

Tracking surfaces / objects across video frames

Readings:

Paper, First dozen pages:
Baker&Matthews, IJCV

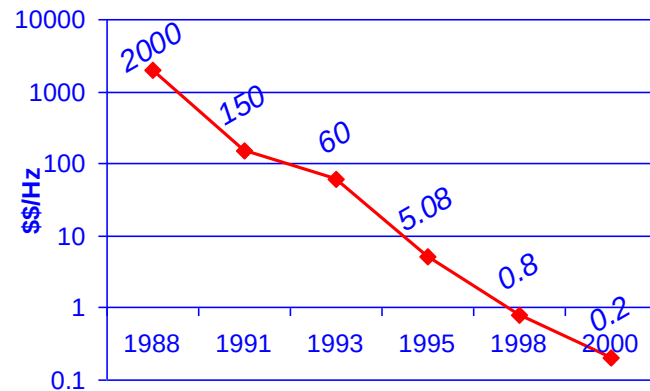
“Lukas-Kanade 20 years on”

Szeliski 8.1.3, 4.1

Ma et al Ch 4.

Forsythe and Ponce Ch 17.

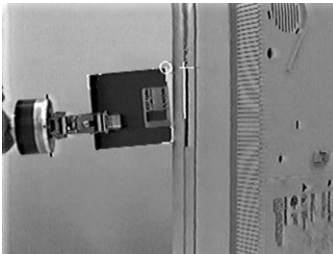
Why Visual Tracking?



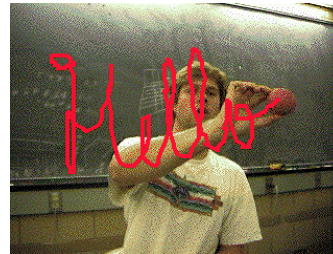
Computers are fast enough!

Related technology is cheap!

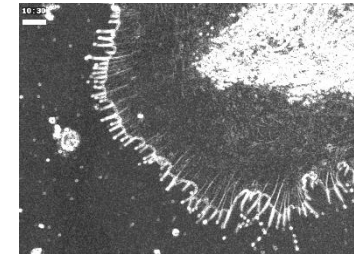
Applications abound



Motion Control



HCI



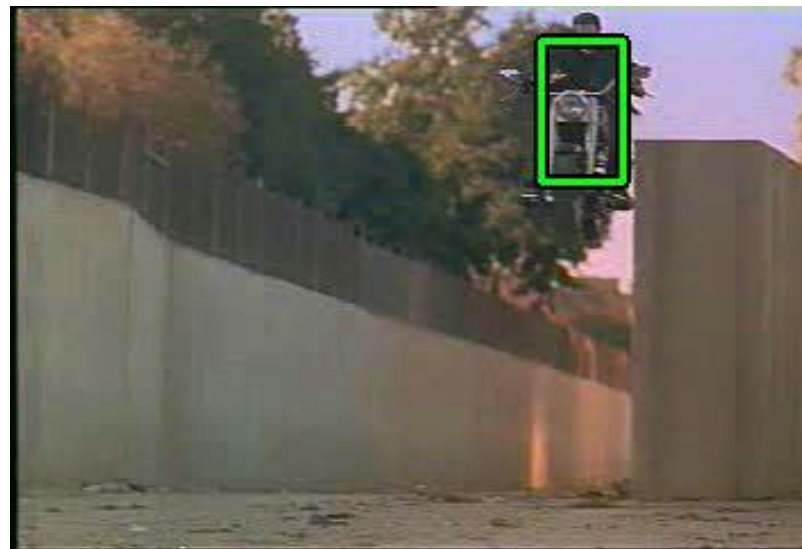
Measurement

Applications: Watching a moving target

- Camera + computer can determine how things move in an scene over time.

Uses:

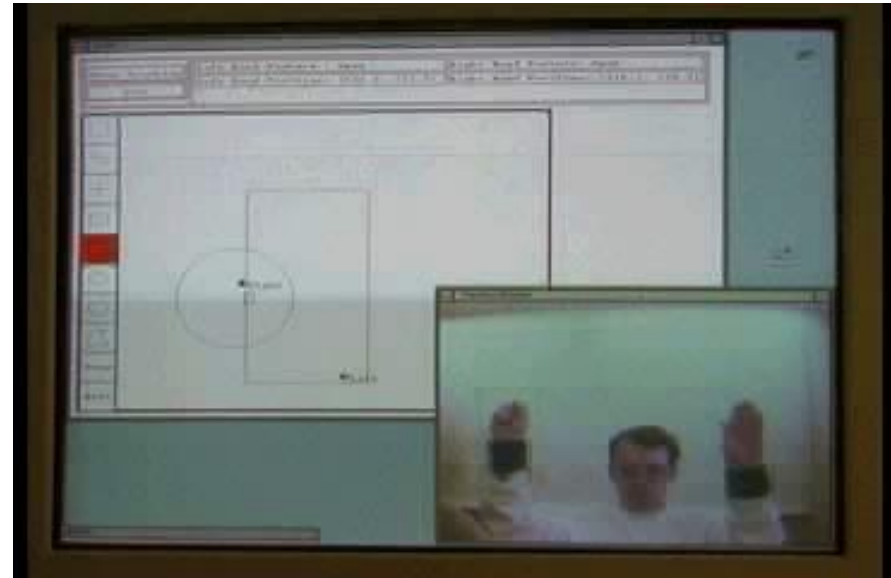
- Security: e.g. monitoring people moving in a subway station or store
- Measurement: Speed, alert on colliding trajectories etc.



Applications

Human-Computer Interfaces

- Camera + computer tracks motions of human user and interprets this in an on-line interaction.
- Can interact with menus, buttons and e.g. drawing programs using hand movements as mouse movements, and gestures as clicking
- Furthermore, can interpret physical interactions

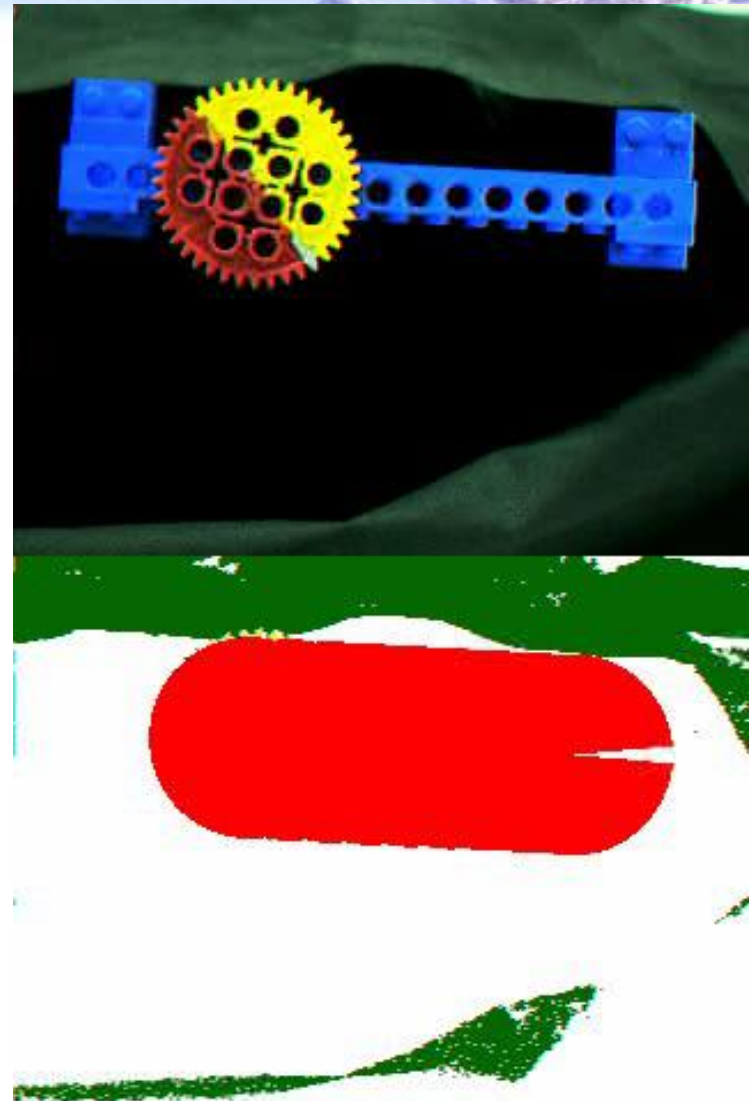


Applications

Interpreting tasks and functionality

Use tracking to interpret:

1. Physics of a mechanism
2. How a car is repaired.
3. How a human cooks in a kitchen



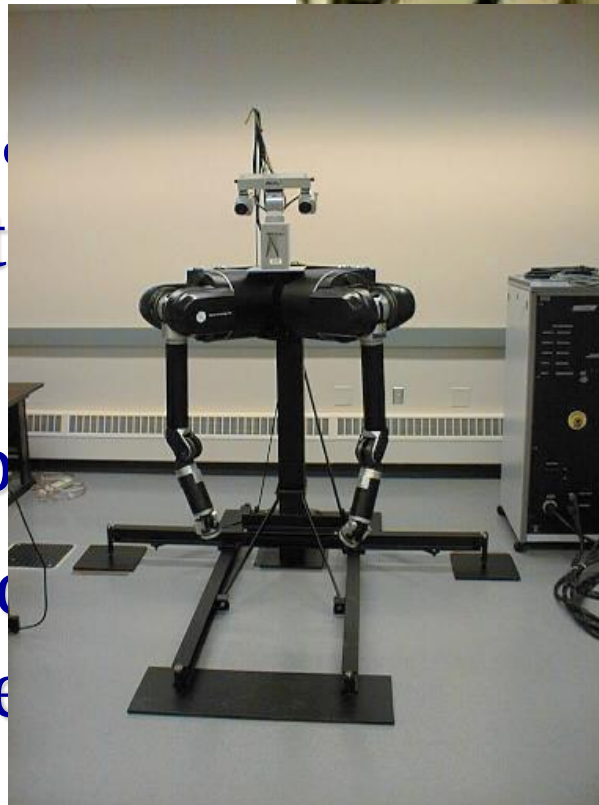
Applications

Human-Machine Interfaces

- Camera + computer tracks motions of human user, interprets this and controls machine/robot to perform task.



- Remote manipulation
- Service robotics for the handicapped and elderly



Applications

Human-Human Interfaces

- Camera + computer tracks motions and expressions of human user, interprets, codes and transmits to render at remote location
- Ultra low bandwidth video communication
- Handheld video cell phone



BANDWIDTH and PROCESSING REQUIREMENTS: TV camera

Binary

1 bit * 640x480 * 30 = 9.2 Mbits/second

Grey

1 byte * 640x480 * 30 = 9.2 Mbytes/second

Color

3 bytes * 640x480 * 30 = 27.6 Mbytes/second (actually about 37 mbytes/sec)

Typical operation: 8x8 convolution on grey image
64 multiplies + adds → 600 Mflops

Consider 800x600, 1200x1600 (2MP)...

Today's PC's are getting to the point they
can process images at frame rate
For real time: process small window in image

Characteristics of Video Processing

$$\text{abs}(\text{Image 1} - \text{Image 2}) = ?$$



Note: Almost all pixels change!

