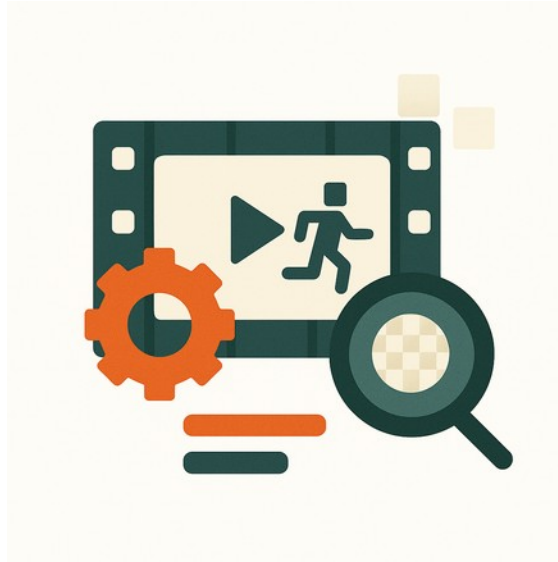




Video Processing

Video Perception

- Human vision integrates over time (~10–20 ms windows)



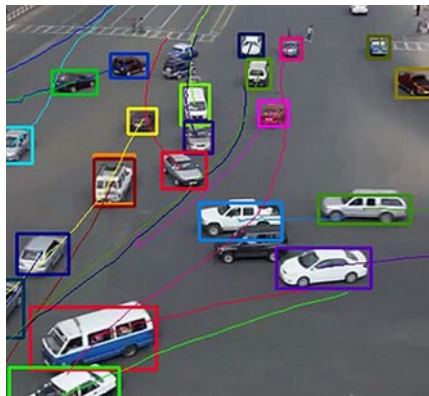
Processing Video

- Video = sequence of images
 - Frames per second
 - Locality of motion
- Animate image processing
 - Process every frame individually
 - Change parameters over time
- Analyze motion (work with multiple frames)
- Detect transitions

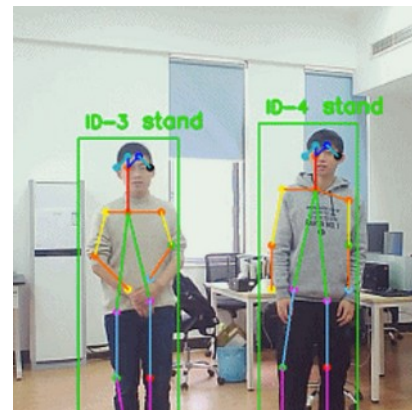
Motion Analysis



Optical Flow
Pixel-level, Local



Object Tracking
Entire video, Entire objects



Action Recognition
Actions, Understanding

Motion Estimation in Multimedia

- Estimate movement in video
 - Scene movement
 - Object movement
 - Camera movement
- Building block of many applications
 - Video stabilization
 - Video compression
 - 3D reconstruction
 - Augmented reality

Optical Flow

- Perceived motion in pixel (x,y) at time t
- Basic building block
 - Video compression
 - Stabilization
 - Object tracking
 - Scene understanding



Problem Definition

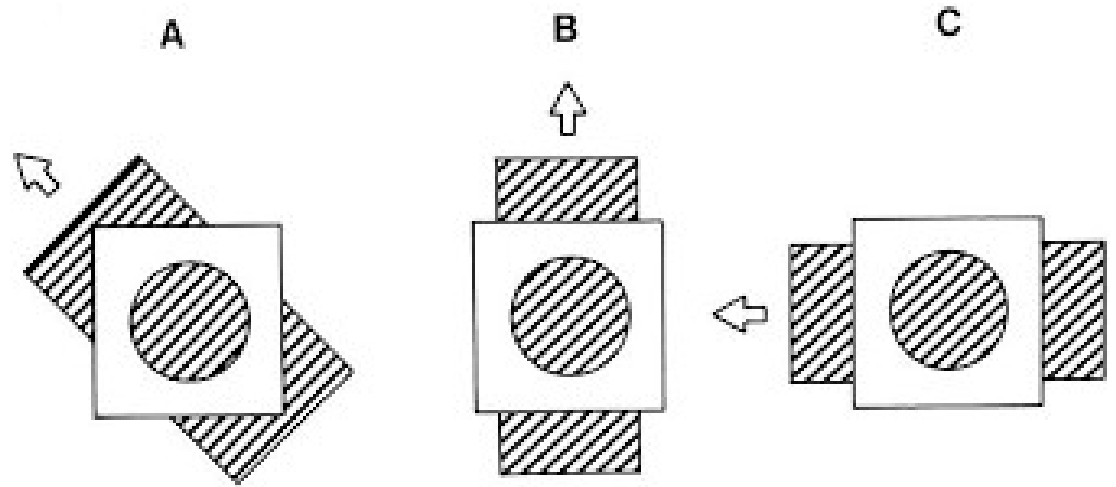
- Assumptions
 - Constant brightness
 - Small displacements
- Calculate displacements over pair of frames

