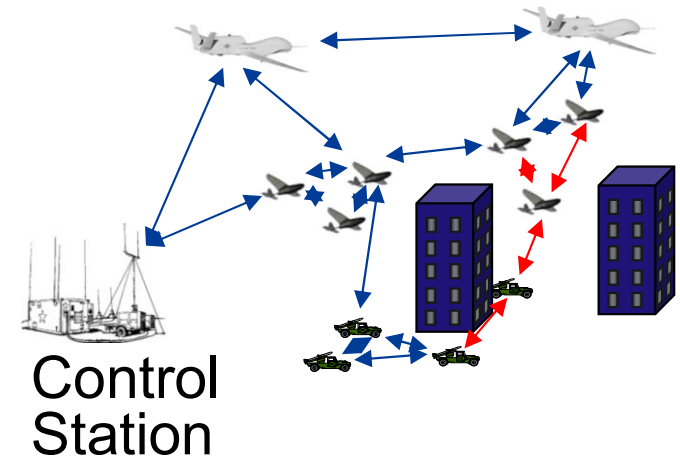
Vision-Based Control & Estimation

- **Vision-based control and estimation:** use of image data in feedback control and state estimation of moving agents (e.g., robot manipulators, mobile robots, or unmanned vehicles, etc).



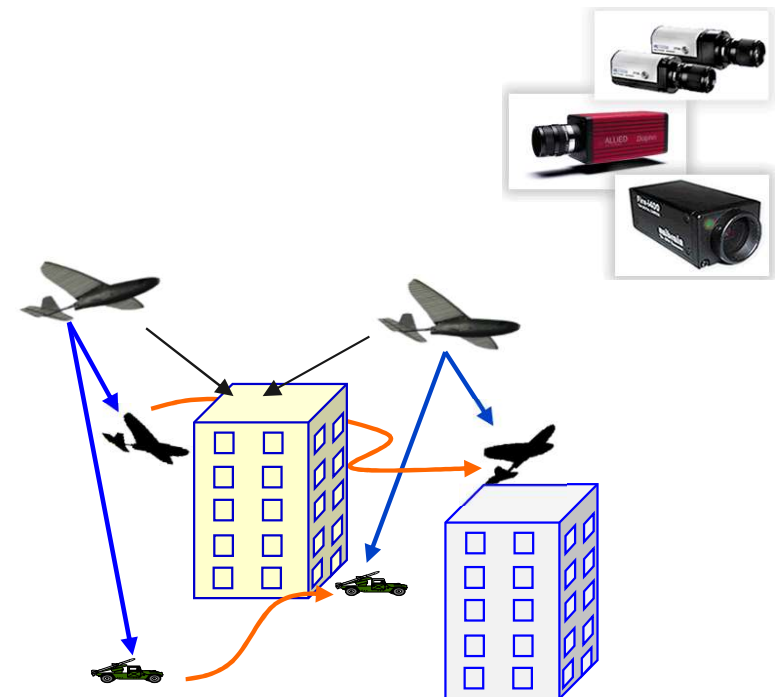
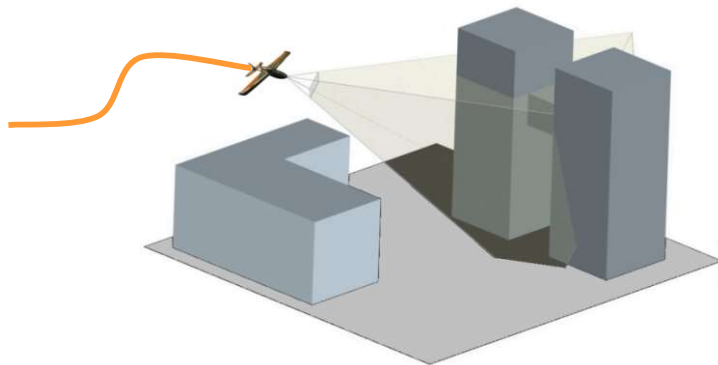
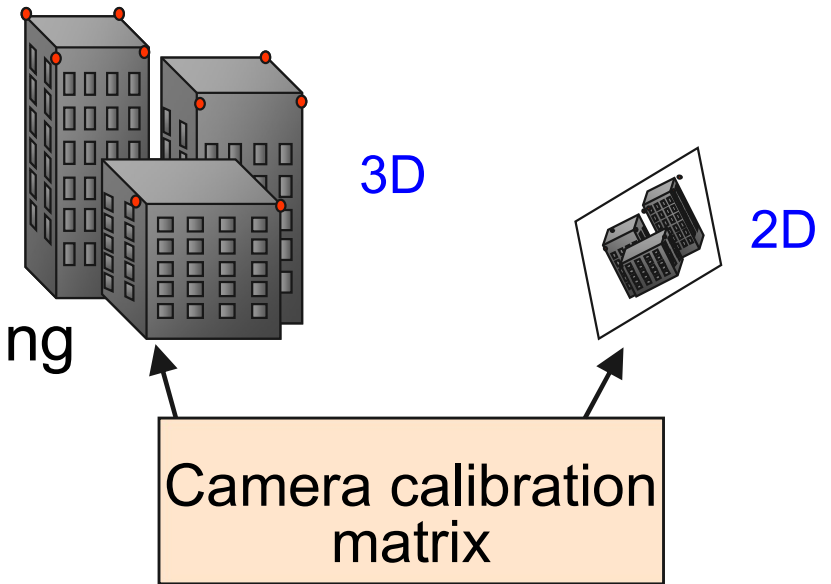
Motivation – Vision-based Control

- **Why study vision-based control (also called visual servo control)?**
 - Position & orientation is typically required in navigation and control of autonomous vehicles
 - GPS may not be available, IMU has error drift
- **Advantages of vision:**
 - Vision is a rich data set, a lot of potential information
 - Vision is a passive sensor, can't be detected like sonar, radar, laser, etc.
 - Vision is intuitive to humans
 - Cameras are relatively cheap and versatile

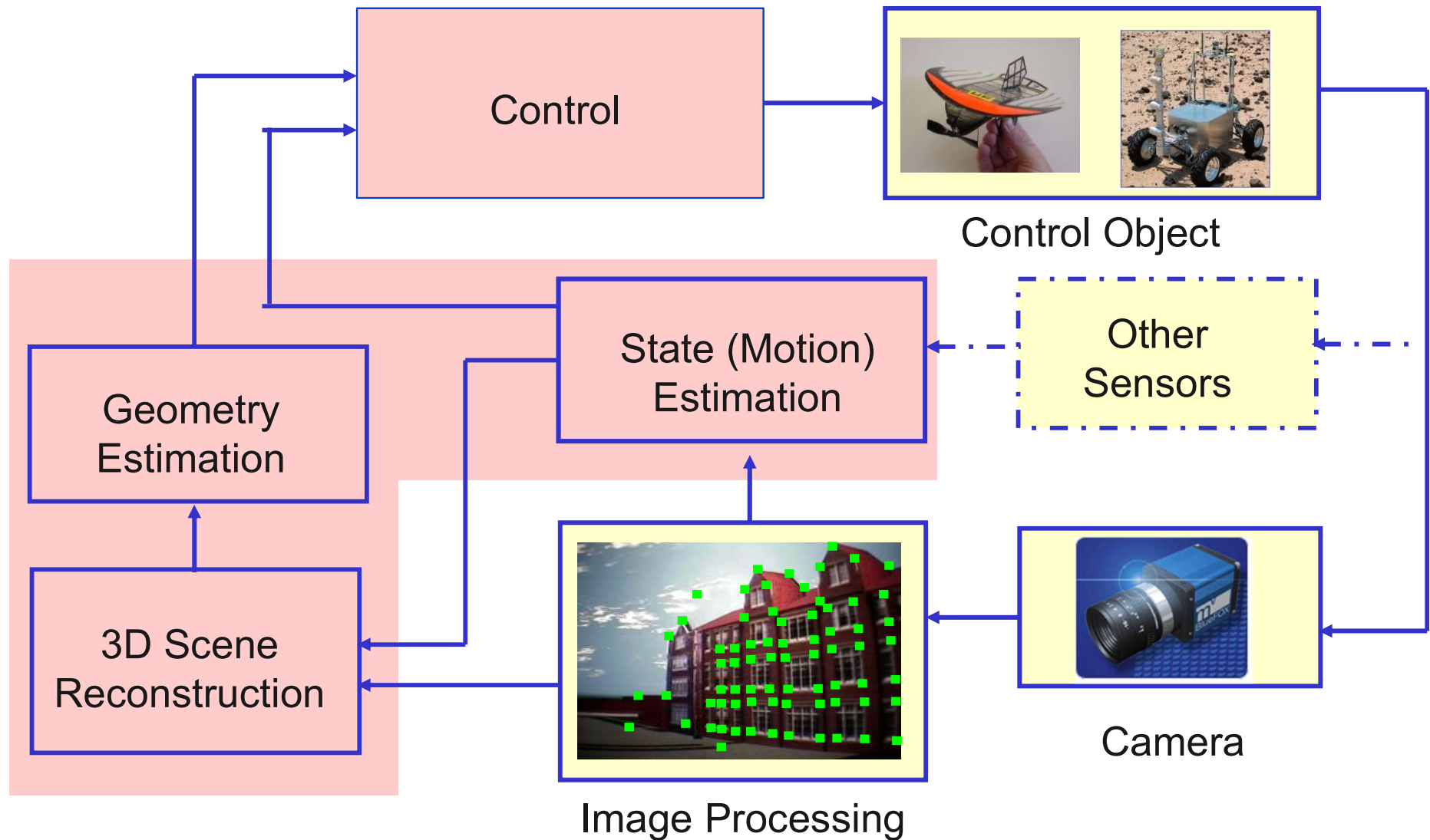


Challenges – Vision-based Control

- Robust and real-time vision estimation
- Feedback through a transformation: from 3D to 2D
- Loss of depth information during imaging projection
- Camera calibration uncertainty
- Limited field of view
- Relative motion between targets
- Nonlinear, multivariable differential equations with unmeasurable states



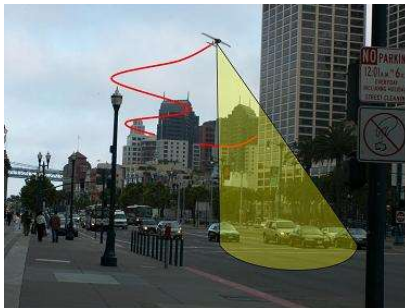
Vision-Based Control & Estimation



Applications

Systems:

- Autonomous ground vehicles
- Smart cars
- Unmanned air vehicles
- Mobile sensor networks
- Nano/micro manipulation
- Mobile manipulators
-