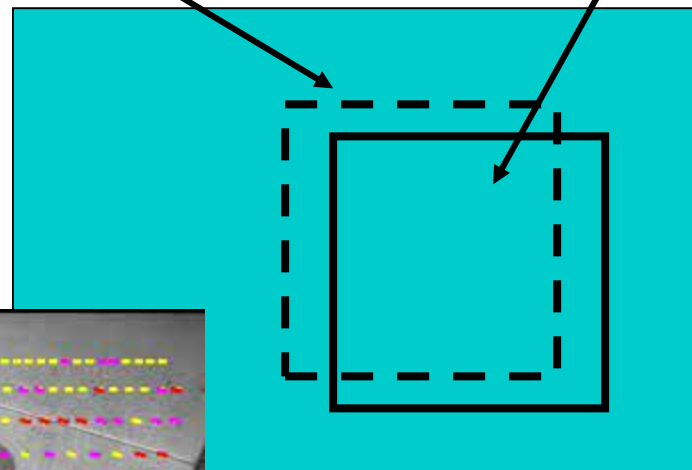
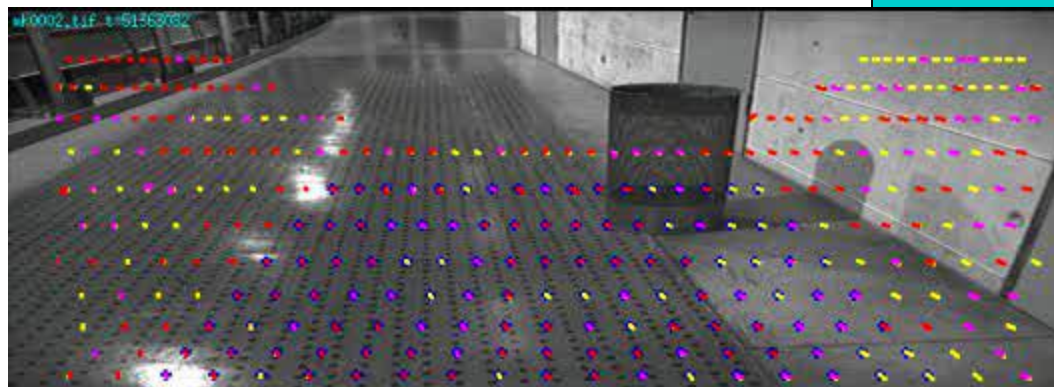
Constancy: The physical scene is the same

How do we make use of this?

Fundamental types of video processing “Visual motion detecton”

- Relating two adjacent frames: (small differences):

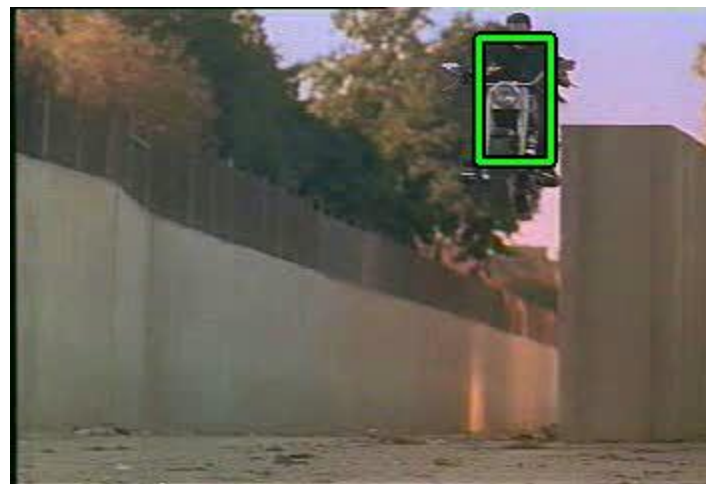
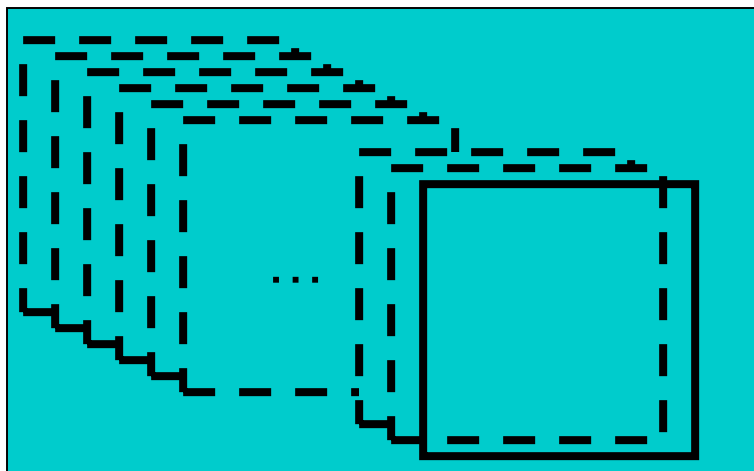
$$\text{Im}(x + \delta x, y + \delta y, t + \delta t) = \text{Im}(x, y, t)$$



Fundamental types of video processing

“Visual Tracking” / Stabilization

- Globally relating all frames: (large differences):



Types of tracking

- **Point tracking**

Extract the point (pixel location) of a particular image feature in each image.

- **Segmentation based tracking**

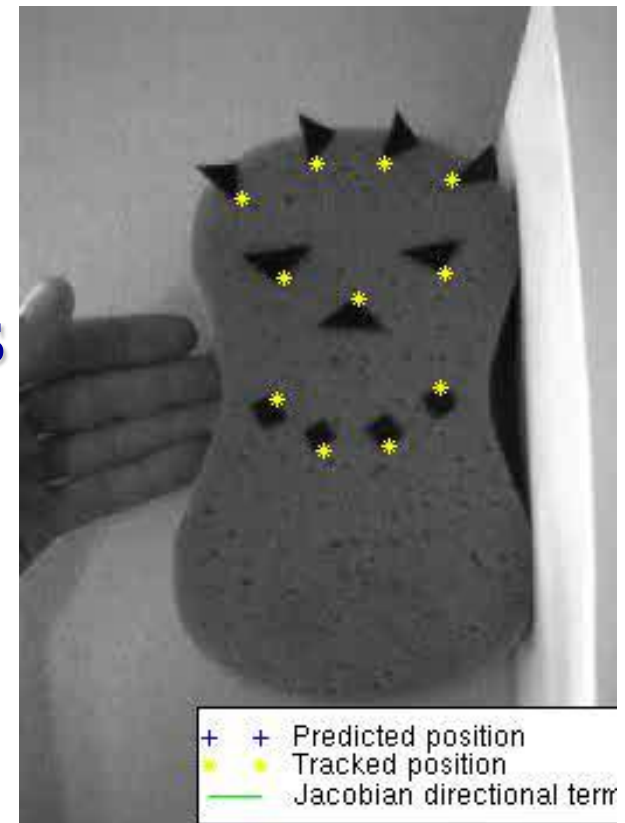
Define an identifying region property (e.g. color, texture statistics). Repeatedly extract this region in each image.

- **Stabilization based tracking**

Formulate image geometry and appearance equations and use these acquire image transform parameters for each image.

Point tracking

- Simplest technique. Already commercialized in motion capture systems.
- Features commonly LED's (visible or IR), special markers (reflective, patterns)
- Detection: e.g. pick brightest pixel(s), cross correlate image to find best match for known pattern.



Commercial point trackers: “Motion capture”



Region Tracking (Segmentation-Based)

- Select a “cue:” $\gamma(\mathbf{I}(x, y))$
 - foreground enhancement
 - background subtraction
- Segment
 - threshold
 - “clean up”
- Compute region geometry
 - centroid (first moment)
 - orientation (second moment)
 - scale (second moment)

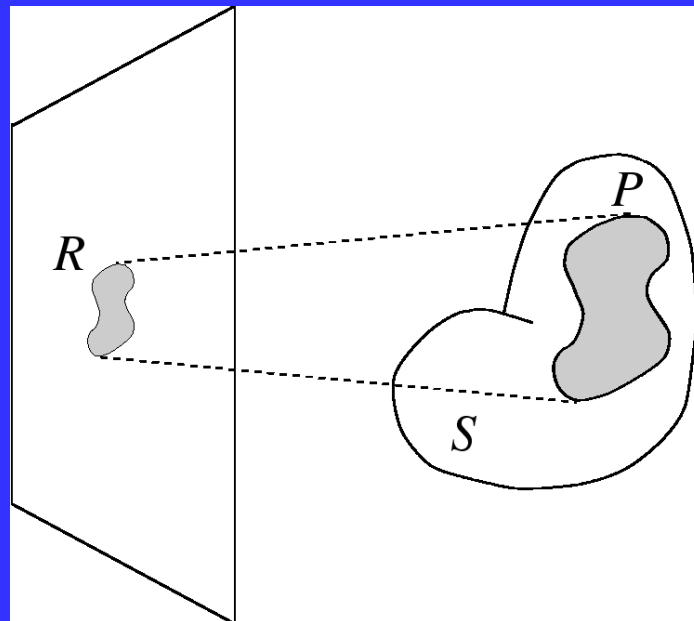
$$u = (x, y)'$$
$$m_i = \sum_i S(u) u^i$$

$$c = m_1 / m_0$$

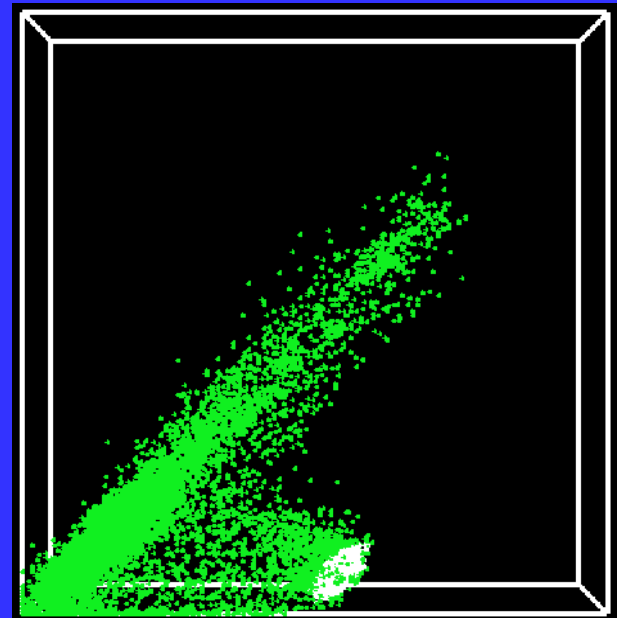
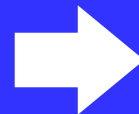
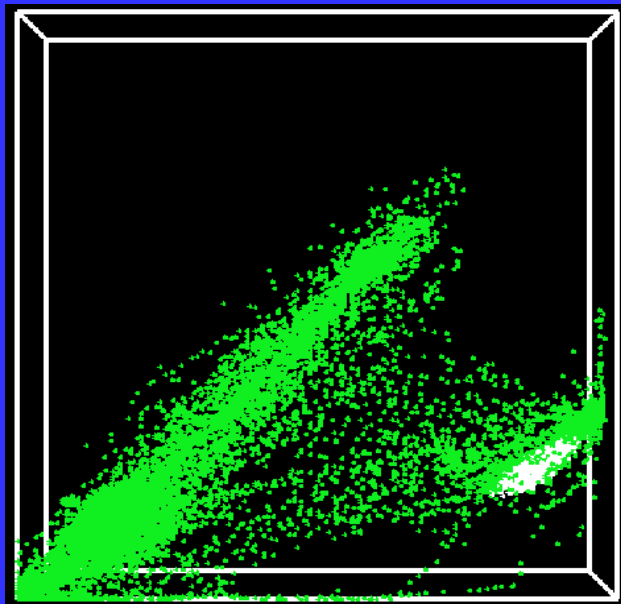
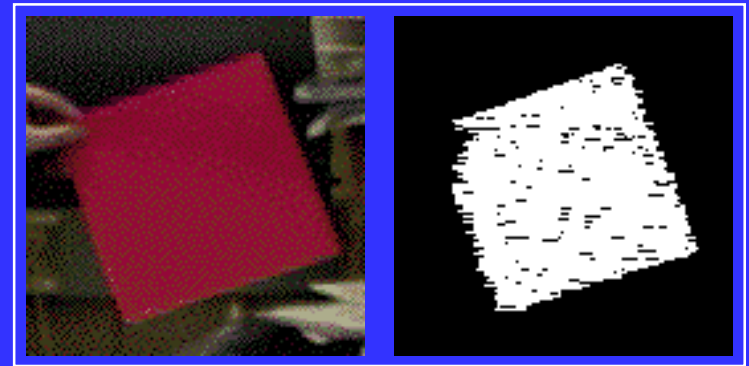
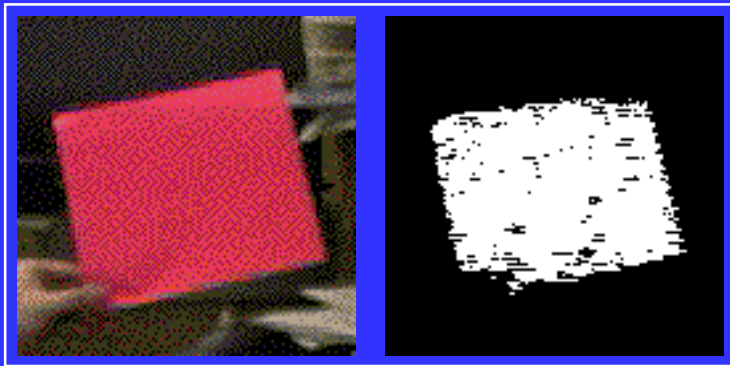
$$\Lambda = m_2 / m_0 - m_1^2$$