$$I(x, y, t) - I(x + u, y + v, t + 1) = 0$$

$$I_x u + I_y v + I_t = 0$$

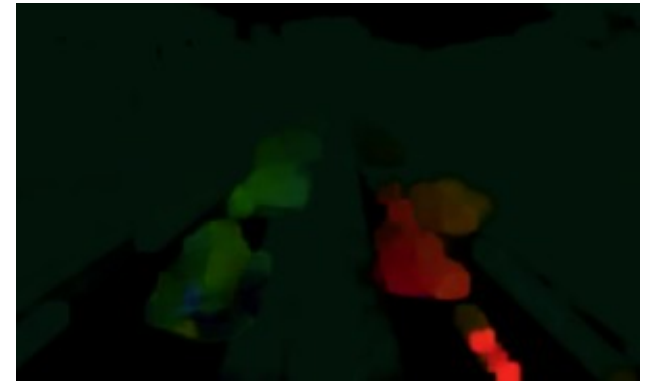
Challenges

- Projection of 3D motion to image
- Aperture problem



Optical Flow Approaches

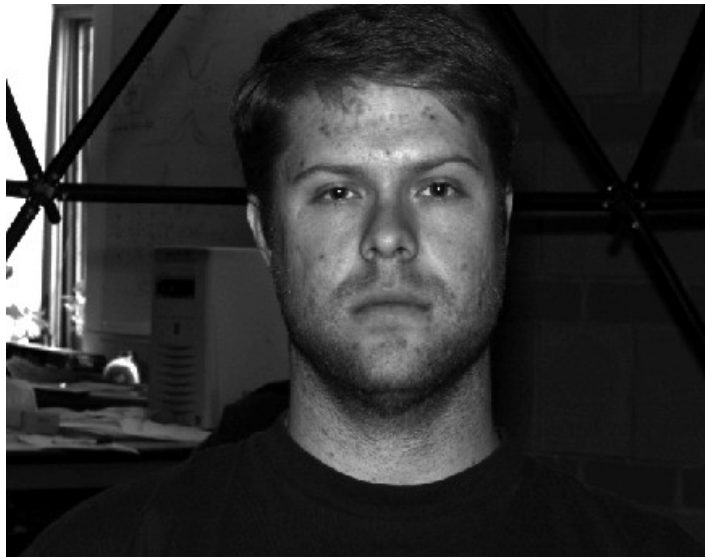
- Lucas & Kanade – fast
 - Assumes constant velocity in a local patch
 - Considers nearby pixels (least squares)
- Horn & Schunk – slow
 - Optimizes entire flow field
 - Slower
- RAFT
 - Deep learning
 - Synthetic data



Feature Tracking

- Only look for regions in image that can be reliably positioned in frames
 - Corners
 - Blobs
- Features have to be visible all the time
- Use difference in position to determine transformation

Normalized Cross Correlation



Search image, F



Model, H

$\psi(\mathbf{A})$... reshape pixels in A in a vector.