Imaging-Introduction

- Cameras are composed of several key components
 - The lens collects and focuses light
 - Imaging surface measures intensity/frequency of light
- We will discuss **simple models for imaging** that are accurate especially when using quality cameras
- We will discuss **camera calibration**, which is essential for image based pose and structure estimation, and can increase the accuracy of simple models, even for low quality cameras
- We will discuss common, simple **image processing routines** that may prove useful

Imaging-Introduction

Reference Books:

- Computer Vision: A Modern Approach, by Forsyth and Ponce
- Computer and Robot Vision, by Haralick and Shapiro
- An Invitation to 3-D Vision by Ma, Soatto, Kosecka and Sastry

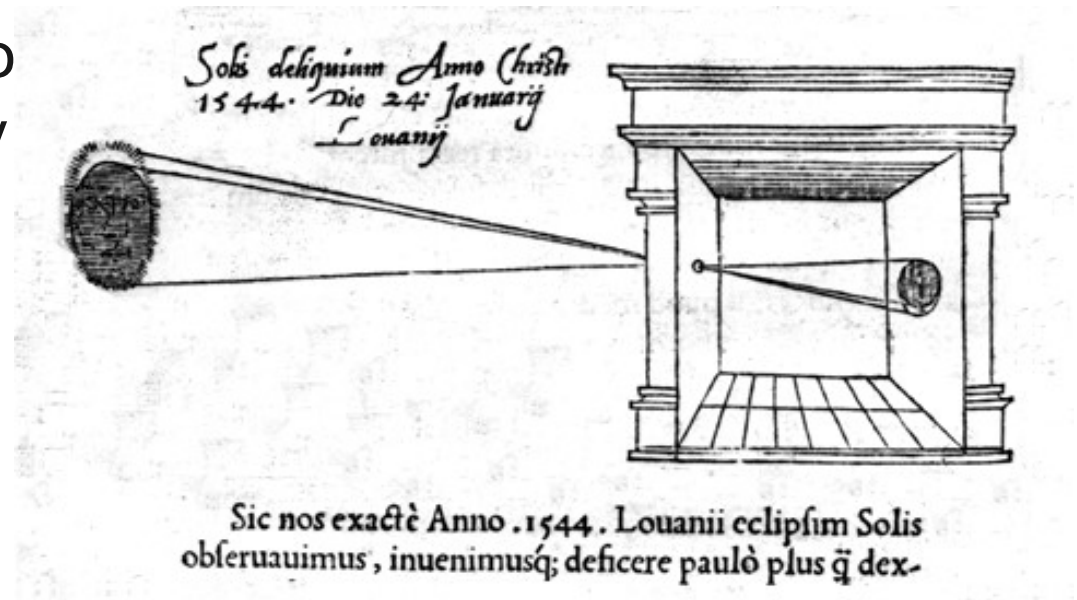
Imaging-Introduction

Free software resources for image processing:

- Intel Open Source Computer Vision Library for C++ (OpenCV)
 - <http://www.intel.com/technology/computing/opencv/>
- Machine Vision Toolbox for Matlab
 - <http://www.petercorke.com/Machine%20Vision%20Toolbox.html>
- Camera Calibration Toolbox for Matlab
 - http://www.vision.caltech.edu/bouquetj/calib_doc/
- Image Processing Toolbox for Matlab
 - Included in most full versions of Matlab
- GNU Image Manipulation Program (Image Processing)
 - <http://www.gimp.org/>
- Virtual Dub (Video Processing/Editing)
 - <http://www.virtualdub.org/index>

Camera History

- The **Pinhole Camera Model** was discussed by Aristitotle and Euclid in 3rd Century BC
- Ibn al-Haitham is credited with building the first pinhole camera (camera obscura) in 10th Century AD
- Giovanni Battista della Porta first added a lens to focus light in 15th Century
- Boyle and Hooke made portable models in 17th Century
- First photograph was by Niépce in 1826
- First color photo by Maxwell in 1861



Reinerus Gemma-Frisius, 1544

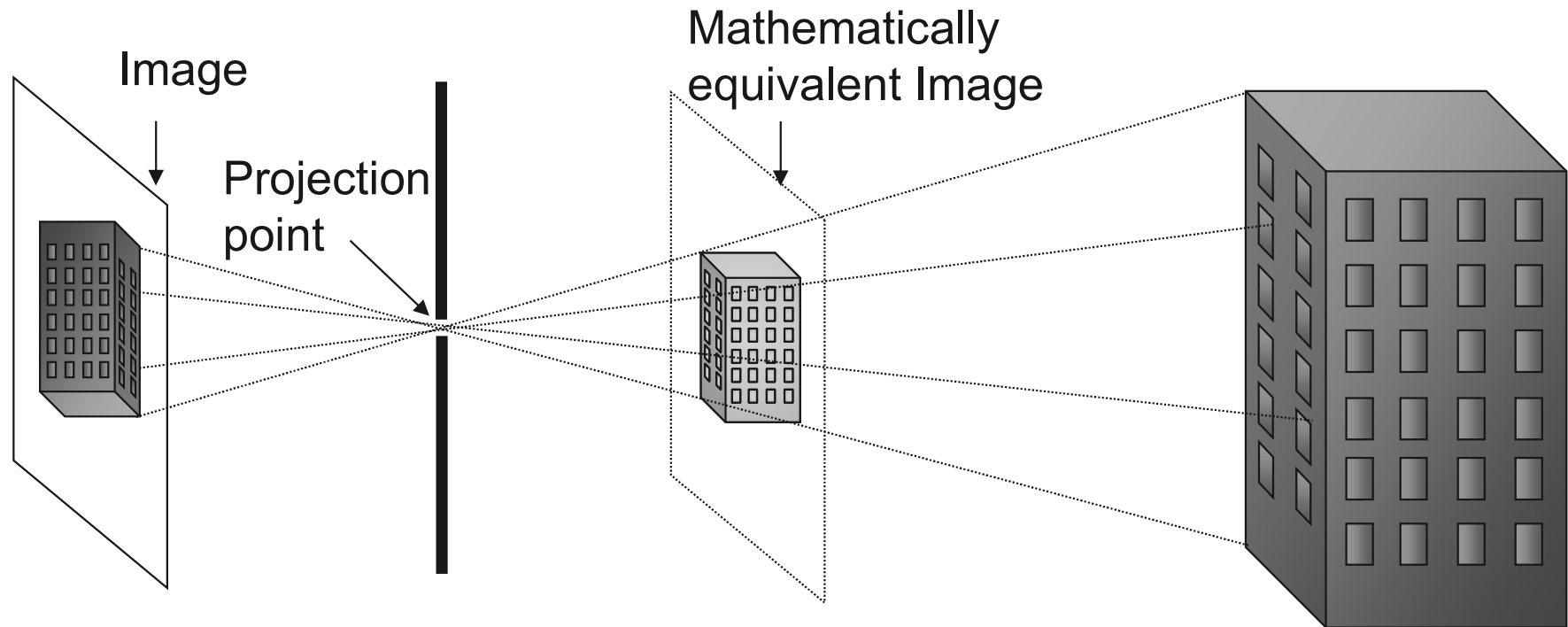
Camera History

- First **flexible film** developed by Eastman Kodak 1885
- First electronic camera (precursor to TV cameras) developed by Farnsworth in 1927
- Video tape recorders introduced in 1951 by Bing Crosby Enterprises
- First digital camera built by Sasson w/ Eastman Kodak in 1973
- First commercial **digital camera** by Eastman Kodak in 1991 (\$13K!)