Regions

- $c_P = P \rightarrow \mathbb{R}^3$ (color space): intrinsic coloration
 - Homogeneous region: $c_P(P)$ is roughly constant
 - Textured region: $c_P(P)$ has significant intensity gradients horizontally and vertically
 - Contour: (local) rapid change in contrast



Homogeneous Color Region: Photometry

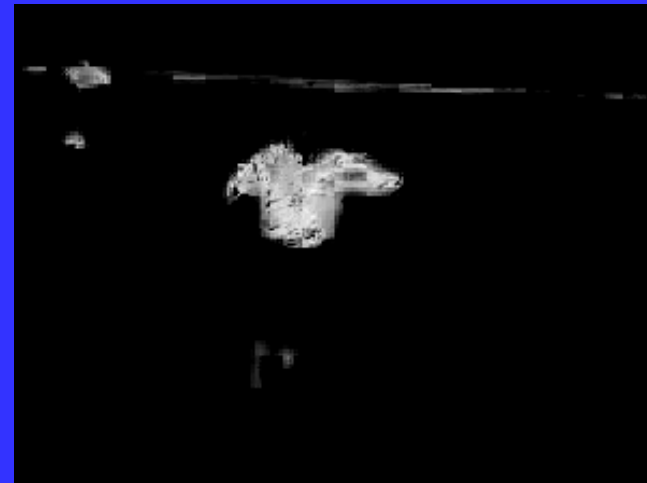


Color Representation

- $c_R = R \rightarrow \mathbb{R}^3$ is irradiance of region R
- Color representation
 - DRM [Klinker et al., 1990]: if P is Lambertian, has *matte* line and *highlight* line
 - User selects *matte* pixels in R
 - PCA fits ellipsoid $(\mathbf{S}, \mathbf{R}^T, \mathbf{T})$ to matte cluster
 - Color similarity $\gamma(\mathbf{I}(x, y))$ is defined by Mahalanobis distance

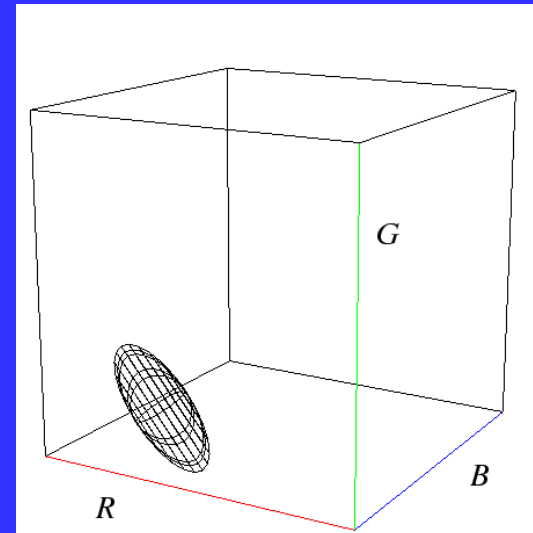
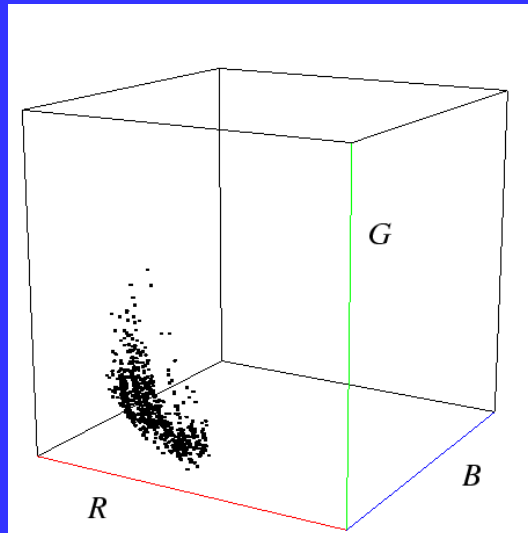
$$|\mathbf{S}^{-1} \mathbf{R}^T (\mathbf{I}(x, y) - \mathbf{T})| < 1 \text{ inside}$$

Homogeneous Region: Photometry



Sample

1/22/2022



PCA-fitted
ellipsoid

Color Extension (Contd.)

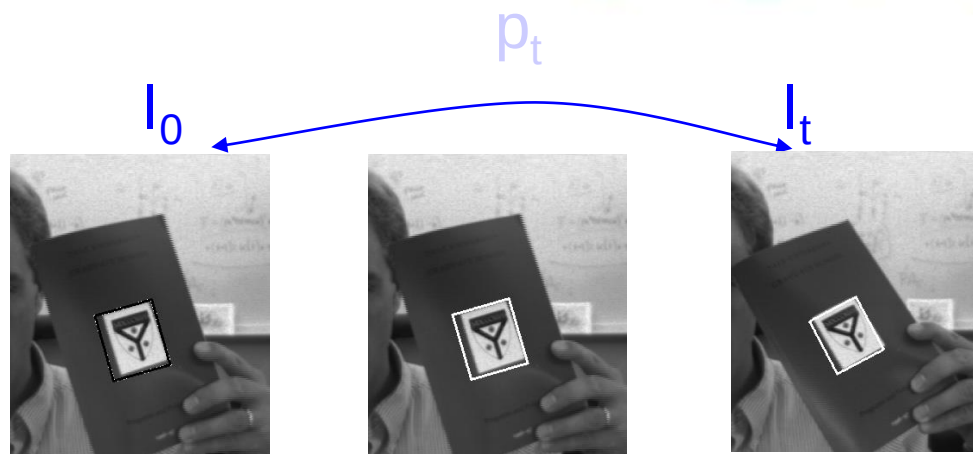
Color Histograms (Swain et al.)

- H_i = number of pixels in class i
- Histograms are vectors of bin counts
- Given histograms H and G , compare by

$$H \cdot G = \frac{\sum H_i G_i}{\sqrt{\sum H_i^2} \sqrt{\sum G_i^2}}$$

- dense, stable signature
- relies on segmentation
- relative color and feature locations lost
- affine transformations preserve area ratios of planar objects

Intro to Registration Tracking



Variability model: $I_t = g(I_0, p_t)$

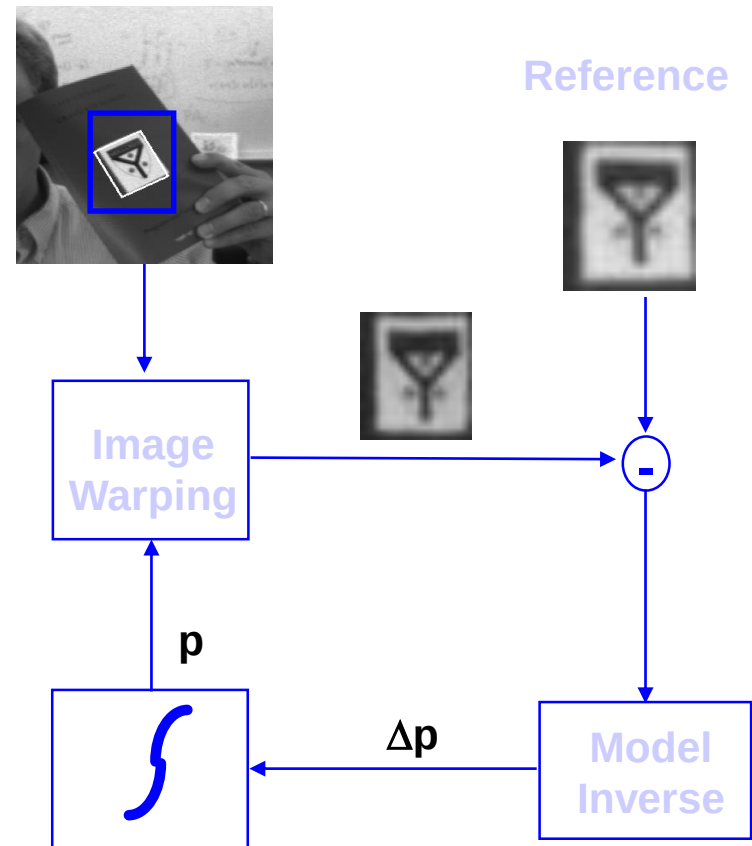
Incremental Estimation: From I_0 , I_{t+1} and p_t compute Δp_{t+1}

$$\| I_0 - g(I_{t+1}, p_{t+1}) \|^2 \Rightarrow \min$$

Visual Tracking = Visual Stabilization

Tracking Cycle

- Prediction
 - Prior states predict new appearance
- Image warping
 - Generate a “normalized view”
- Model inverse
 - Compute error from nominal
- State integration
 - Apply correction to state



Stabilization tracking: Planar Case

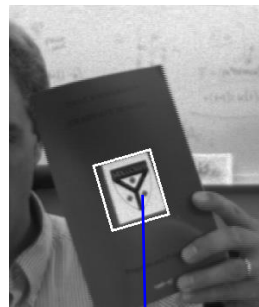
Planar Object +

Linear camera => Affine motion model: $u'_i = A u_i + d$

Subtract these:



-



-



= nonsense

Warping



-



-



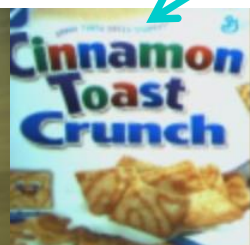
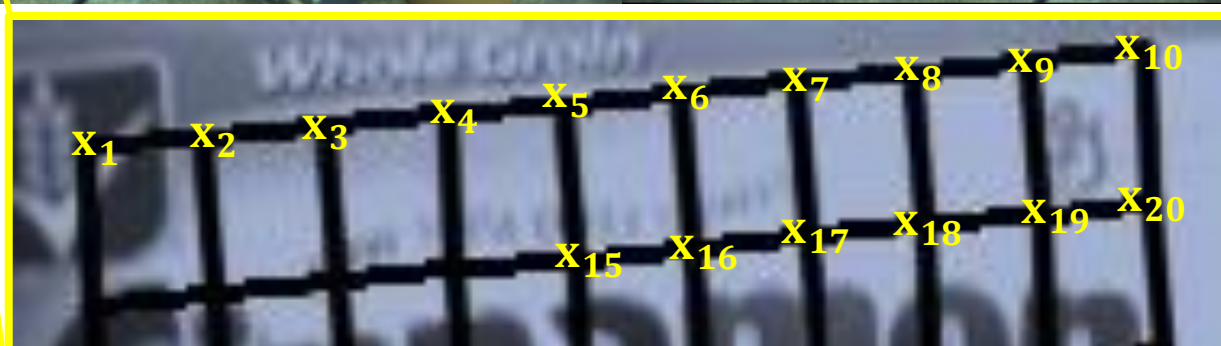
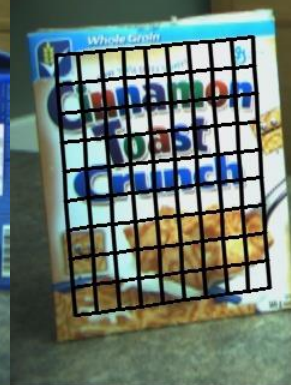
= small variation

But these:

$$I_t = g(p_t, I_0)$$

Registration based Tracking

$$\mathbf{p}_t = \underset{\mathbf{p}}{\operatorname{argmax}} f(\mathbf{I}_0(\mathbf{x}), \mathbf{I}_t(\mathbf{w}(\mathbf{x}, \mathbf{p})))$$


 I_0

 I_t


Motivation

- Learning/detection based trackers are not suitable for tasks requiring **fast** and **high precision** tracking
 - Visual Servoing
 - Virtual reality
 - SLAM

Registration (8DOF)



Learning (3DOF)