$\mathbf{F}_{ij}$... sub-image from F centered at (i,j) .

$$\mathbf{h} = \psi(\mathbf{H})$$

$$\mathbf{f}_{ij} = \psi(\mathbf{F}_{ij})$$

$\hat{h}$... average brightness of H

$\hat{f}_{ij}$... average brightness of F_{ij}

Normalized cross correlation:

$$G(i, j) = \frac{(\mathbf{h}^T - \hat{h})(\mathbf{f}_{ij} - \hat{f})}{\sqrt{\mathbf{h}^T \mathbf{h}} \sqrt{\mathbf{f}_{ij}^T \mathbf{f}_{ij}}}$$

Simple Feature Tracking

- Input: initial position P_1 , frame #1
 - Cut patch of size $N \times N$ around P_1 from frame #1
- For frames $T = 2 \dots N$
 - Cut search region of size $M \times M$ around P_{T-1} from frame # T
 - NCC between patch and search region
 - P_T = Best match location (adjusted for search region offset)

Camera Stabilization

Change positions of image frames through time to remove rapid motion (e.g. hand-held camera, external shaking)

Original



Stabilized



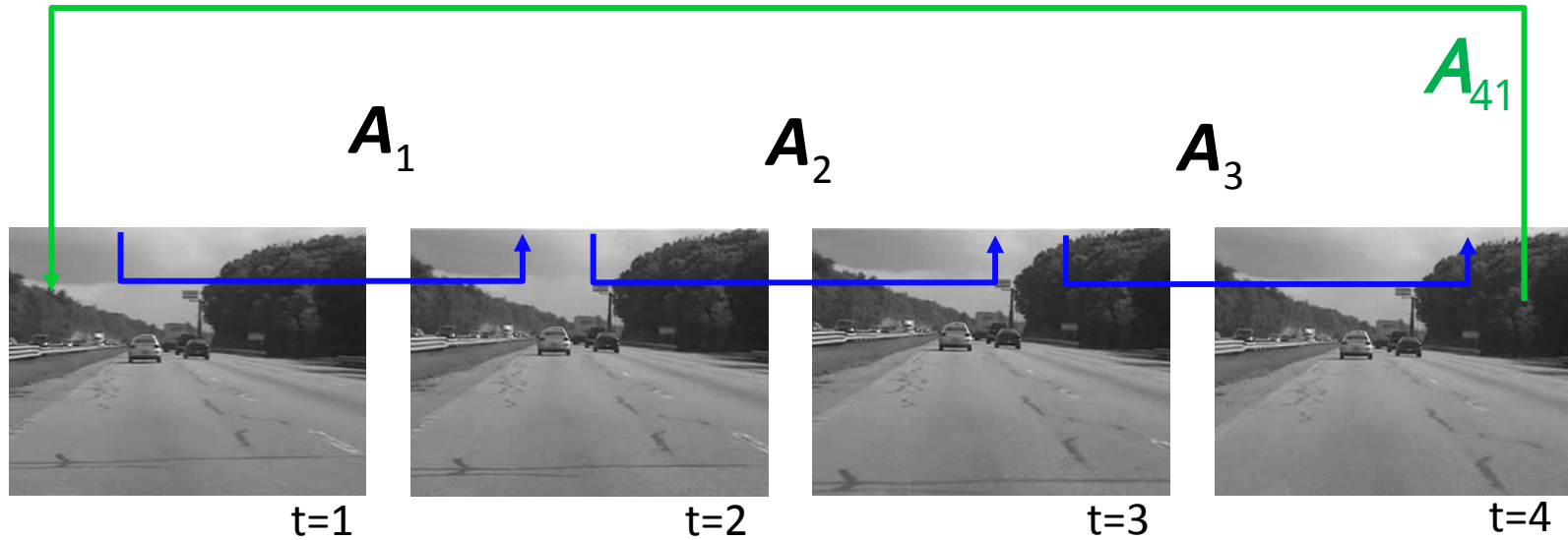
Camera Stabilization Approaches

- Mechanic
 - Move sensor or lenses
 - Stabilize image before it is digitized
 - Lenses (Nikon - 1994, Canon - 1995): detect vibrations and move lens with magnetic field
 - Sensor: move sensor with motors (supports lens changes)
 - External: Steadicam, tripod, dolly
- Digital
 - Post processing
 - Move images, apply geometrical transformations
 - Digital filters in case of blurring