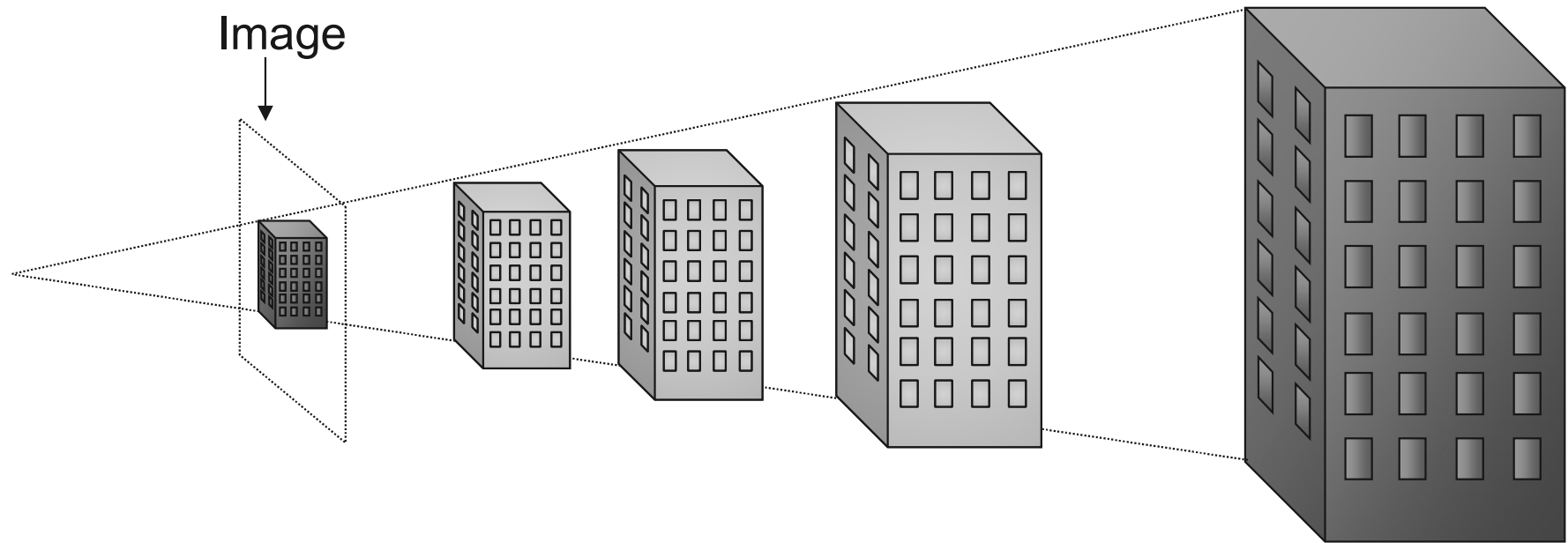
Kodak DCS-100, 1991

Pinhole Projection Model



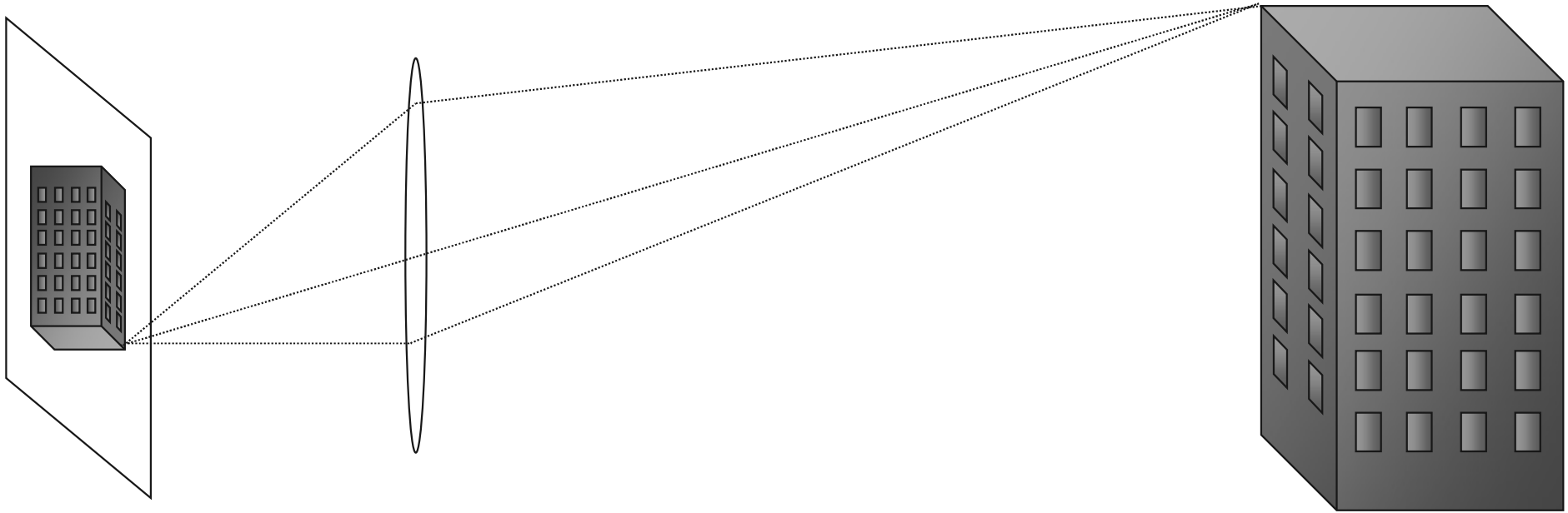
- Rays from every point in the scene intersect at the projection point and continue through to the imaging surface
- Results in an inverted image
- Mathematically, we can consider an imaging surface in front of the projection point, which is not inverted

Pinhole Projection Model



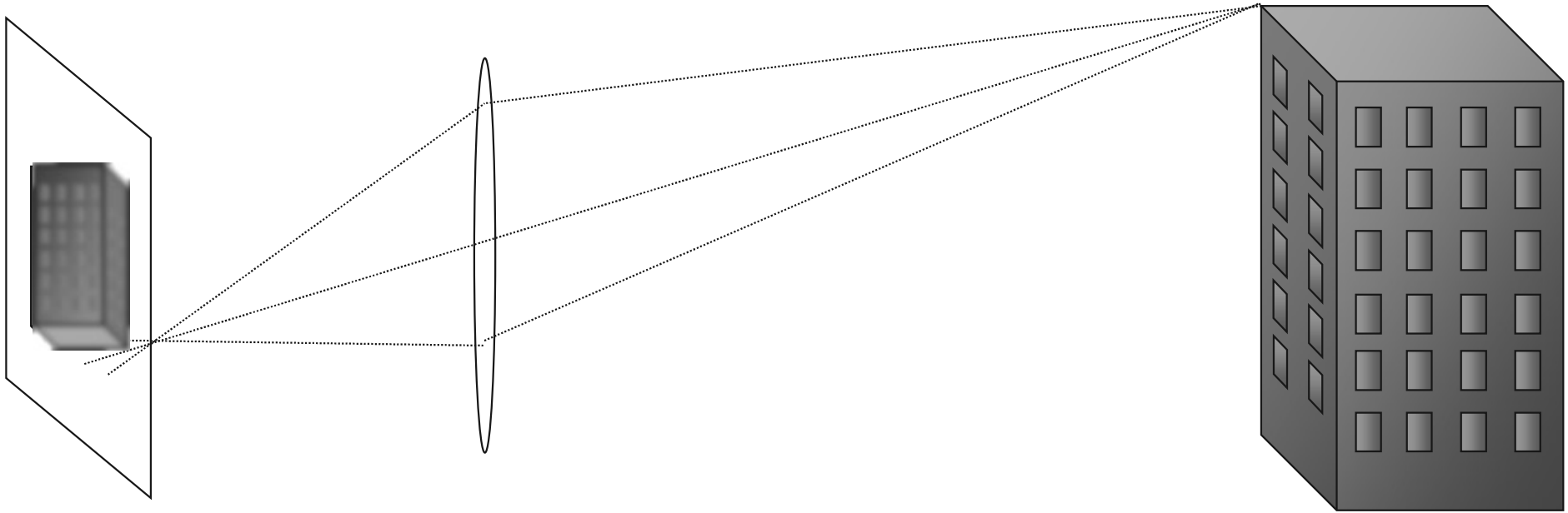
- All point along the rays intersect the image plane at the same point
- This results in a loss of size and depth information
- A priori knowledge or additional sensors/measurements can determine scale
- Fundamental drawback to imaging as a sensor

Perfect Lens Projection Model



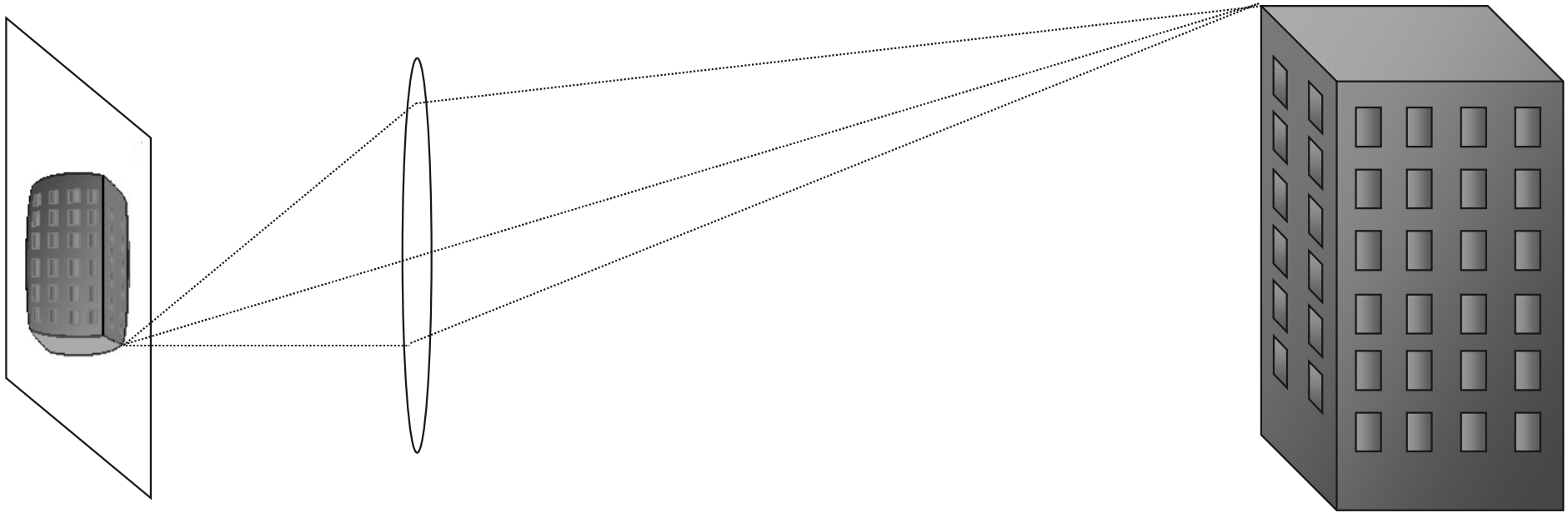
- A lens collects light by focusing many rays from a 3D point to same point on image plane
- A perfect lens is identical to the pinhole camera model at a specific focal length

Imperfect Lens Projection



- If the distance between the lens and imaging surface is not correct, rays from a 3D point will not be focused to a single point on the image
- This results in a blurred image
- Images can be sharpened, but not of much use in estimation and control

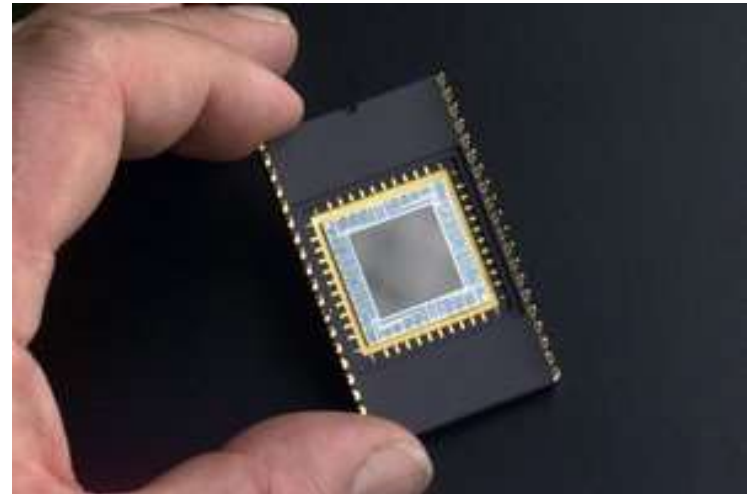
Imperfect Lens Projection

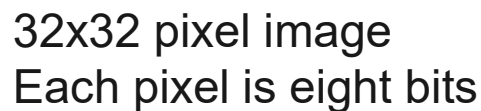


- Real lens will have imperfections which lead to misfocus (blur) or distortion
- Radial distortion occurs when 3D lines are not projected to 2D lines
- Calibration can learn distortion parameters and remove them from an image – approximating pinhole camera model

Digital Imaging

- In digital cameras, the imaging surface is an array of light sensitive elements (e.g. CCD's)
- The amount of incident light on each element is recorded as a number
- The image is discretized in two ways
 - The image is broken into discrete pixels with coordinates $[u,v]$
 - The value of each pixel takes discrete values in some range
- Video is further discretized temporally
- This results in some amount of quantization noise

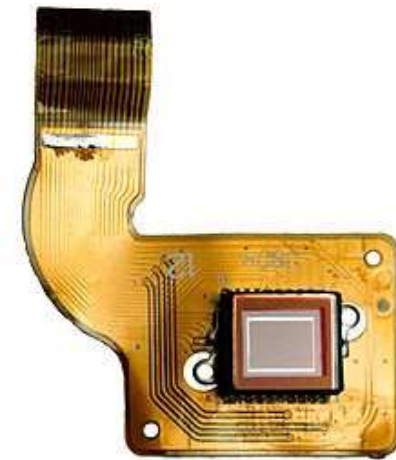


$[0,0] \curvearrowright$ [illegible]