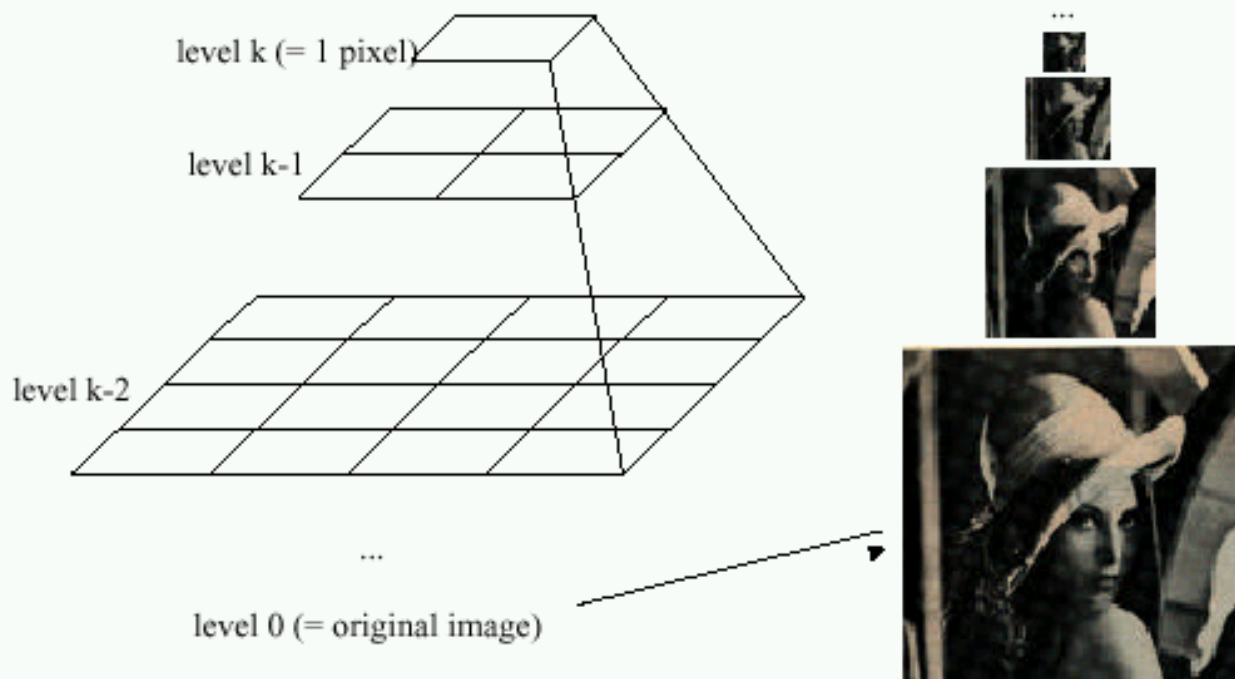


Image Pyramids

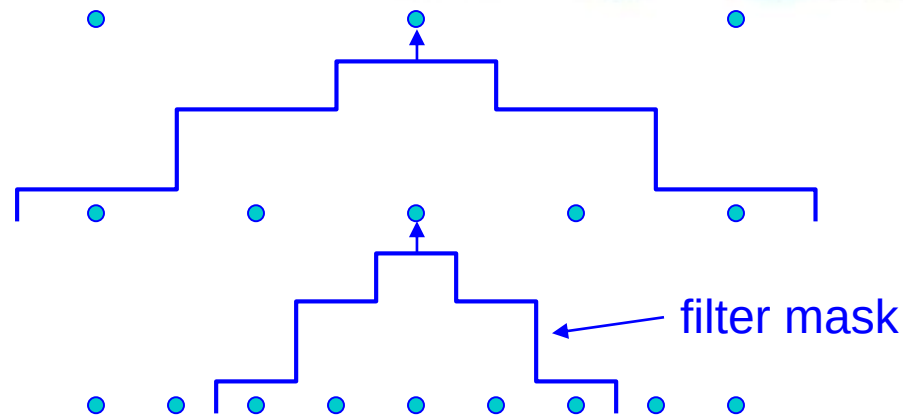


Image Pyramids

Idea: Represent $N \times N$ image as a “pyramid” of $1 \times 1, 2 \times 2, 4 \times 4, \dots, 2^k \times 2^k$ images (assuming $N=2^k$)



Pyramid Creation

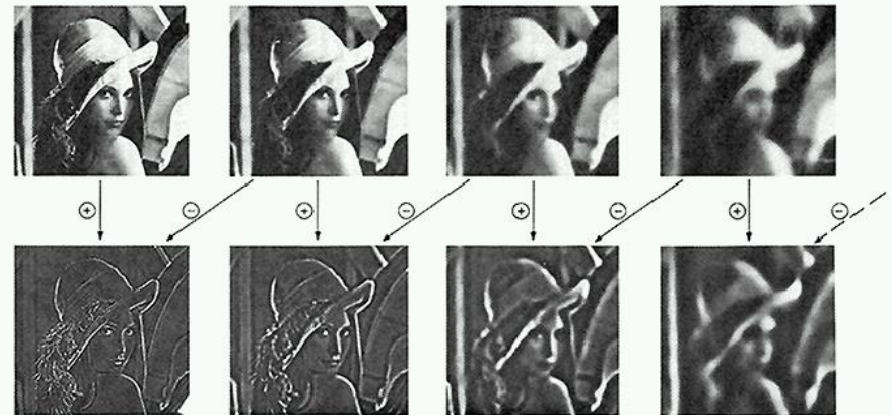


“Gaussian” Pyramid

• “Laplacian” Pyramid

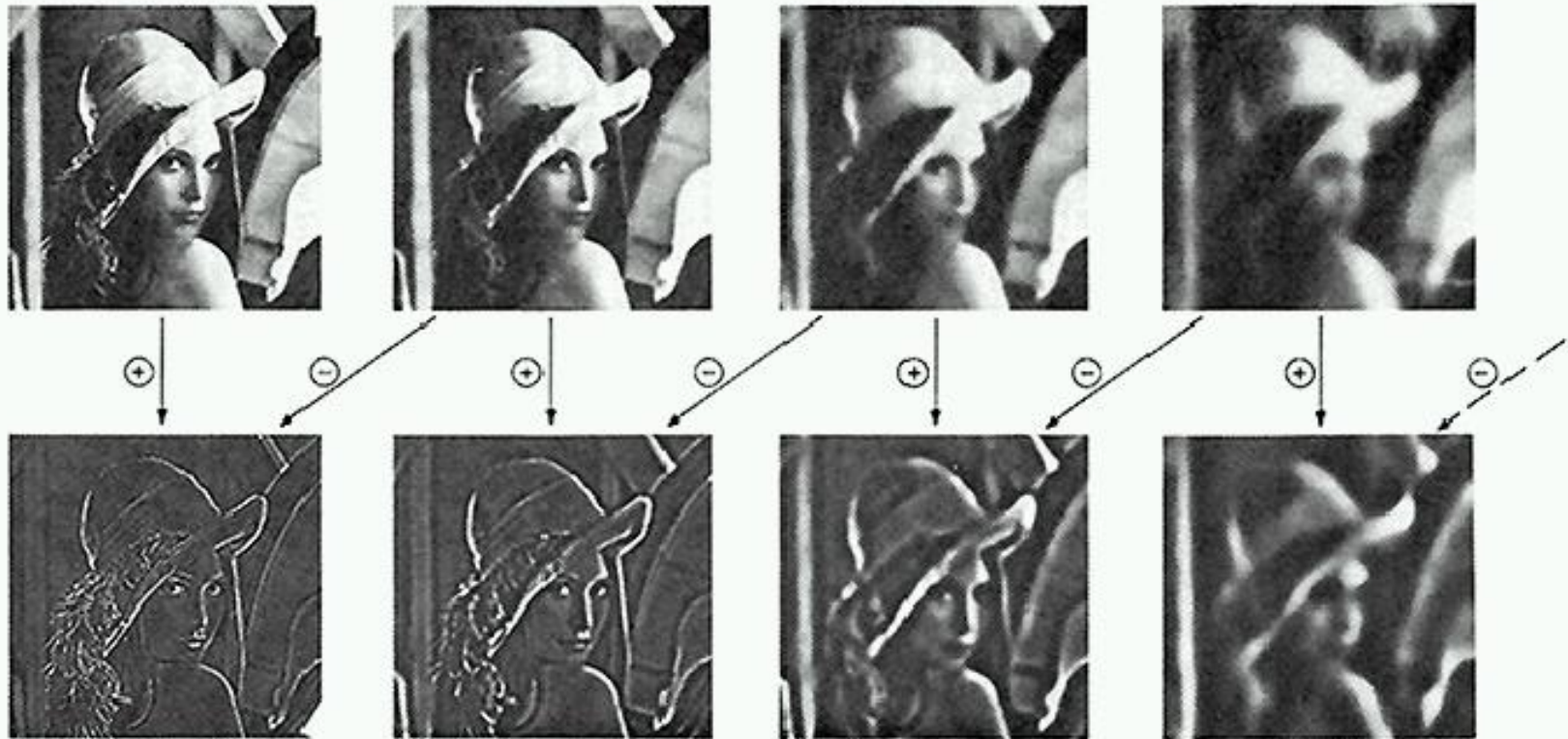
- Created from Gaussian pyramid by subtraction

$$L_1 = G_1 - \text{expand}(G_{l+1})$$



Octaves in the Spatial Domain

Lowpass Images

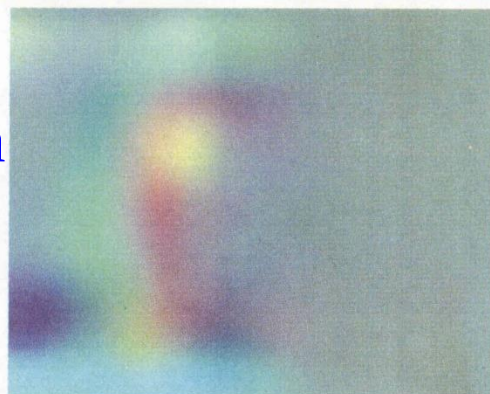


• Bandpass Images

Pyramids

- Advantages of pyramids
 - Faster than Fourier transform
 - Avoids “ringing” artifacts
- Many applications
 - small images faster to process
 - good for multiresolution processing
 - compression
 - progressive transmission
- Known as “mip-maps” in graphics community
- Precursor to wavelets
 - Wavelets also have these advantages

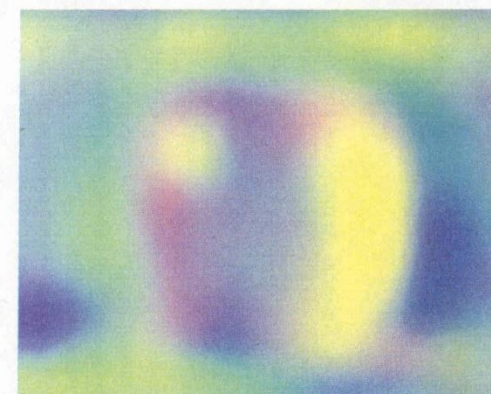
Laplacian
level
4



(c)

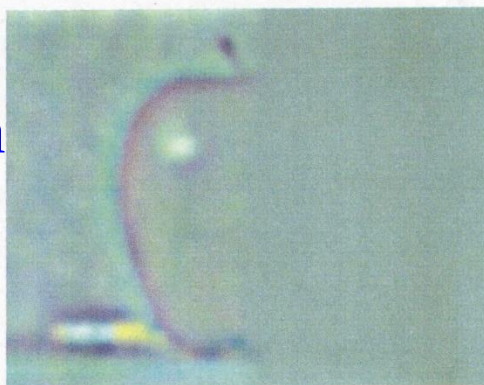


(g)

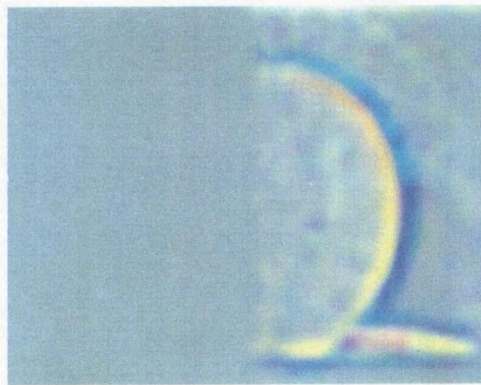


(k)

