

# Computer Vision for Linear Algebra

Hunter Wills

April 24, 2014

- 1 Basics
  - Homogenous coordinates
  - Transformations
- 2 Least Squares
- 3 Singular Value Decomposition
- 4 Benefits of Linear Algebra
- 5 Applications
  - Matrix Decompositions
  - Efficiency
  - Structure from Motion
  - Convolution
  - Eigenfaces
- 6 Sources

# What is Computer Vision?

- Artificial intelligence
- Having a computer describe what it sees in the world around it the way a human or animal can
- An inverse problem recovering unknowns from insufficient data to fully describe a “solution”

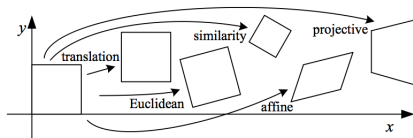
# Homogenous coordinates



- Adding an extra dimension to the Euclidean system
- Account for the concept of infinity

# Transformations

- Linear transformations used to manipulate the image
- Represented through matrices which act on image vectors through multiplication
- Camera projection matrix
- Types of transformations:



- Real world data is error prone
- Total Least Squares
- Robust Least Squares
- Non-Linear Least Squares

- Rotation, scaling, rotation
- Principal Component Analysis
- Generalized inverse

- Most situations can be approximated well linearly
- Estimation of lost data



# Matrix Decompositions

- Inverting the transformation from 3D to 2D
- Speedy Calculations
- Accurate Computations
- Projections
- Positive Definite Matrices

# Efficiency

- Space efficiency
- Time efficiency

Basics  
Least Squares  
Singular Value Decomposition  
Benefits of Linear Algebra  
Applications  
Sources

Structure from Motion  
Convolution  
Eigenfaces

# Modern Uses of Computer Vision



Hunter Wills

Computer Vision for Linear Algebra

## Structure from Motion

- Process of using a series of 2D images to reconstruct a 3D image
- Depth has been lost in a single 2D image
- Transformations that cannot be inverted have occurred in the process of shifting from 3D to 2D
- Each camera has its own coordinate system so the stationary coordinate system of the object must be used

## Method

- Clearly identifiable points are identified on the images
- The generalized inverse of the camera's projection matrix is calculated for a single image
- The attempt at an inverted image is transformed into the system of the second image
- The location of identified points in the second image are compared to those of the transformed image
- Additional transformations are estimated to better align the key points
- The process is repeated until key points are reasonably well aligned

# Example



# Convolution

- Form of linear filtering
- Utilizes a convolution kernel to perform an action on a larger image matrix
- Examples: Blurring, Sharpening, Smoothing, Edge-Identifying, and more

## Method





- Find the appropriate  $n \times n$  convolution kernel
- For every pixel in the image matrix form an  $n \times n$  sub-matrix with the adjacent pixels.
- Define the following convolution action on a segment of the image matrix,  $I$ , by the convolution kernel  $K$  as:




$$b = \sum_{i=0}^n \sum_{j=0}^n I_{i,j} K_{i,j}$$

- Replace each pixel in the image matrix with the convolution action of the pixel's sub matrix.



# Example

<b>Original</b>	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
<b>Edge-Detect</b>	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	

<b>Sharpen</b>	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
<b>Blur*</b>	$\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	

# Eigenfaces

- Used for face identification and recognition
- Eigenfaces are the eigenvectors of the covariance matrix for a set of face images.
- Each face image is a linear combination of the eigenfaces
- Only the “most important” eigenfaces are stored

## Method

- Take a set of  $n \times m$  face picture matrices and treat them as a set of  $nm$  dimensional vectors.

$$\begin{bmatrix} i_{1,1} & \dots & i_{n,1} \\ \dots & \dots & \dots \\ i_{1,m} & \dots & i_{n,m} \end{bmatrix} \rightarrow \begin{bmatrix} i_{1,1} \\ \dots \\ i_{n,1} \\ i_{1,2} \\ \dots \\ i_{n,m} \end{bmatrix} = \mathbf{i}$$