- For an eight-bit image, pixels take integer values in range 0...255
- Typically pixel coordinates are counted from top left to bottom right, though some cameras count from bottom left

Digital Imaging

- “Charge coupled device” (CCD) and “complementary metal oxide semiconductor” (CMOS) are typical light sensing technologies
- Performance and cost of the two are converging, but typically:
 - CCD more prevalent
 - CCD delivers less noisy image than CMOS
 - Light sensitivity for CCD better than CMOS
 - CMOS requires less power than CCD
 - CMOS cheaper to manufacture than CCD

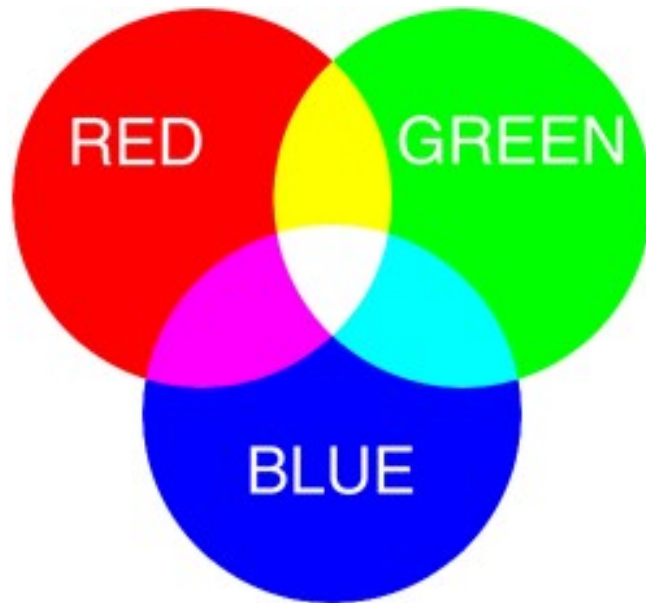


A CCD image sensor on a flexible circuit board



Digital Imaging

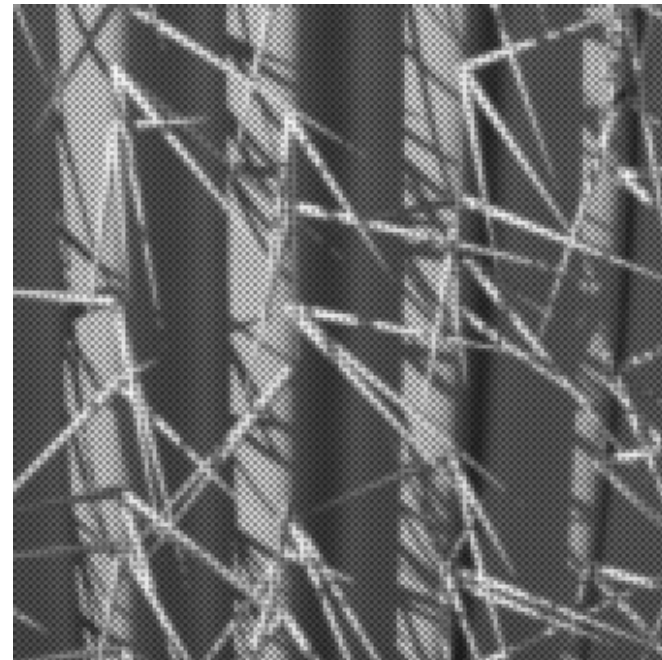
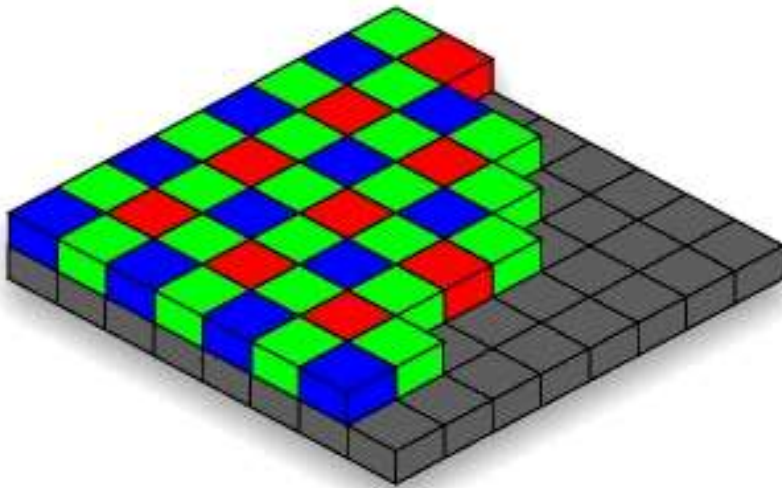
- In grayscale images, pixel has a single measurement of light intensity from pitch black to pure white
- In color images, each pixel has three measurements associated with it, typically red, green and blue (RGB), which indicate the intensity of light at that frequency



- RGB are primarily color of light and combine to form other colors
- The human eye is more sensitive to green light, so color cameras generally are more sensitive to green as well.
- RGB to grayscale conversion is not simply the norm of RGB values

Digital Imaging

- Note that most color cameras do not have separate receptors for each color
- A pattern of color filters, known as “Bayer Pattern” are placed over a single surface
- Resulting image is filtered by camera software/firmware to provide RGB image, but high speed camera may deliver raw Bayer image

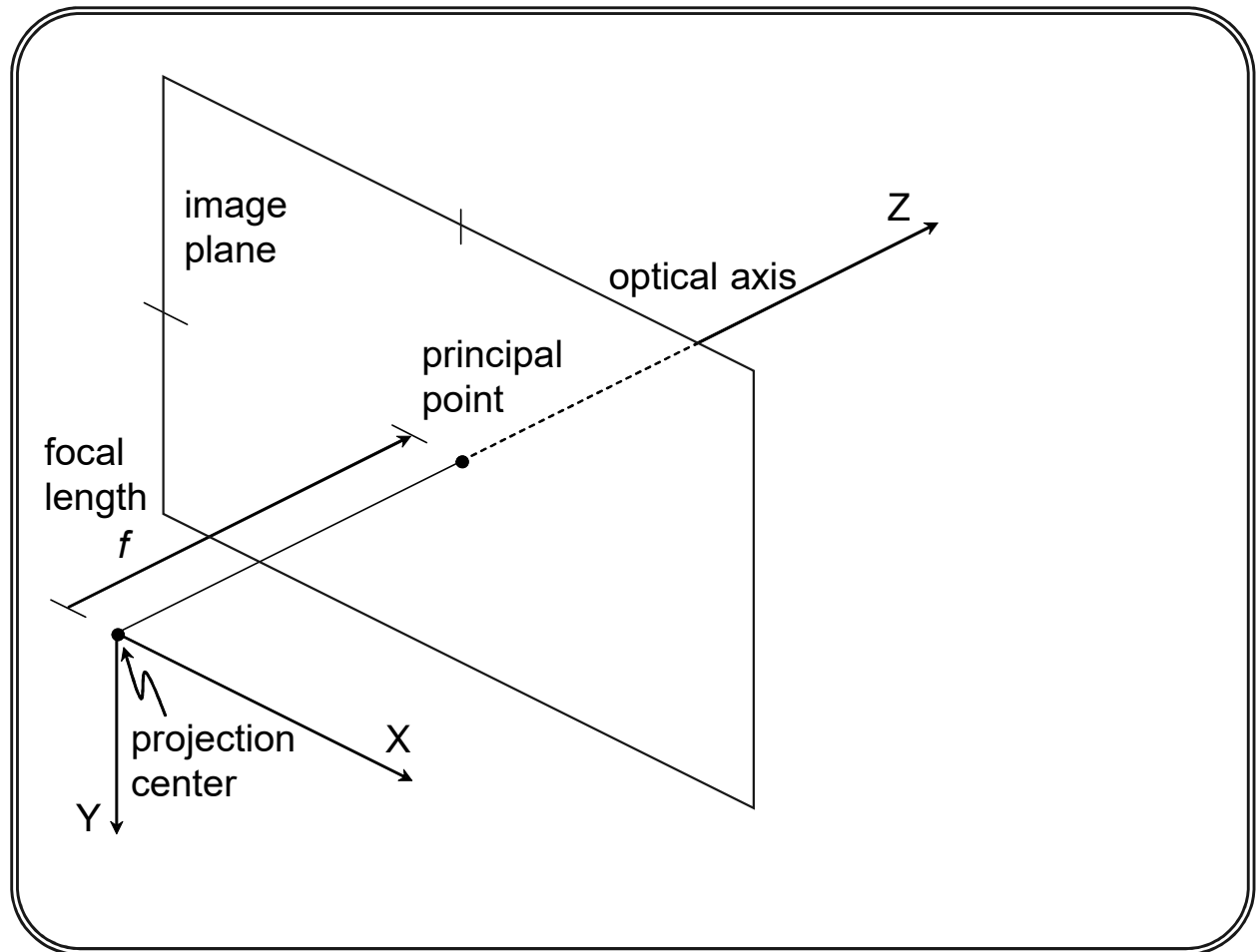


Pinhole Camera Model

- The pinhole camera model is a first order approximation of camera optics
- Widely used and essential for structure from motion algorithms
- Mathematics are simple and accurate for most quality cameras
- If higher order optical effects are pervasive, proper camera calibration can often make the first order approximation valid