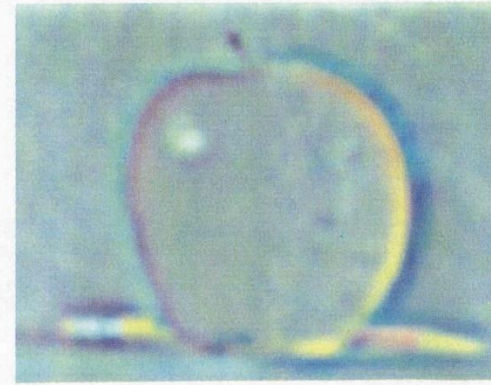
Laplacian
level
2



(b)

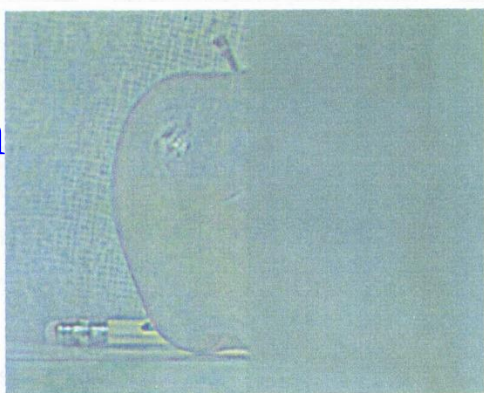


(f)

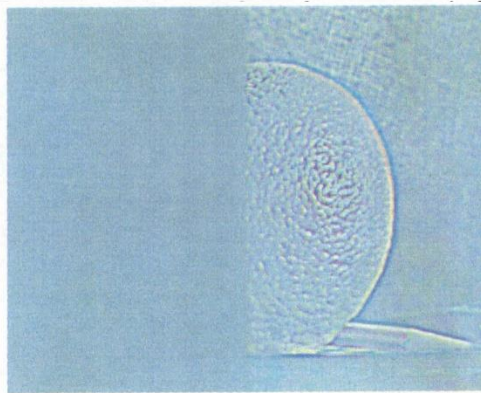


(j)

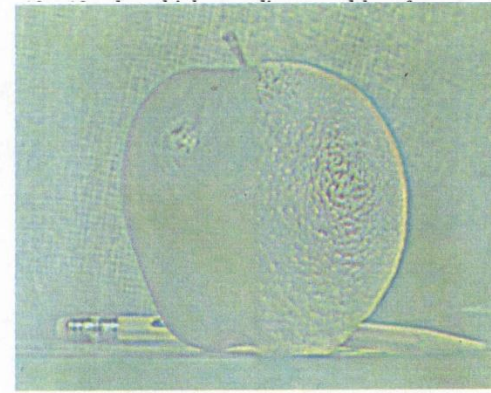
Laplacian
level
0



(a)



(e)



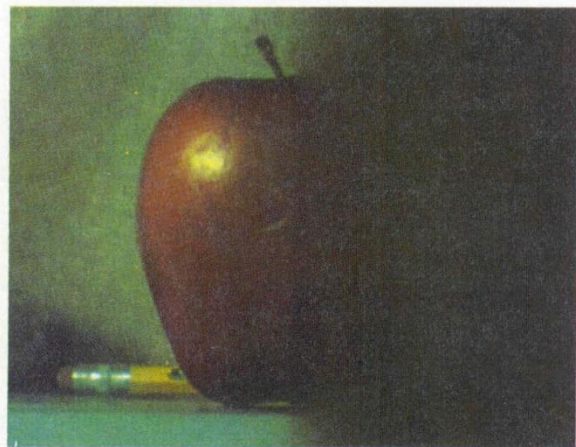
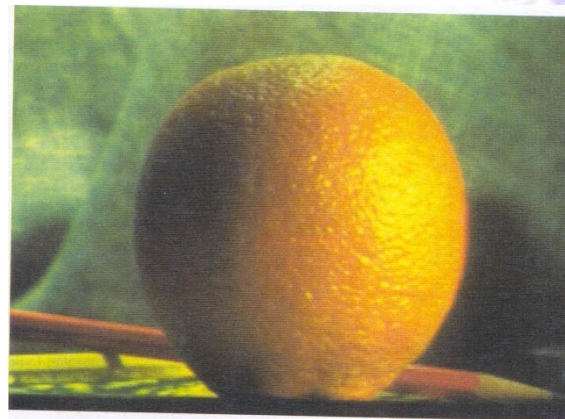
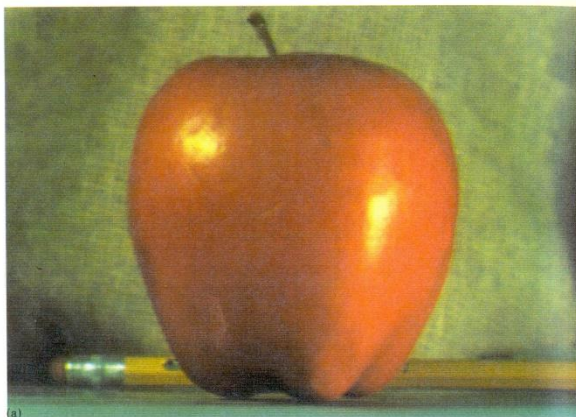
(i)

left pyramid

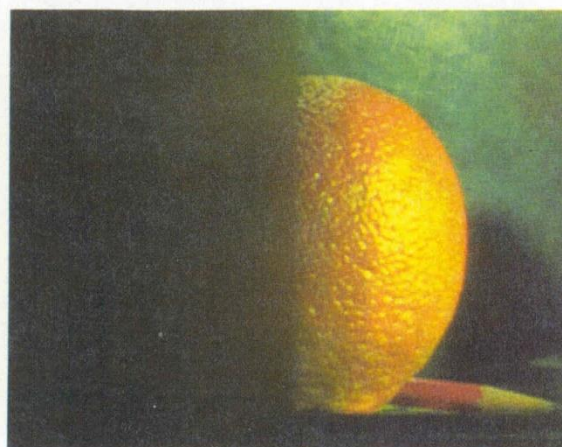
right pyramid

blended pyramid

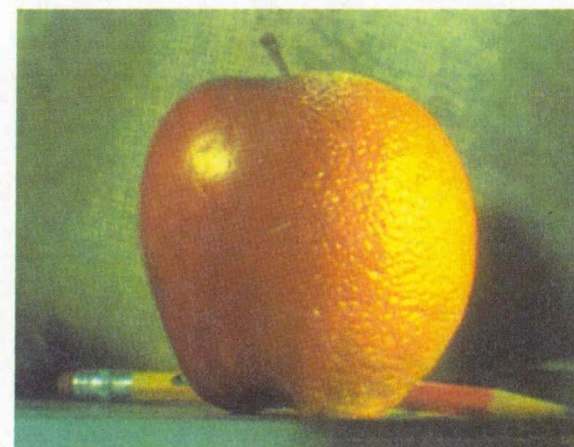
Pyramid Blending



(d)



(h)



(l)

Image Warping



Parametric (global) warping

- Examples of parametric warps:



translation



rotation



aspect



affine



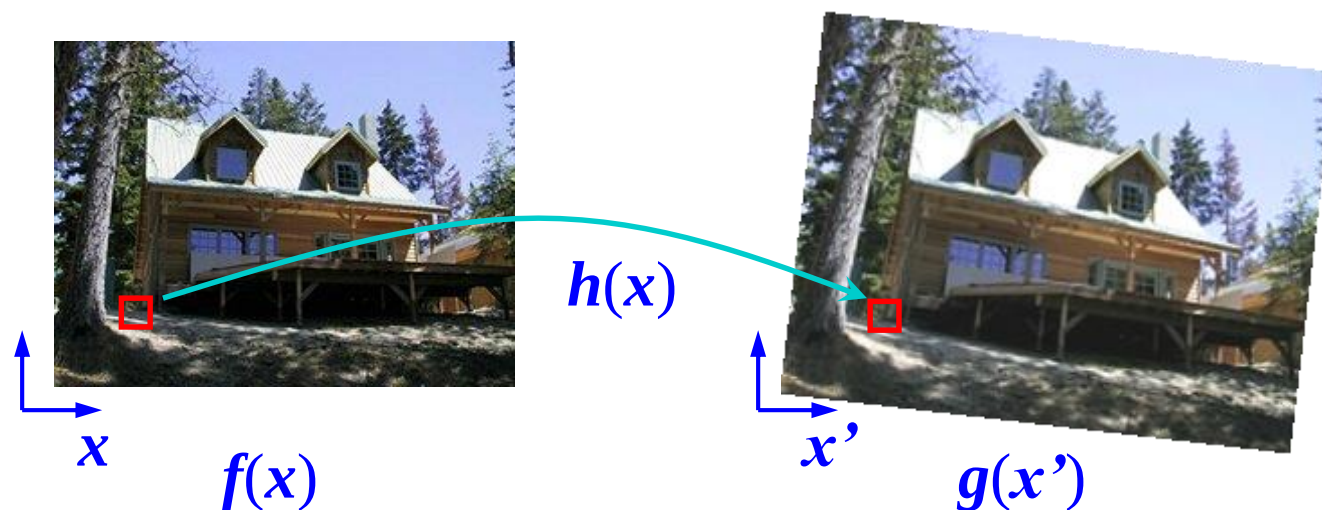
perspective



cylindrical

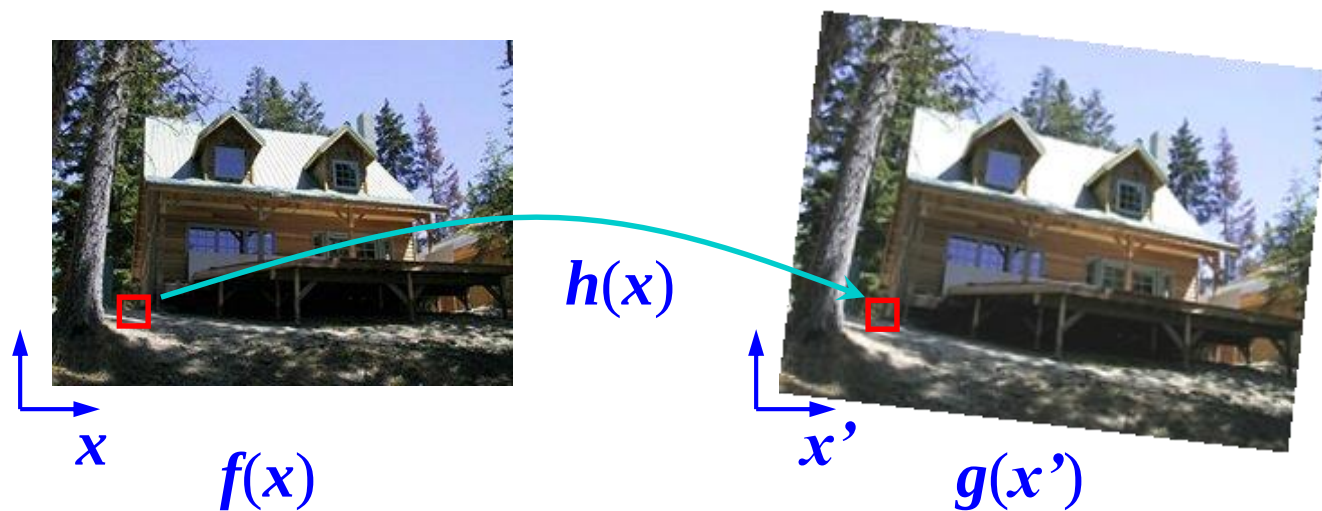
Image Warping

- Given a coordinate transform $\mathbf{x}' = \mathbf{h}(\mathbf{x})$ and a source image $f(\mathbf{x})$, how do we compute a transformed image $g(\mathbf{x}') = f(\mathbf{h}(\mathbf{x}))$?