- Find the average face:  $\mathbf{a} = \frac{1}{m} \sum_{j=1}^m \mathbf{i}_j$
- Form the image matrix with columns of the difference between each face vector and the average face.  $\mathbf{i}_j - \mathbf{a}$
- The right singular vectors of this matrix are the eigenfaces

# Face Recognition

- Treat the face picture matrix as a face vector,  $\mathbf{f}$ .
- Find the face vector's eigenface components:  $w_i = \mathbf{e}_i^*(\mathbf{f} - \mathbf{a})$
- Form these eigenface components into a component vector,  $\mathbf{w}$
- Calculate the Euclidian distance between the unknown face's component vector and each known face's component vectors as the square of their inner product.
- The face which minimizes the Euclidian distance is the one to which the unknown face belongs

# Example



## Sources

- Szeliski, Richard. 2011. Computer vision algorithms and applications. London: Springer.
- Trefethen, Lloyd N., and David Bau. 1997. Numerical linear algebra. Philadelphia, PA: Society for Industrial and Applied Mathematics.
- Doornik, Jurgen A. 2011. Robust Estimation Using Least Trimmed Squares. Oxford, UK: Oxford Martin School.
- Smith, Lindsay I. 2002. A Tutorial on Principal Components Analysis.
- Turk, Matthew, and Alex Pentland. 1991. Eigenfaces for Recognition. Massachusetts Institute of Technology. Journal of Cognitive Neuroscience.

## Sources

- Massachusetts Institute of Technology. Chemical Engineering Notes: Cholesky Decomposition.
- Shah, Mubarak. 1997. Fundamentals of Computer Vision. Orlando, FL: University of Central Florida.
- Golub, Gene H., and Charles F. Van Loan. 1983. Matrix computations. Baltimore: Johns Hopkins University Press.
- Lui, Yui M. 2012. Human Gesture Recognition on Product Manifolds. Journal of Machine Learning Research.
- Ahn, Song H. 2005. Homogenous Coordinates.

## Sources

- Castro, Luis P., Saburou Saitoh, and Nguyen Minh Tuan. 2012. Convolutions, Integral Transforms, and Integral Equations by means of the Theory of Reproducing Kernels. Opuscula Mathematica Vol. 32.
- O'Hagan, Anthony, Caitlin E. Buck, Alireza Daneshkhah, J. Richard Eiser, Paul H. Garthwaite, David J. Jenkinson, Jeremy E. Oakley, and Tim Rakow. 2006. Uncertain Judgements: Eliciting Experts' Probabilities. West Sussex: John Wiley and Sons Ltd.
- Interviews of industry computer scientists coming from a Ph.D. program in Computer Vision from Georgia Tech University. 2014.



## Sources

- “PlayMotion SPG: Special Projects Group,” PlayMotion Labs, accessed April 21, 2014, <http://www.playmotion.com/services.html>
- “Google: Self-driving cars in 3-5 years. Feds: Not so fast,” ExtremeTech, accessed April 21, 2014, <http://www.extremetech.com/extreme/147940-google-self-driving-cars-in-3-5-years-feds-not-so-fast>
- “Robotic surgery coming this fall to Southcoast Hospitals,” Southcoast Health System, accessed April 21, 2014, [www.southcoast.org/enews/2008/2008-07-enews.html](http://www.southcoast.org/enews/2008/2008-07-enews.html)

## Sources

- “Video Analytics,” Vision Systems Electrical and Security Solutions, accessed April 21, 2014, [www.visionsystems.co.nz/Systems-Services/Security-Systems/smart-video-surveillance-intelligent-security-camera-analysis-...I.2021](http://www.visionsystems.co.nz/Systems-Services/Security-Systems/smart-video-surveillance-intelligent-security-camera-analysis-...I.2021)