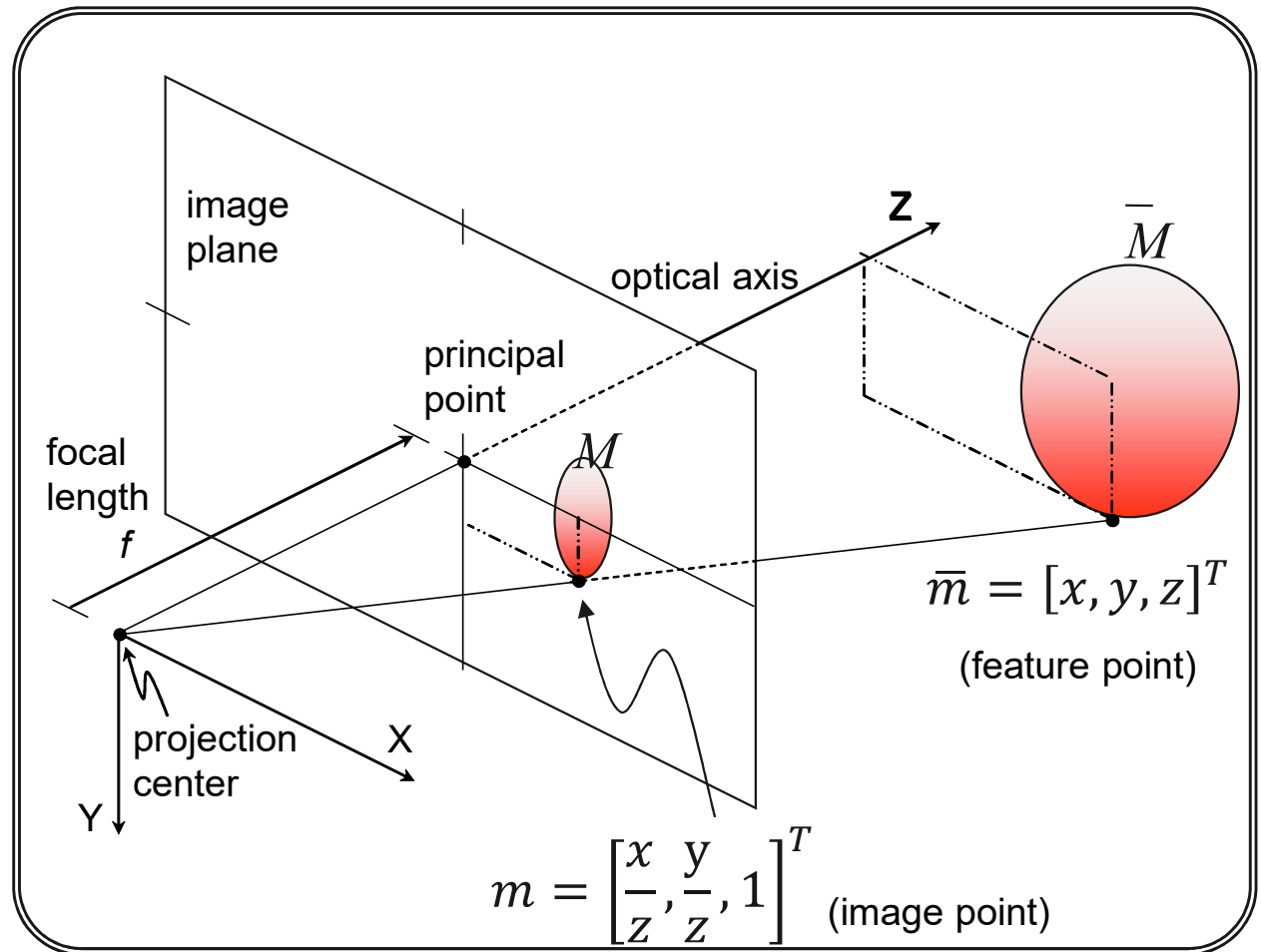
Pinhole Camera Model

- Reference frame \mathcal{F} is attached to the camera.
- The origin of \mathcal{F} is the “projection center”
- The imaging surface is a plane orthogonal to the z axis and intersects the z axis at a distance f
- Point of intersection is the “principal point”
- f is the “focal length” of the camera, for simplicity assume $f=1$



Pinhole Camera Model

- A feature point has 3D coordinates $\bar{m} = [x, y, z]^T$ in the camera frame
- It projects to a point in the image plane with coordinates $m = \left[\frac{x}{z}, \frac{y}{z}, 1 \right]^T$
- The projection of a point can be denoted by function $m = \pi(\bar{m}) = \frac{1}{z} \bar{m}$
- A curve or surface given as a set of 3D points \bar{M} projects to $M = \pi(\bar{M})$



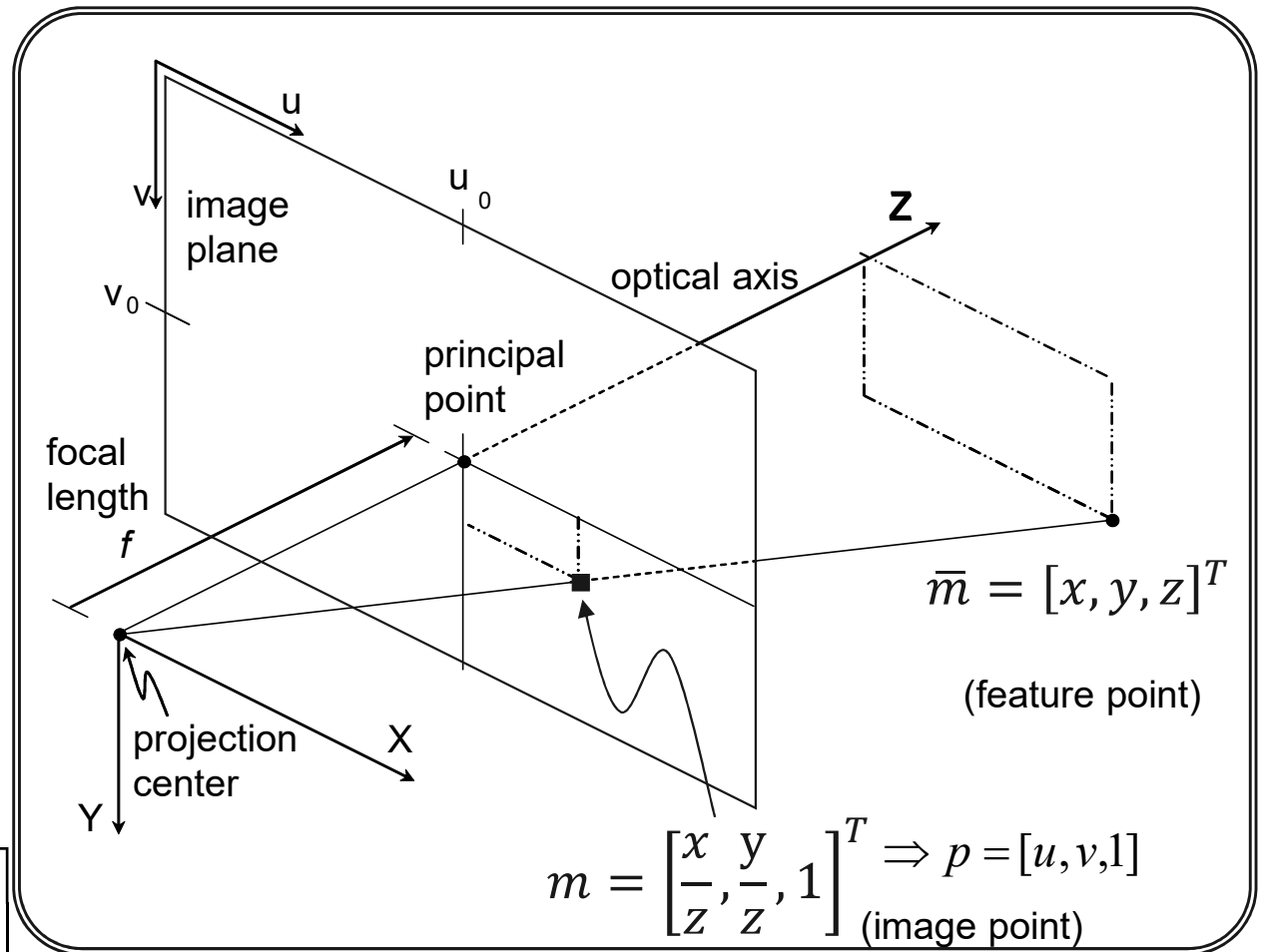
Pinhole Camera Model

- When dealing with a digital camera, we must account for the number of pixels, shape of pixels, and size of pixel elements

- Image point m is discretized to pixel coordinates $p = [u, v, 1]^T$

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f\sigma_x & -f\sigma_x \tan \alpha & u_0 \\ 0 & f\sigma_y \sec \alpha & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{x}{z} \\ \frac{y}{z} \\ 1 \end{bmatrix}$$

$$p = Am$$

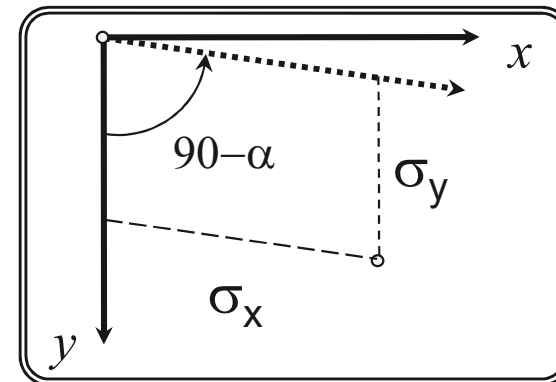
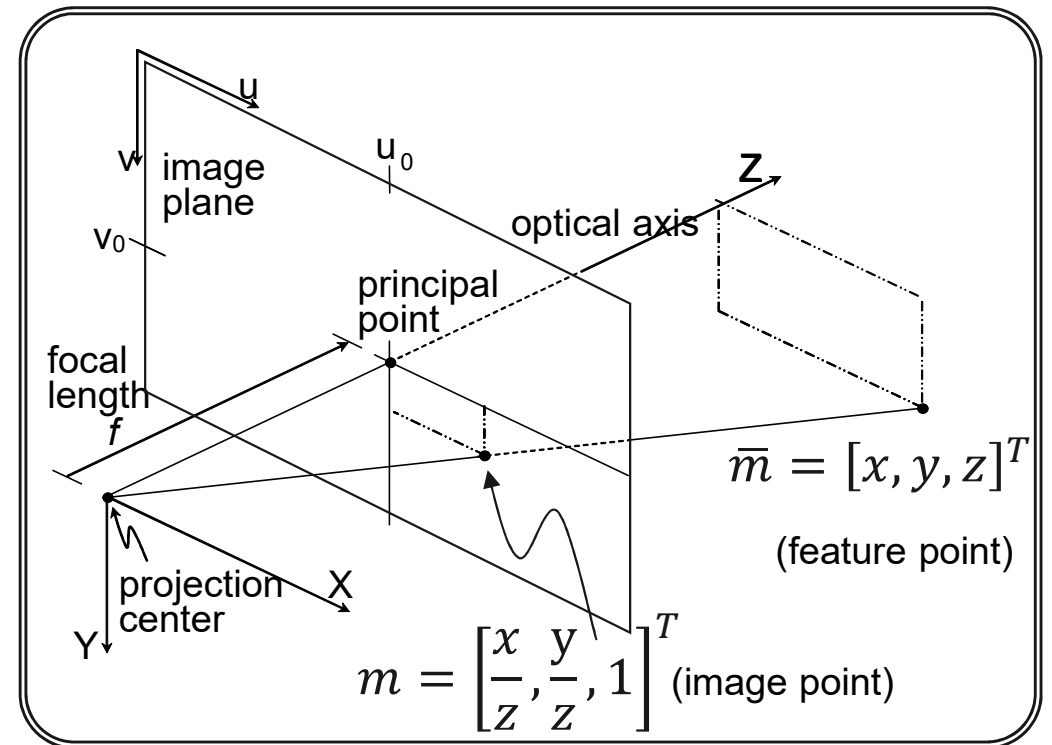