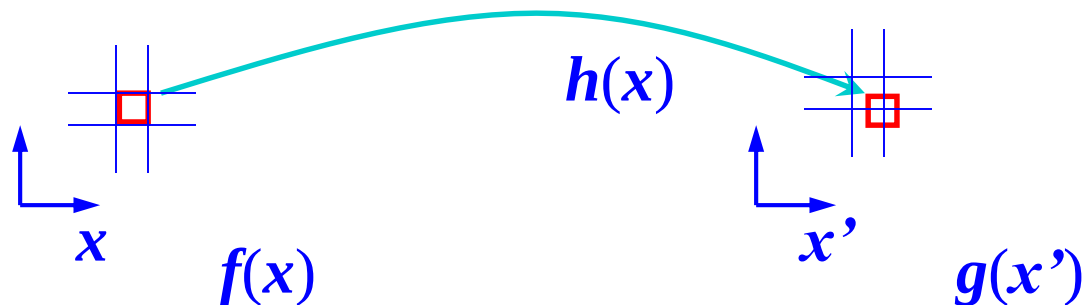
Forward Warping

- Send each pixel $f(x)$ to its corresponding location $x' = h(x)$ in $g(x')$
 - What if pixel lands “between” two pixels?



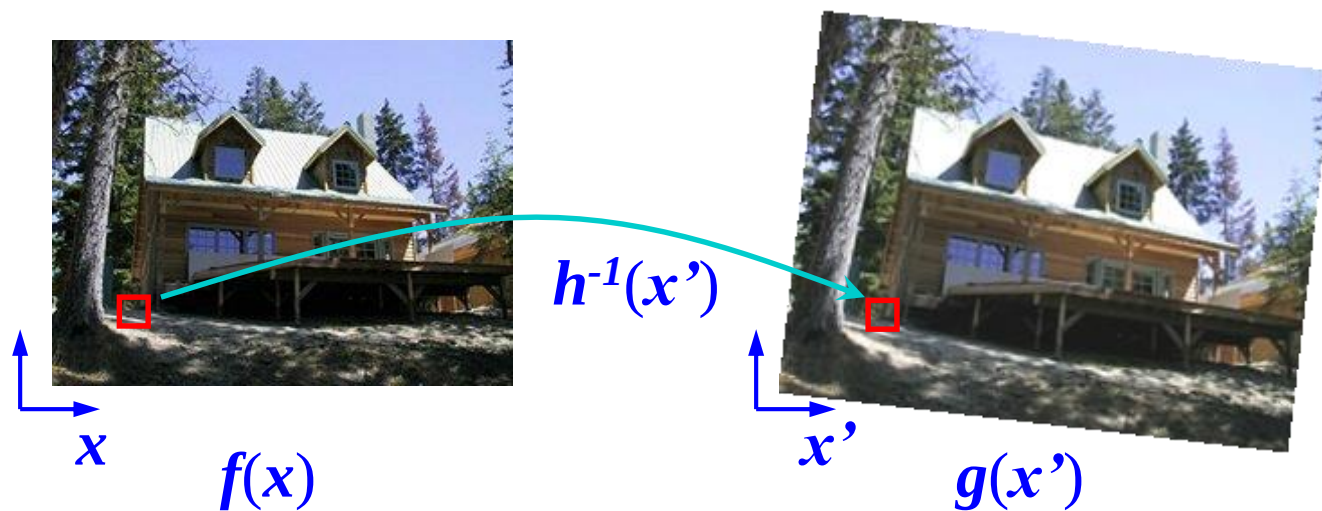
Forward Warping

- Send each pixel $f(x)$ to its corresponding location $x' = h(x)$ in $g(x')$
 - What if pixel lands “between” two pixels?
 - Answer: add “contribution” to several pixels, normalize later (*splatting*)



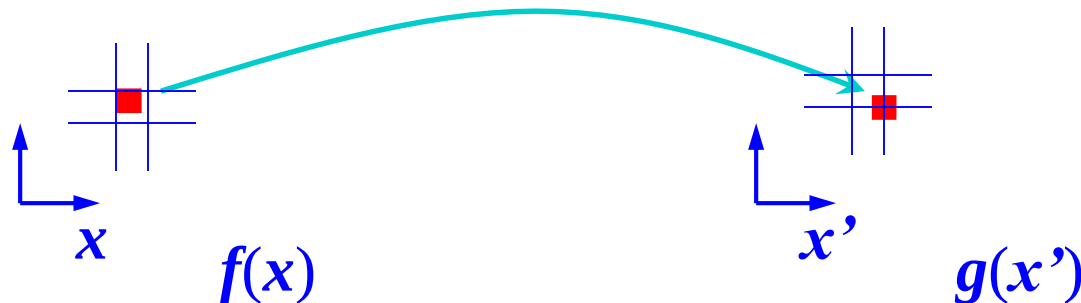
Inverse Warping

- Get each pixel $g(x')$ from its corresponding location $x = h^{-1}(x')$ in $f(x)$
 - What if pixel comes from “between” two pixels?



Inverse Warping

- Get each pixel $g(x')$ from its corresponding location $x = h^{-1}(x')$ in $f(x)$
 - What if pixel comes from “between” two pixels?
 - Answer: *resample* color value from *interpolated (prefiltered)* source image



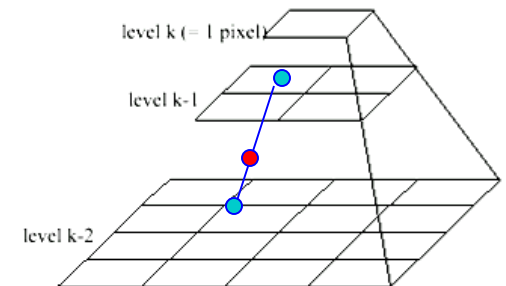
Interpolation

- Possible interpolation filters:
 - nearest neighbor
 - bilinear
 - bicubic (interpolating)
 - sinc / FIR
- Needed to prevent “jaggies”
and “texture crawl” (see [demo](#))



Prefiltering

- Essential for *downsampling* (*decimation*) to prevent *aliasing*
- MIP-mapping [Williams'83]:
 1. build pyramid (but what decimation filter?)
 - block averaging
 - Burt & Adelson (5-tap binomial)
 - 7-tap wavelet-based filter (better)
 2. *trilinear* interpolation
 - bilinear within each 2 adjacent levels
 - linear blend *between* levels (determined by pixel size)

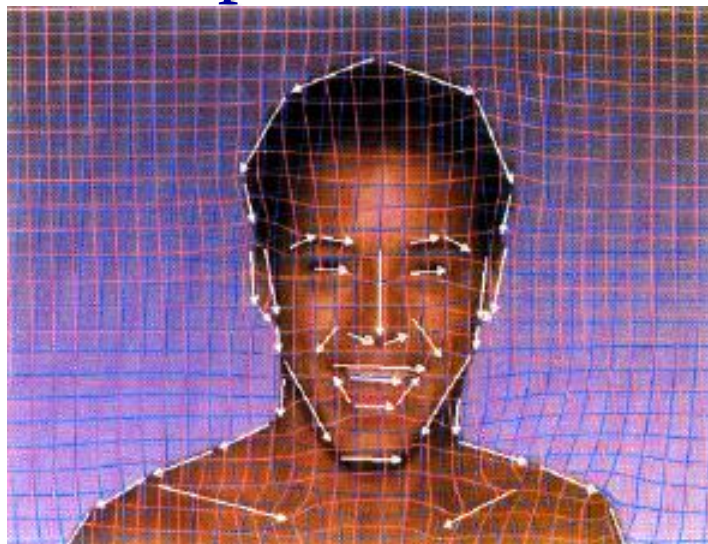


Prefiltering

- Essential for *downsampling* (*decimation*) to prevent *aliasing*
- Other possibilities:
 - summed area tables
 - elliptically weighted Gaussians (EWA) [Heckbert'86]

Image Warping – non-parametric

- Specify more detailed warp function



- Examples:
 - splines
 - triangles
 - optical flow (per-pixel motion)