Pinhole Camera Model

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f\sigma_x & -f\sigma_x \tan \alpha & u_0 \\ 0 & f\sigma_y \sec \alpha & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{x}{z} \\ \frac{y}{z} \\ 1 \end{bmatrix}$$

$$p = Am$$

- A is intrinsic calibration matrix
- f is camera focal length
- σ_x, σ_y are size of pixels in focal lengths
- $[u_0, v_0]$ is the principal point in pixels
- α is skew angle, usually ≈ 0



Pinhole Camera Model (Summary)

- 3D feature point with **Euclidean coordinates** in camera frame \mathcal{F}

$$\bar{m} = \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

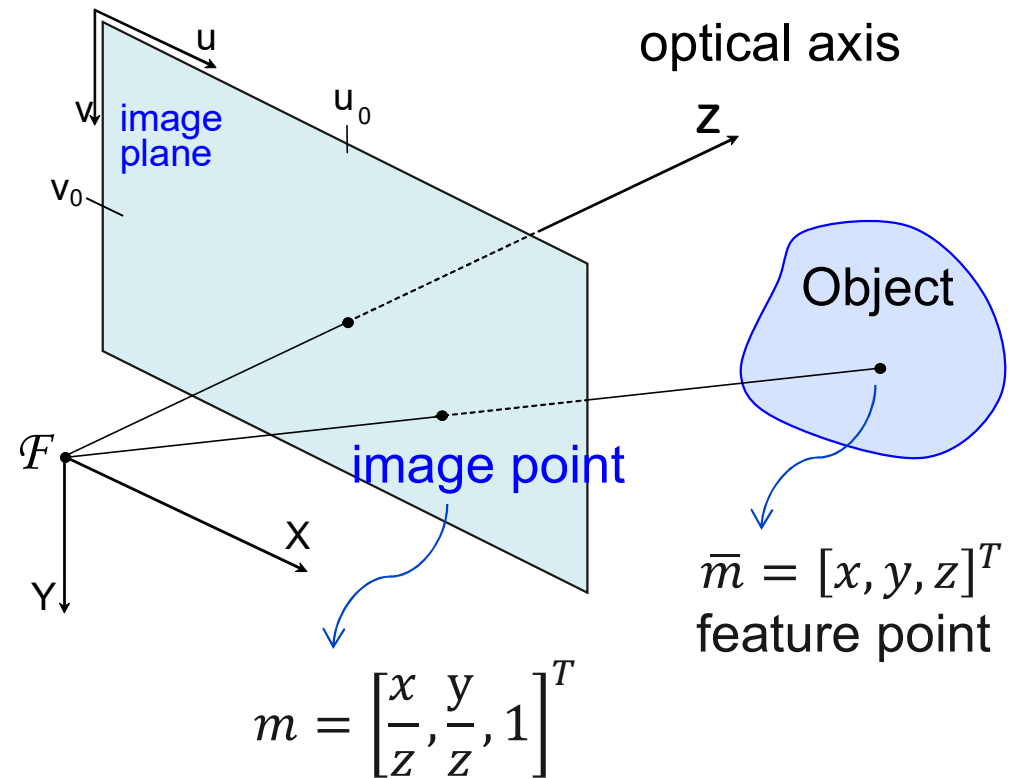
- Projected to image plane with **normalized coordinates** in \mathcal{F}

$$m = \begin{bmatrix} m_x \\ m_y \\ 1 \end{bmatrix} = \frac{\bar{m}}{z} = \begin{bmatrix} x/z \\ y/z \\ 1 \end{bmatrix}$$

- Mapped to **pixel coordinates** by Calibration Matrix

$$p = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = Am = \begin{bmatrix} f\sigma_x & -f\sigma_x \tan \alpha & u_0 \\ 0 & f\sigma_y \sec \alpha & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} m_x \\ m_y \\ 1 \end{bmatrix}$$

A: camera calibration matrix



Pinhole Camera Model (Remarks)

- Many estimation and control schemes require normalized coordinates for points
- Given pixel coordinates p of a point in the image and knowledge of calibration matrix A , recover normalized coordinates


$$m = A^{-1} p$$


- There is no way to recover the Euclidean coordinates without additional information. Depth ambiguity is a consequence of imaging.


Camera Calibration

- Consider an inertial, world reference frame \mathcal{F}_w
- The camera frame \mathcal{F}_c has translation T and rotation R w.r.t. \mathcal{F}_w .
- A point has coordinates $m_w = [x_w, y_w, z_w]^T$ in the world frame.
- Pixel coordinates of the point in the image are given by

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f\sigma_x & -f\sigma_x \tan \alpha & u_0 \\ 0 & f\sigma_y \sec \alpha & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1/z & 0 & 0 & 0 \\ 0 & 1/z & 0 & 0 \\ 0 & 0 & 1/z & 0 \end{bmatrix} \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix}$$


 Intrinsic
calibration matrix


 Projection
matrix


 Extrinsic
calibration matrix

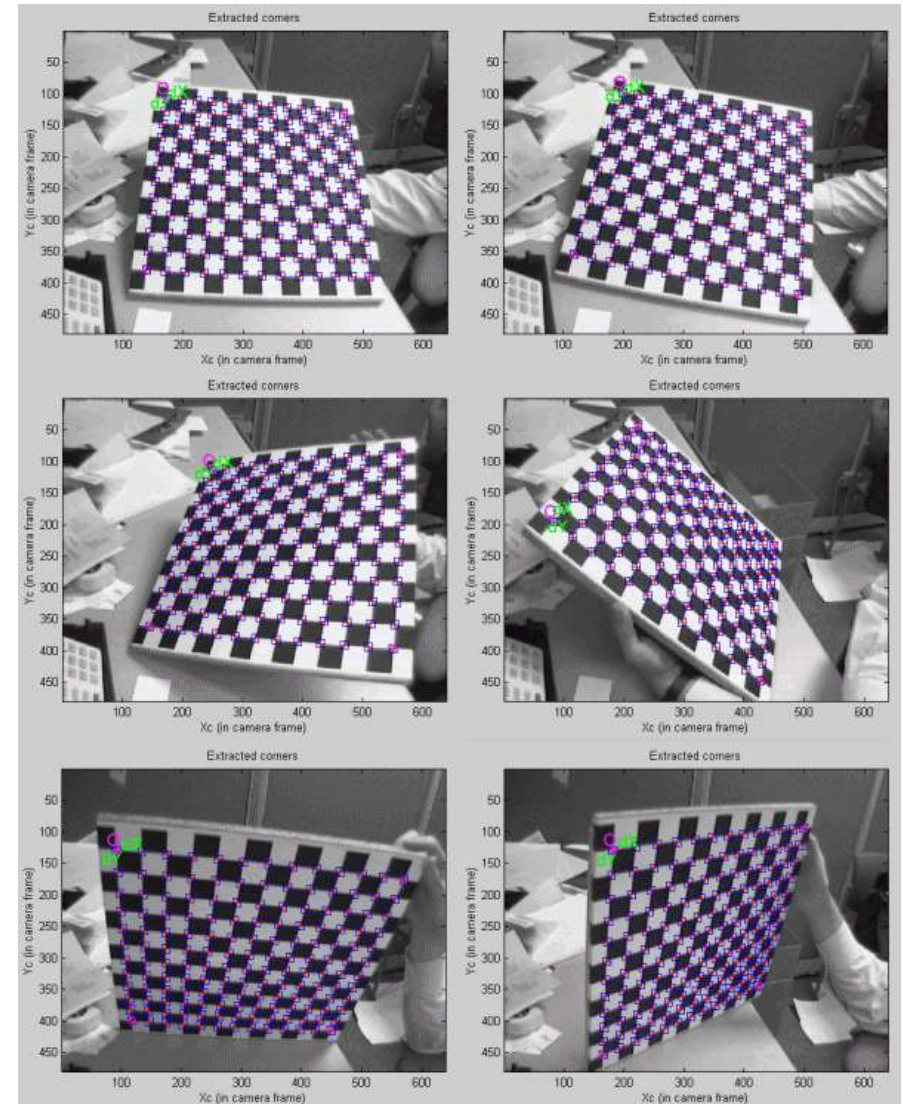
- Calibration is the processing of recovering these parameters

Camera Calibration

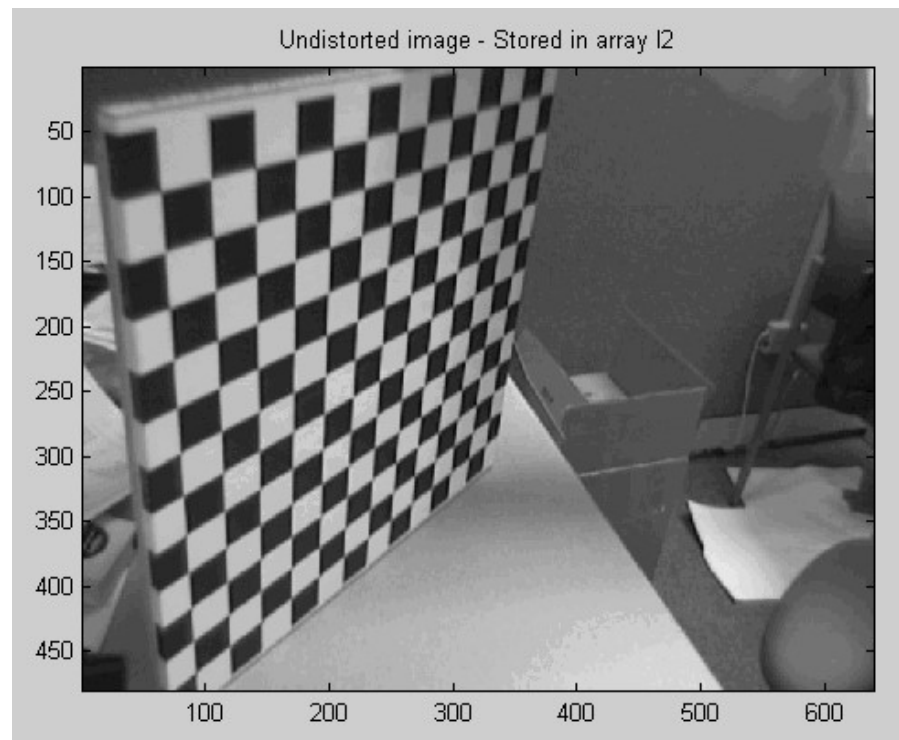
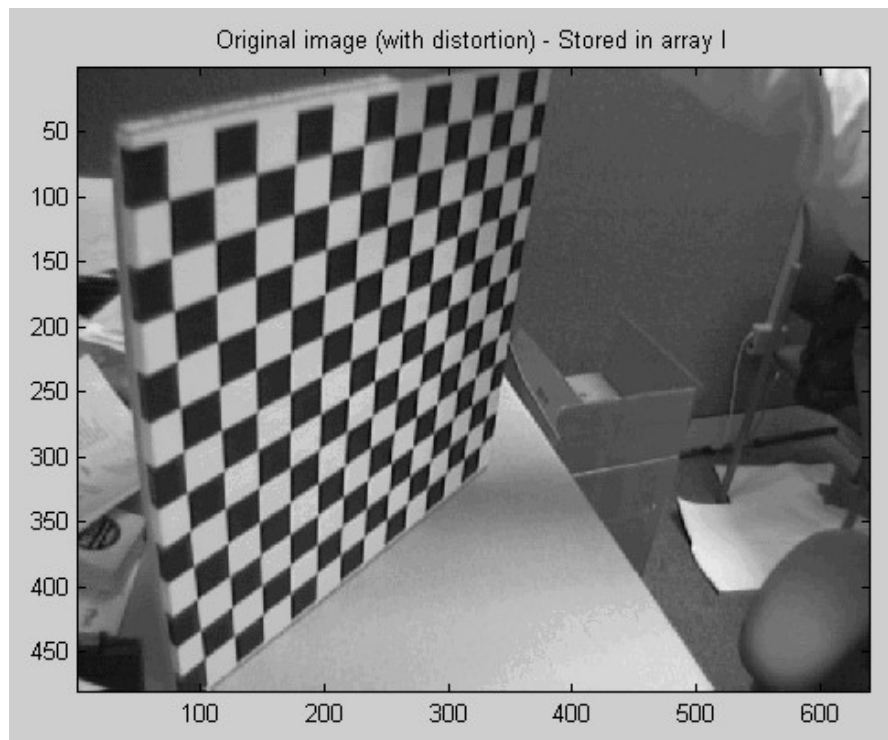
- There are many calibration techniques, and many free resources
- Intel Open Source Computer Vision Library
 - <http://www.intel.com/technology/computing/opencv/>
- Camera Calibration Toolbox for Matlab
 - http://www.vision.caltech.edu/bouguetj/calib_doc/
- The DLR Camera Calibration Toolbox
 - <http://www.dlr.de/rm-neu/desktopdefault.aspx/tabid-3925/>

Camera Calibration

- Most calibration methods require some sort of known target such as a calibration board
- Numerous images of target are taken
- Features, such as corners, are extracted
- Comparison of known target and image points allows solving of intrinsic and extrinsic camera parameters
- Intrinsic calibration parameters are usually solved simply as the elements of the calibration matrix A



Camera Calibration



- In addition to intrinsic calibration matrix, most calibration methods also give nonlinear distortion parameters which can undistort images

$$m_d = \left(1 + k_1 r^2 + k_2 r^4 + k_5 r^6\right) \begin{bmatrix} m_x \\ m_y \end{bmatrix} + \begin{bmatrix} 2k_3 m_x m_y + k_4 (r^2 + 2m_x^2) \\ 2k_4 m_x m_y + k_3 (r^2 + 2m_y^2) \end{bmatrix}$$

Exercise (not mandatory)

Try one of the calibration example by yourself using matlab

There are many calibration techniques, and many free resources

Intel Open Source Computer Vision Library

<http://www.intel.com/technology/computing/opencv/>

Camera Calibration Toolbox for Matlab

http://www.vision.caltech.edu/bouguetj/calib_doc/

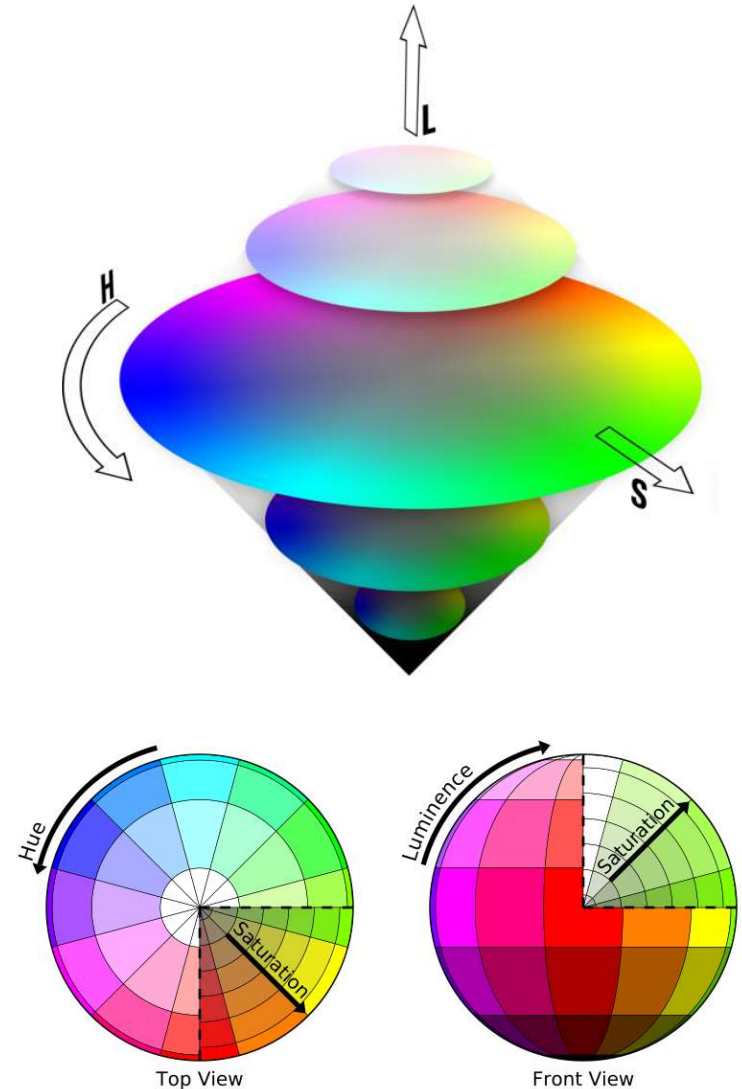
The DLR Camera Calibration Toolbox

<http://www.dlr.de/rm-neu/desktopdefault.aspx/tabid-3925/>

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- The following slides are for reference reading if interested

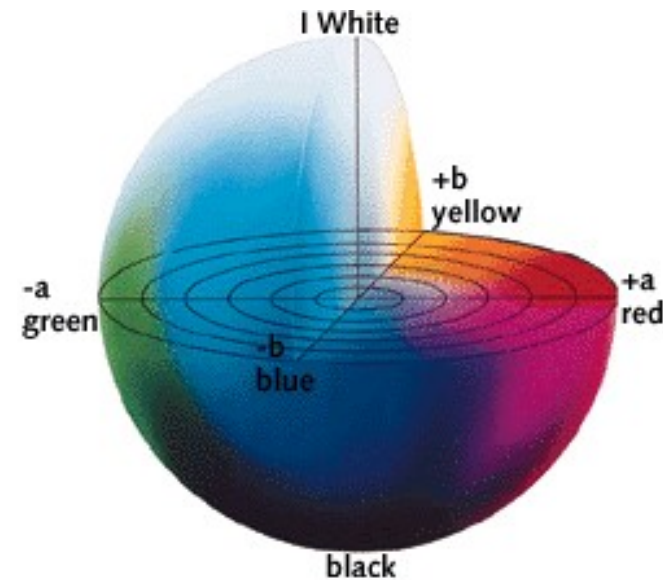
Useful Imaging Methods - Color Spaces

- Several useful alternatives to RGB color space
- Hue Saturation Luminescence (HSL) color space
 - Color mapped to Hue value which is cyclical
 - Light intensity (white to black) maps to Luminescence
 - Color intensity (grey to bright) maps to Saturation
- Particularly useful for finding objects of similar colors



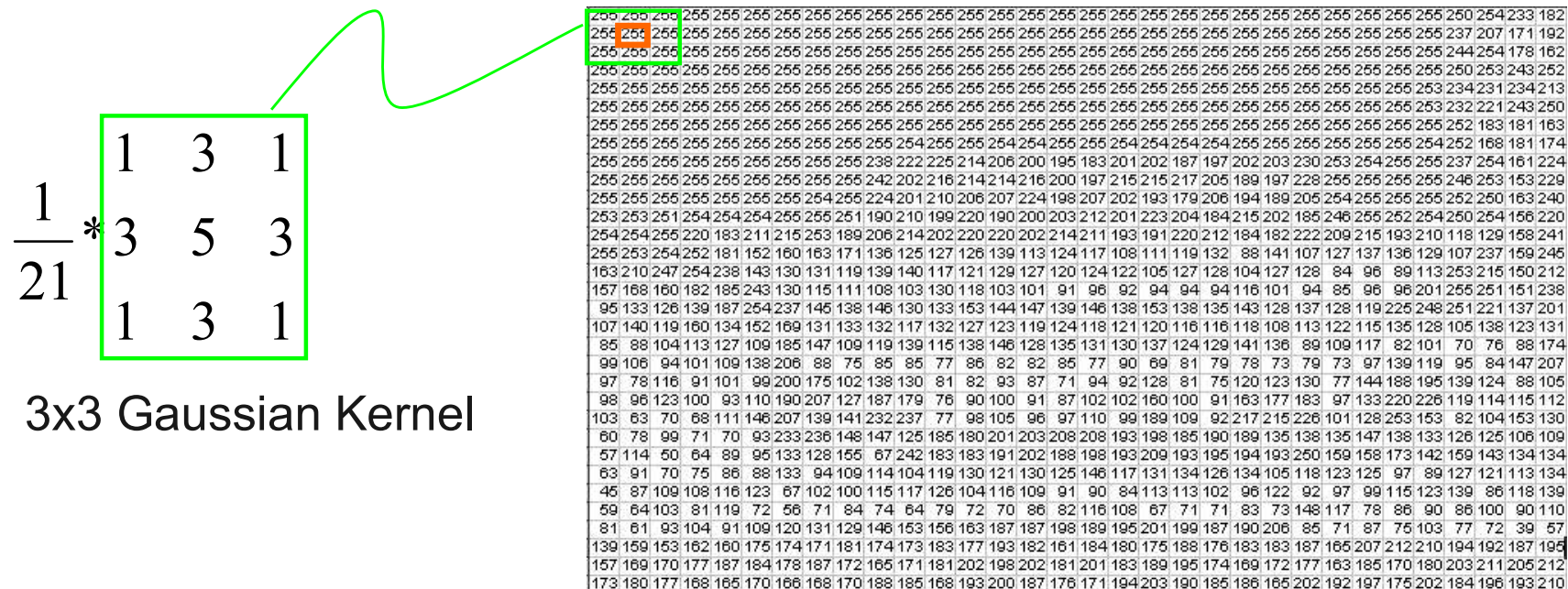
Useful Imaging Methods - Color spaces

- CIELAB color space
 - Light intensity (white to black) maps to Luminescence
 - A and B denote color and intensity
- A “linear” color space
- Useful when “distance” between colors is needed to differentiate objects



Useful Imaging Methods - Image Processing

- In filtering a small 2D “window” or “kernel” of values is convolved with each pixel of the image
- For each pixel in the image, take the sum of products of multiplying the kernel by the pixel values



What is Image Filtering?