Image Warping – non-parametric

- Move control points to specify spline warp

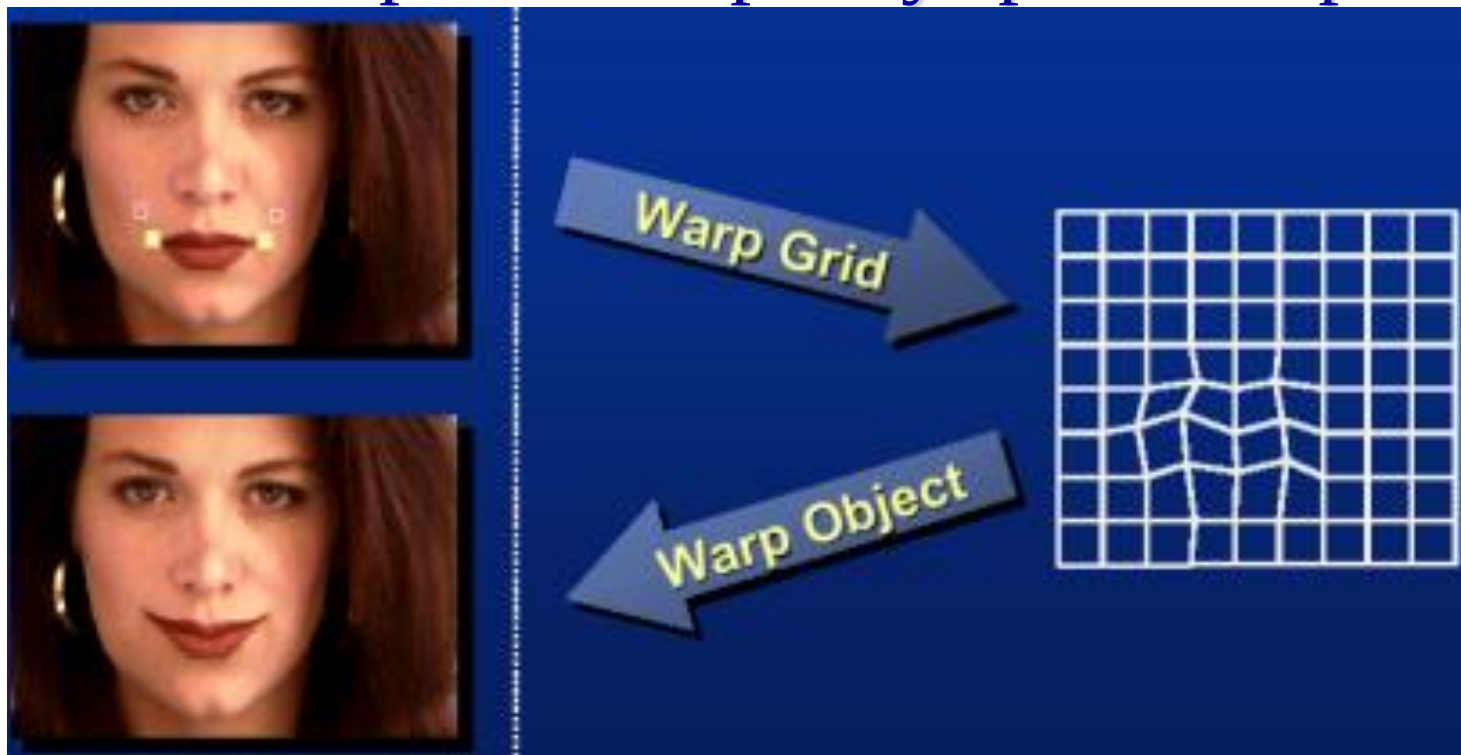


Image Morphing

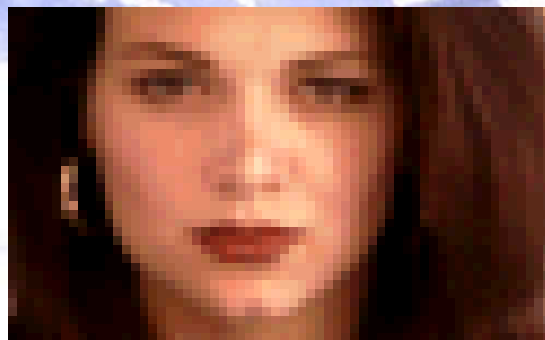
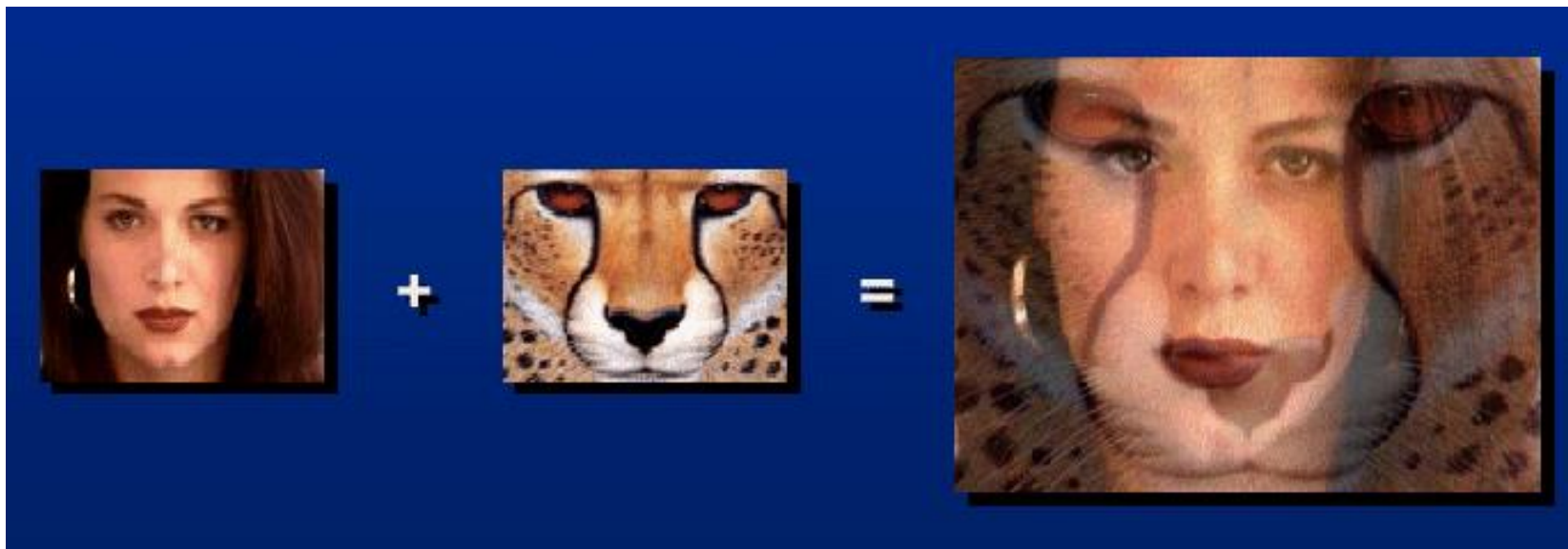


Image Morphing

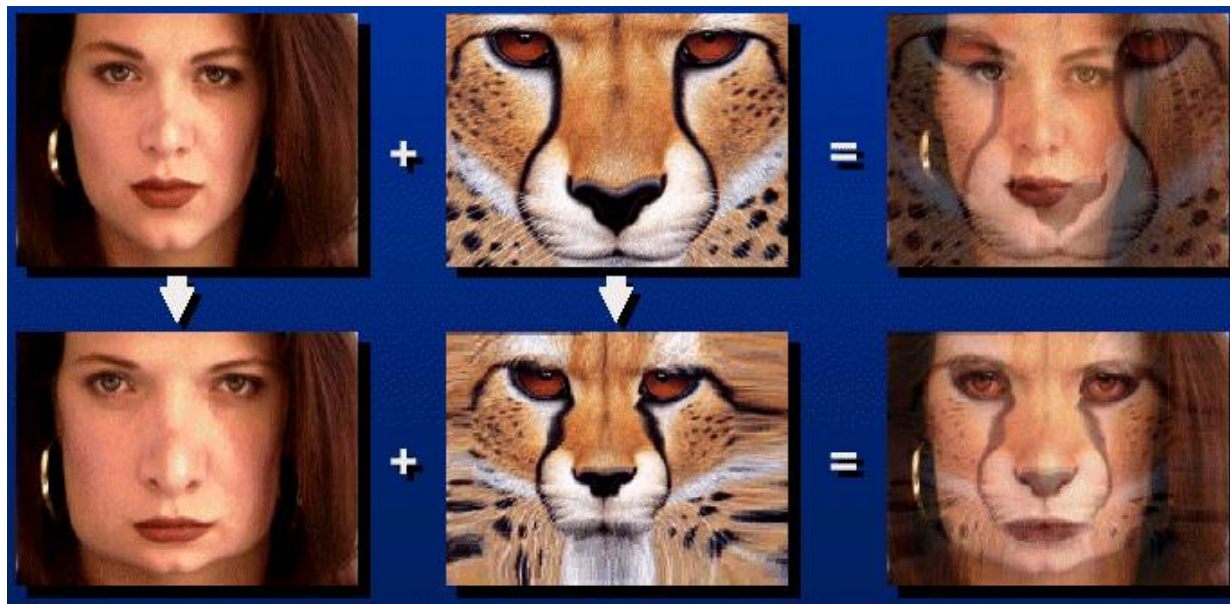
- How can we *in-between* two images?
 1. Cross-dissolve



(all examples from [Gomes *et al.*'99])

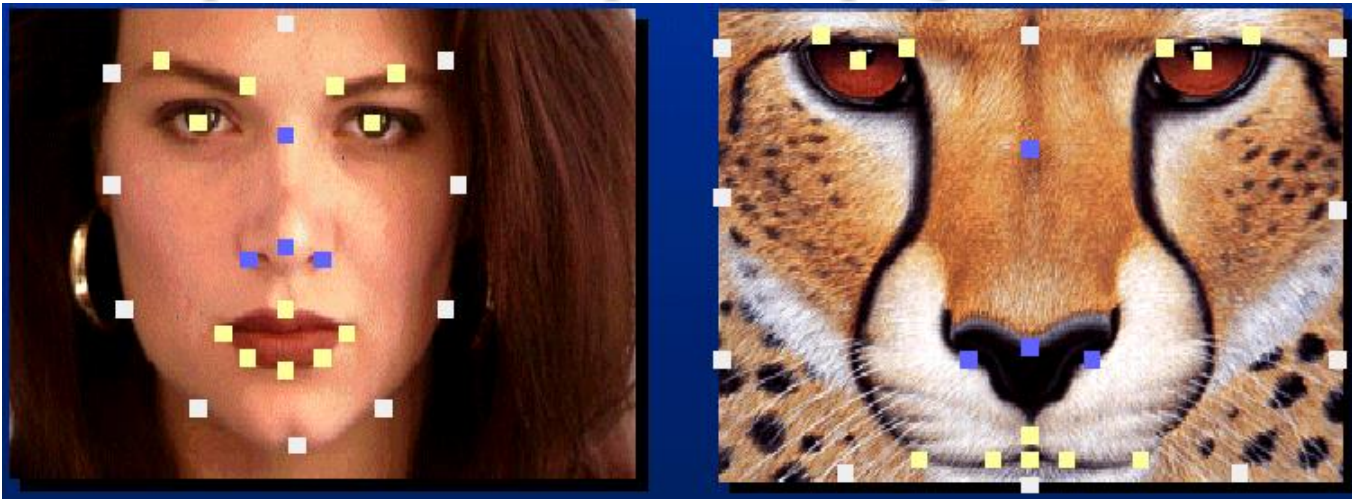
Image Morphing

- How can we *in-between* two images?
2. Warp then cross-dissolve = *morph*



Warp specification

- How can we specify the warp?
 1. Specify corresponding *points*
 - *interpolate* to a complete warping function



- Nielson, *Scattered Data Modeling* [IEEE CG&A'93]

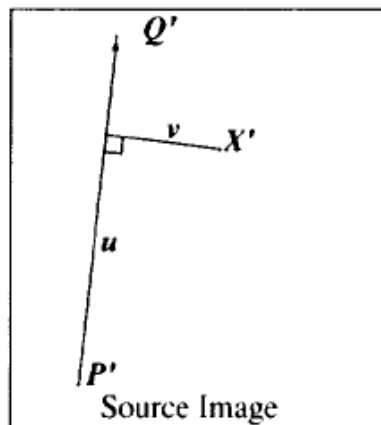
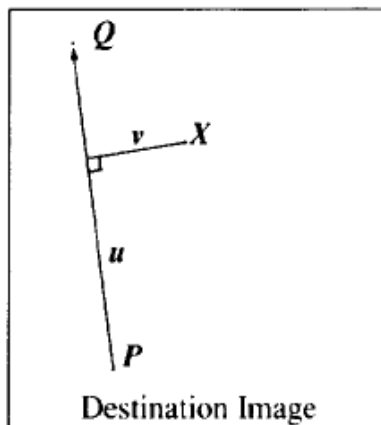
Warp specification

- How can we specify the warp?
 2. Specify corresponding *vectors*
 - *interpolate* to a complete warping function



Warp specification

- How can we specify the warp?
- 2. Specify corresponding *vectors*
 - *interpolate* [Beier & Neely, SIGGRAPH'92]



For each pixel X in the destination

$DSUM = (0,0)$

$weightsum = 0$

For each line $P_i Q_i$

calculate u, v based on $P_i Q_i$

calculate X'_i based on u, v and $P'_i Q'_i$

calculate displacement $D_i = X'_i - X_i$ for this line

$dist$ = shortest distance from X to $P_i Q_i$

$weight = (length^p / (a + dist))^b$

$DSUM += D_i * weight$

$weightsum += weight$

$X' = X + DSUM / weightsum$

$destinationImage(X) = sourceImage(X')$

Warp specification

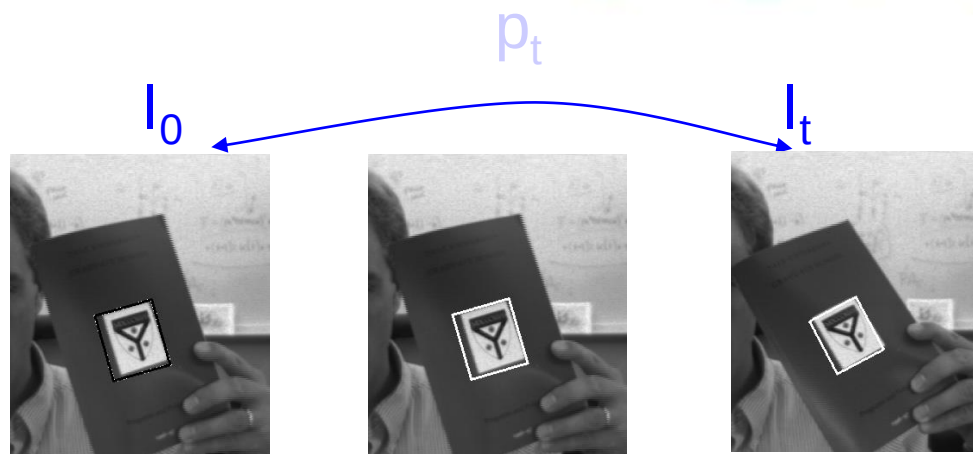
- How can we specify the warp?
 3. Specify corresponding *spline control points*
 - *interpolate* to a complete warping function



Final Morph Result



Intro to Registration Tracking



Variability model: $I_t = g(I_0, p_t)$

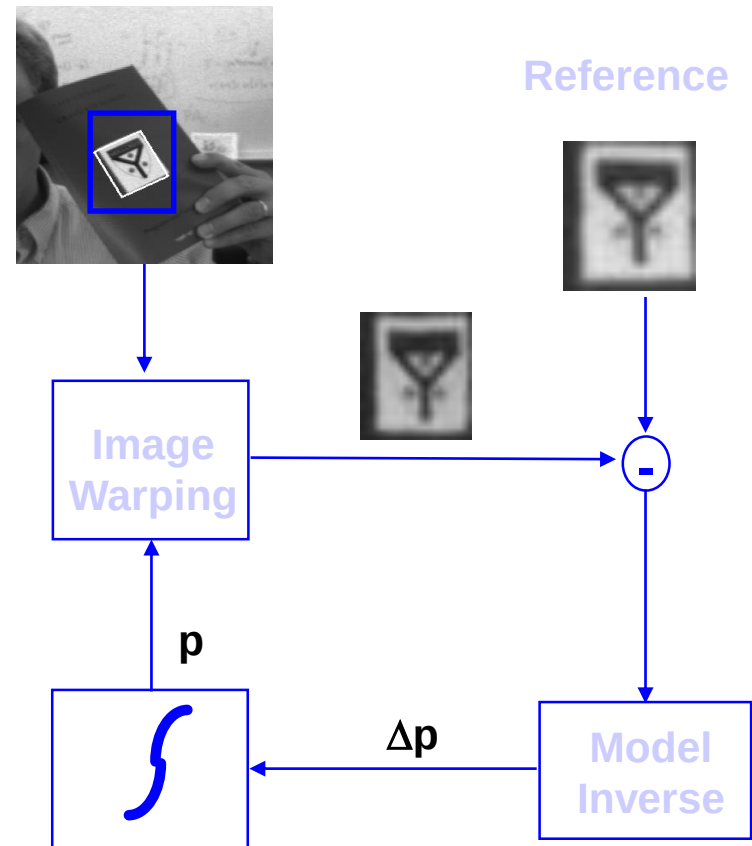
Incremental Estimation: From I_0 , I_{t+1} and p_t compute Δp_{t+1}

$$\| I_0 - g(I_{t+1}, p_{t+1}) \|^2 \Rightarrow \min$$

Visual Tracking = Visual Stabilization

Tracking Cycle

- Prediction
 - Prior states predict new appearance
- Image warping
 - Generate a “normalized view”
- Model inverse
 - Compute error from nominal
- State integration
 - Apply correction to state



Stabilization tracking: Planar Case

Planar Object +

Linear camera => Affine motion model: $u'_i = A u_i + d$

Subtract these:



-



-



= nonsense

Warping



-



-



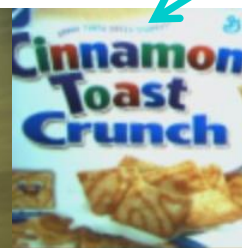
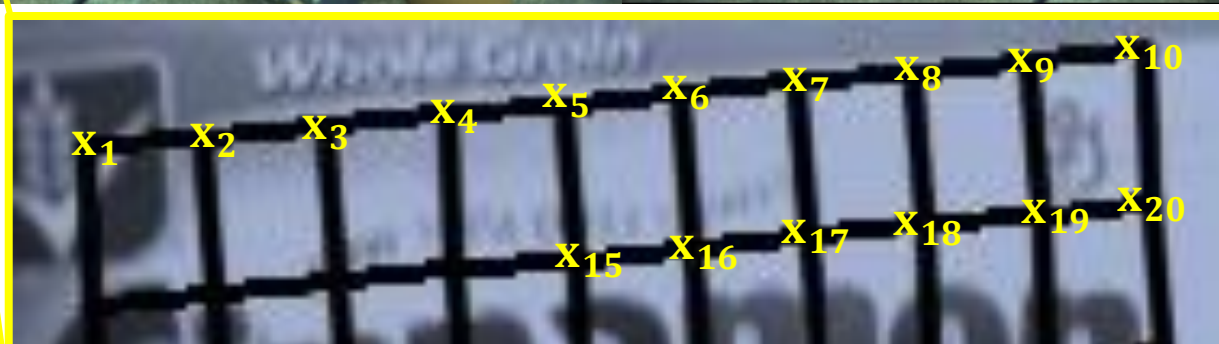
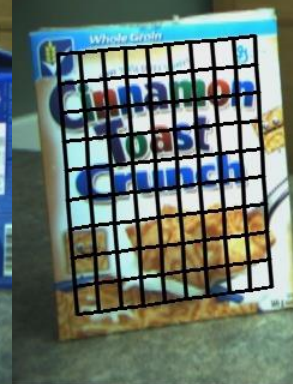
= small variation

But these:

$$I_t = g(p_t, I_0)$$

Registration based Tracking

$$\mathbf{p}_t = \underset{\mathbf{p}}{\operatorname{argmax}} f(\mathbf{I}_0(\mathbf{x}), \mathbf{I}_t(\mathbf{w}(\mathbf{x}, \mathbf{p})))$$


 I_0

 I_t


Motivation

- Learning/detection based trackers are not suitable for tasks requiring **fast** and **high precision** tracking
 - Visual Servoing
 - Virtual reality
 - SLAM

Registration (8DOF)



Learning (3DOF)



Evaluation Benchmarks

TMT



PAMI



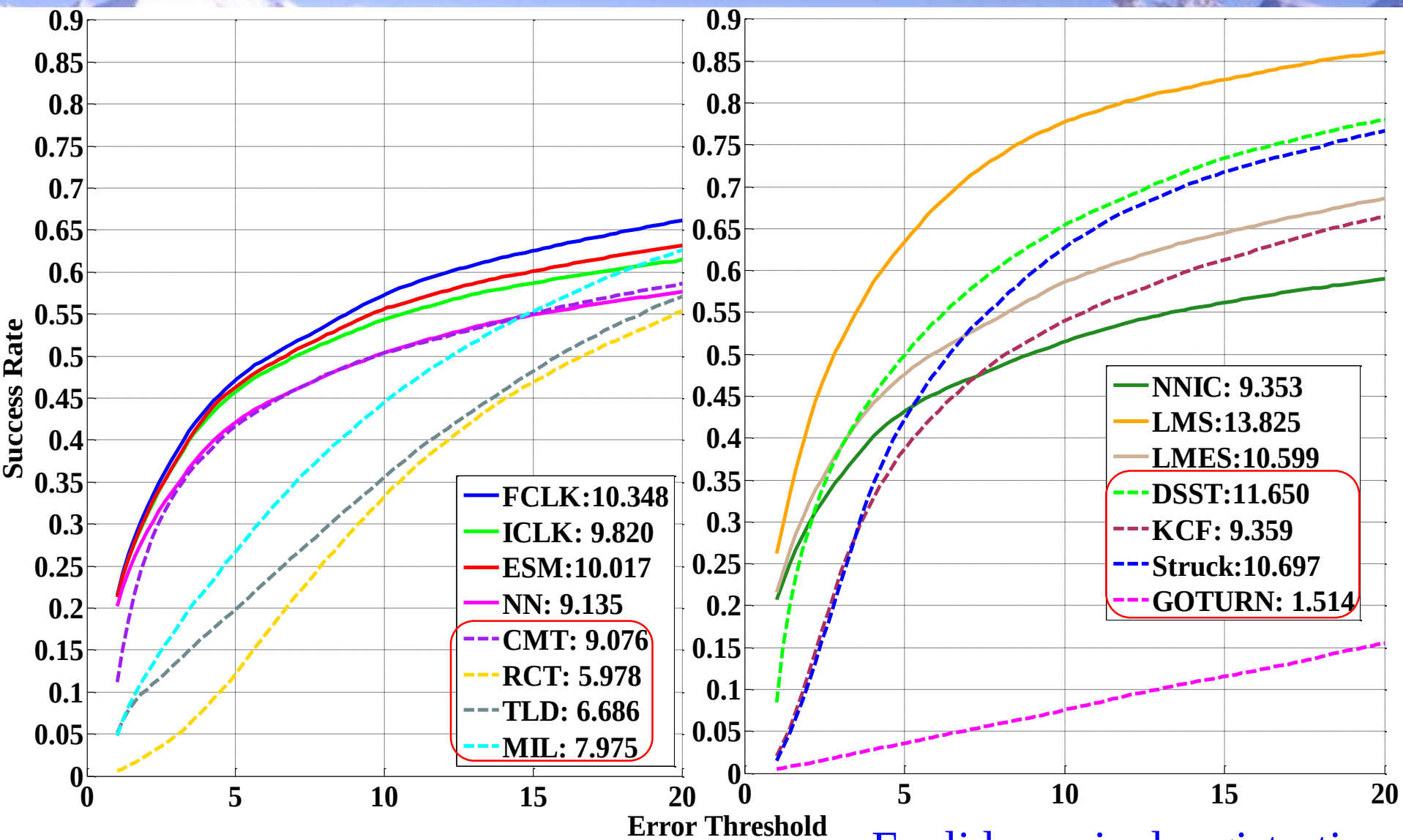
UCSB



LinTrack



Results: Learning vs. 2DOF Registration Based Trackers (Accuracy)



Euclidean pixel registration c

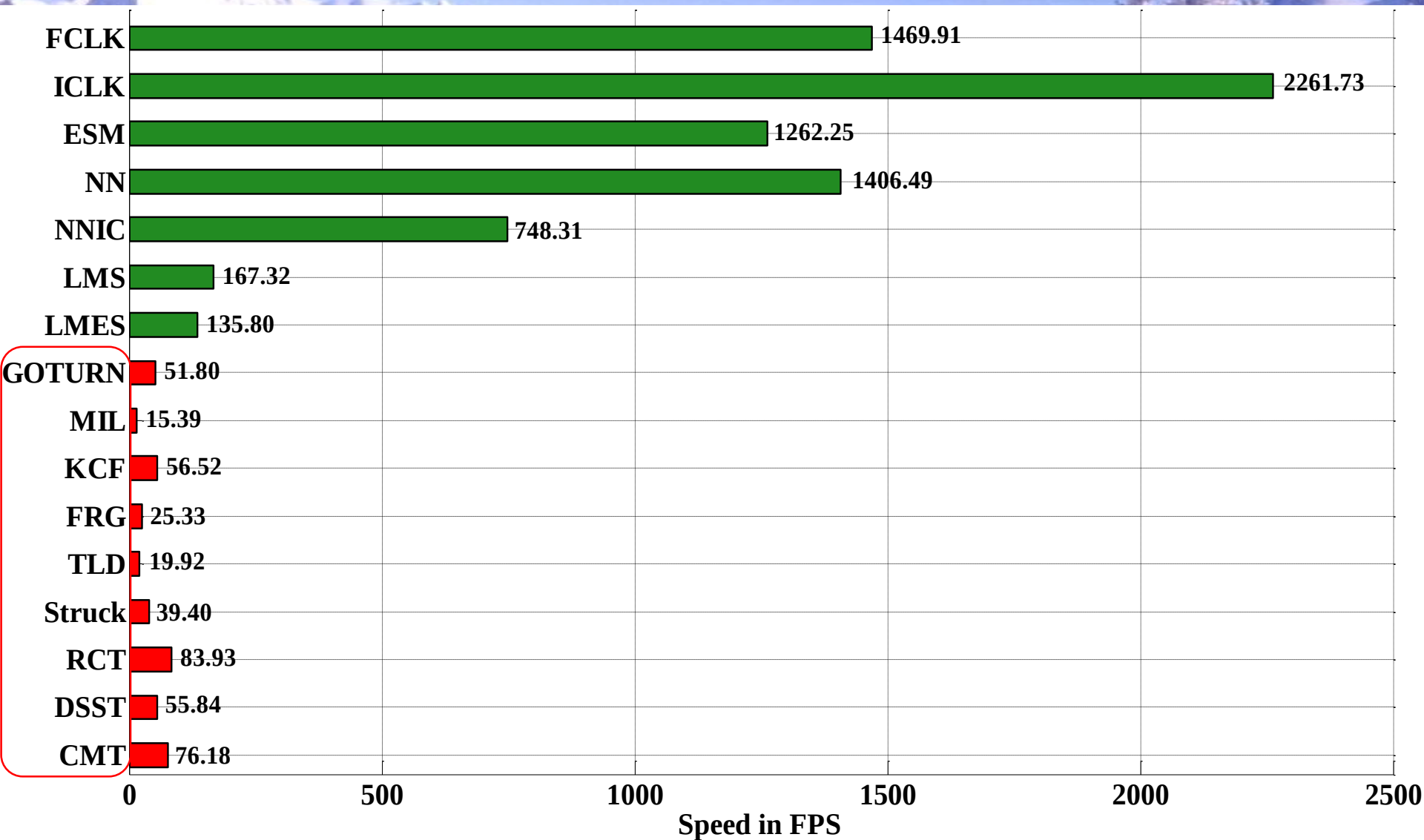
RBT vs Learn vs GoTurn

nl_cereal_s3: frame 1

GOTURN DSST ESMLMES



Results: Learning vs. 2DOF Registration Based Trackers (Speed)



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