Modify the pixels in an image based on some function of a local neighborhood of the pixels

10	5	3
4	5	1
1	1	7

Some function



	7	

Linear Filtering

- Linear case is simplest and most useful
 - Replace each pixel with a linear combination of its neighbors.
- The prescription for the linear combination is called the convolution kernel.

10	5	3
4	5	1
1	1	7

 \otimes

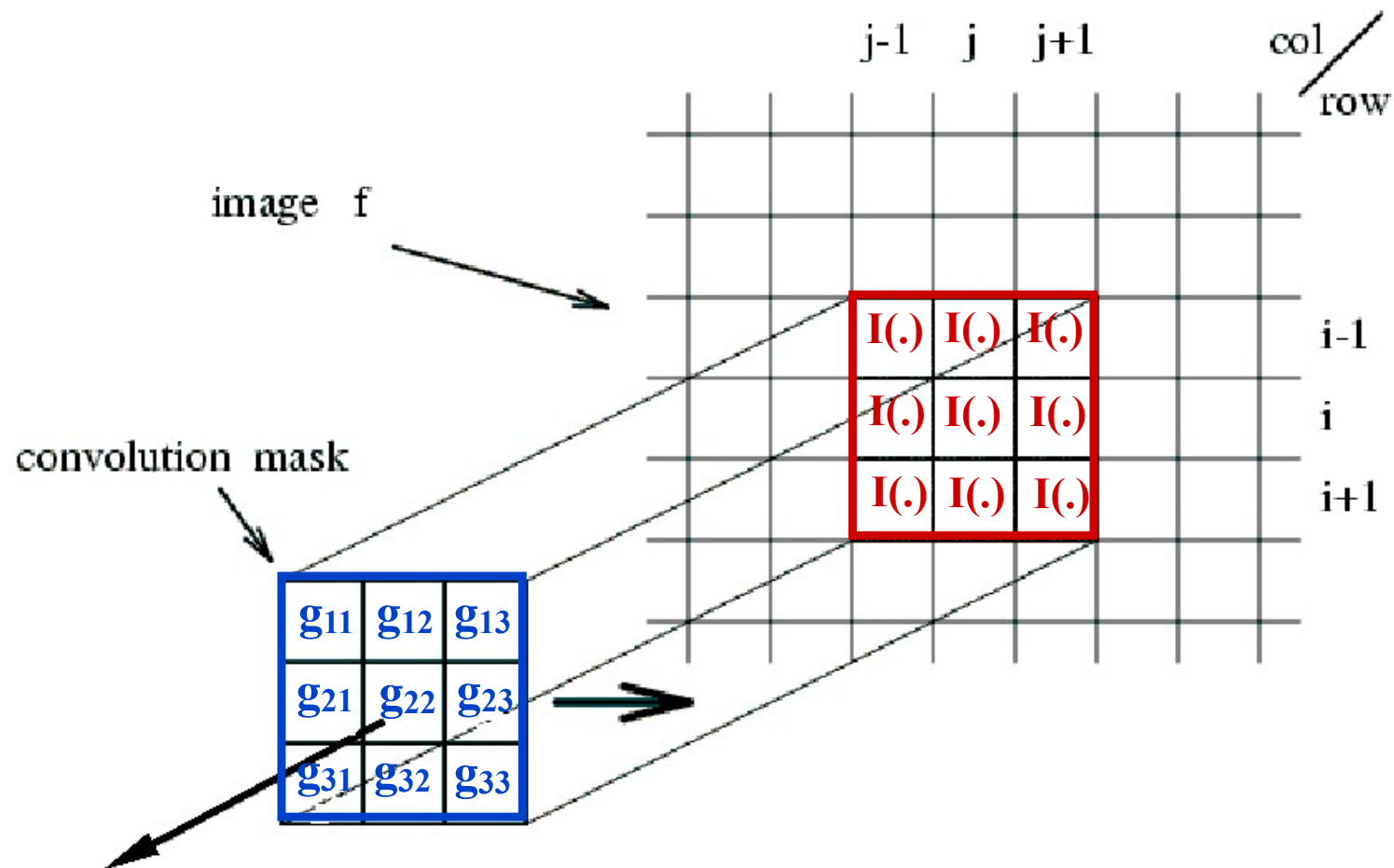
0	0	0
0	0.5	0
0	1.0	0.5

 $=$

	7	

kernel

Linear Filter = Convolution



$$\begin{aligned}
 f(i,j) = & \quad g_{11} I(i-1,j-1) \quad + \quad g_{12} I(i-1,j) \quad + \quad g_{13} I(i-1,j+1) \quad + \\
 & g_{21} I(i,j-1) \quad + \quad g_{22} I(i,j) \quad + \quad g_{23} I(i,j+1) \quad + \\
 & g_{31} I(i+1,j-1) \quad + \quad g_{32} I(i+1,j) \quad + \quad g_{33} I(i+1,j+1)
 \end{aligned}$$

Linear Filter = Convolution

$$f[m, n] = I \otimes g = \sum_{k, l} I[m - k, n - l] g[k, l]$$

with $\sum_{k, l} g[k, l] = 1$

Useful Imaging Methods - Image Processing

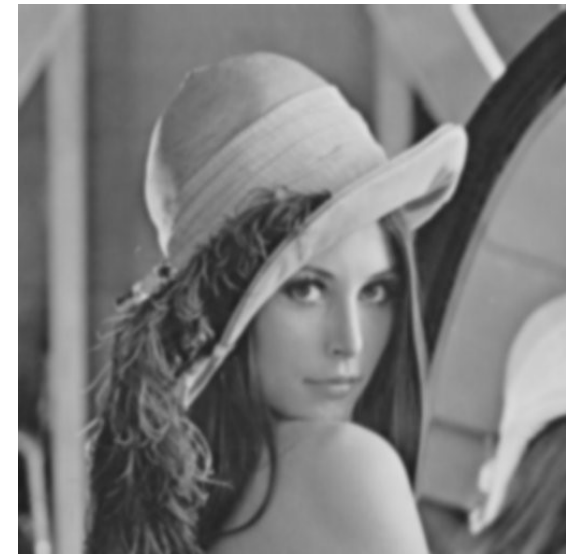
- Gaussian Filtering convolves a low-pass filter with the image, which gives a smoothed image
- This can reduce pixilation effects and aid in false positives for corner detection
- Too much results in blurred image which can make corner detection hard

$$\frac{1}{21} \begin{matrix} 1 & 3 & 1 \\ 3 & 5 & 3 \\ 1 & 3 & 1 \end{matrix}$$

3x3 Gaussian Kernel



Original Image



3x3 Gaussian Filter

Image Smoothing With Gaussian

```
figure(3);
sigma = 3;
width = 3 * sigma;
support = -width : width;
gauss2D = exp( - (support / sigma).^2 / 2);
gauss2D = gauss2D / sum(gauss2D);
smooth = conv2(conv2(bw, gauss2D, 'same'), gauss2D, 'same');
image(smooth);
colormap(gray(255));

gauss3D = gauss2D' * gauss2D;
tic ; smooth = conv2(bw,gauss3D, 'same'); toc
```

Useful Imaging Methods - Image Processing

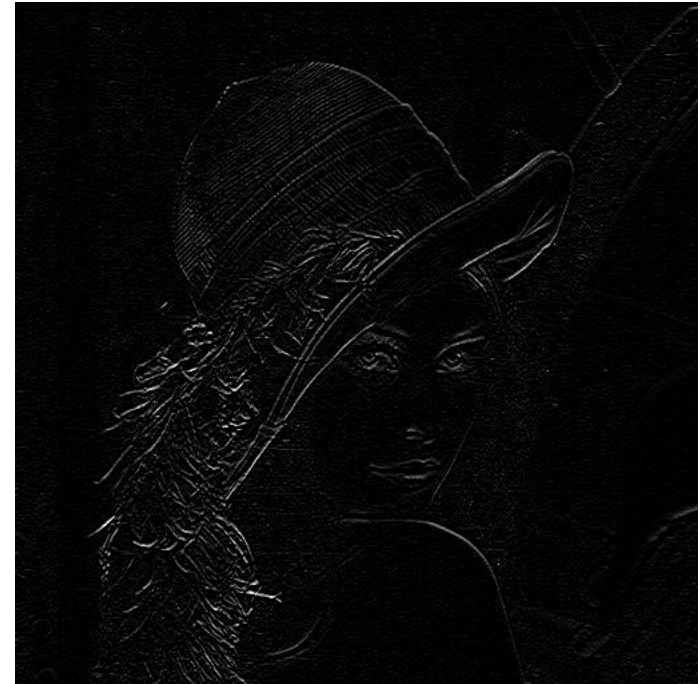
- High Pass filtering can give a simple edge detection
- Subsequent edge detection in two directions gives a simple point detection

0 0 0
-1 2 -1
0 0 0
3x3 vertical
edge detector



Vertical Edge

0 -1 0
0 2 0
0 -1 0
3x3 horizontal
edge detector



Horizontal Edge

Edge Detection With Smoothed Images

```
figure(4);  
[dx,dy] = gradient(smooth);  
gradmag = sqrt(dx.^2 + dy.^2);  
gmax = max(max(gradmag));  
imshow(gradmag);  
colormap(gray(gmax));
```

```
figure(6)  
edge(bw, 'sobel')
```

Useful Imaging Methods - Image Processing

- Median Filtering is a nonlinear filter where the median value in the kernel window is given to the pixel
- Removes “salt and pepper” noise and jittering
- Results in a loss of texture



Noisy Image



3x3 Gaussian Filter



3x3 Median Filter

Useful Imaging Methods - Image Processing

- In thresholding, all pixels with a value below a certain level are rounded to 0, all pixels above are rounded to max
- Thresholding is often a prerequisite to segmentation algorithms which find connected regions
- Centroids of segments make excellent feature points