Simple Digital Stabilization

- Input: $\{I_1 \dots I_N\}$
- Output $\{O_1 \dots O_N\}$
- $A :=$ Identity matrix
- For image pair I_i, I_{i+1}
 - $A_i :=$ Estimate movement from I_i to I_{i+1}
 - $A := A * A_i$
 - $O_{i+1} :=$ transform using A^{-1}

Transformation Chain



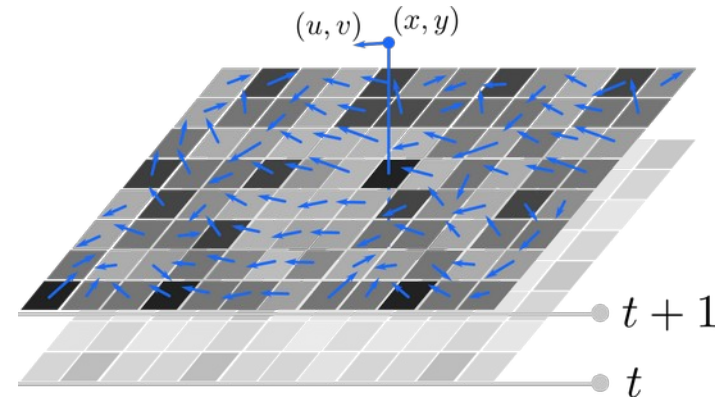
$$\left. \begin{aligned} \mathbf{x}_{t=1} &= \mathbf{A}_1 \mathbf{x}_{t=2} \\ \mathbf{x}_{t=2} &= \mathbf{A}_2 \mathbf{x}_{t=3} \\ \mathbf{x}_{t=3} &= \mathbf{A}_3 \mathbf{x}_{t=4} \end{aligned} \right\} \begin{aligned} \mathbf{x}_{t=1} &= \mathbf{A}_1 \mathbf{A}_2 \mathbf{A}_3 \mathbf{x}_{t=4} \\ \mathbf{A}_{41} &= \mathbf{A}_1 \mathbf{A}_2 \mathbf{A}_3 \end{aligned}$$

Number of Features

- One feature – translation
- Two features – translation + rotation or scale
- Three features – affine transformation
 - Only planar motion
- Four features – perspective transform
 - Assumes planar scene
 - Can lead to destroyed illusion of depth

Optical Flow Stabilization

- Use optical flow instead of keypoints, more dense
- For each pixel compute its most likely translation in the next image
- Fit global transformation to multiple optical flow vectors



Soft Stabilization

- Feature trajectory as a signal
 - High frequencies = shaking, noise
 - Low frequencies = intentional
- Use low-pass filter
 - Filter out noise, keep intentional movement
 - Mind the boundaries (start, end)

2D stabilization result



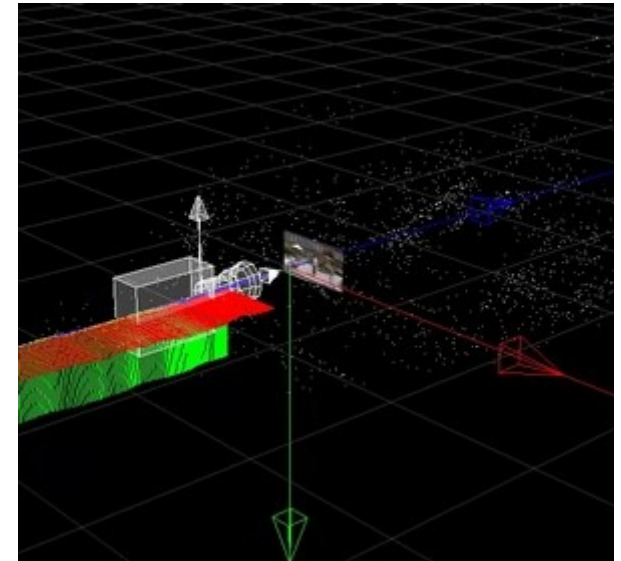
Raw video



2D stabilization

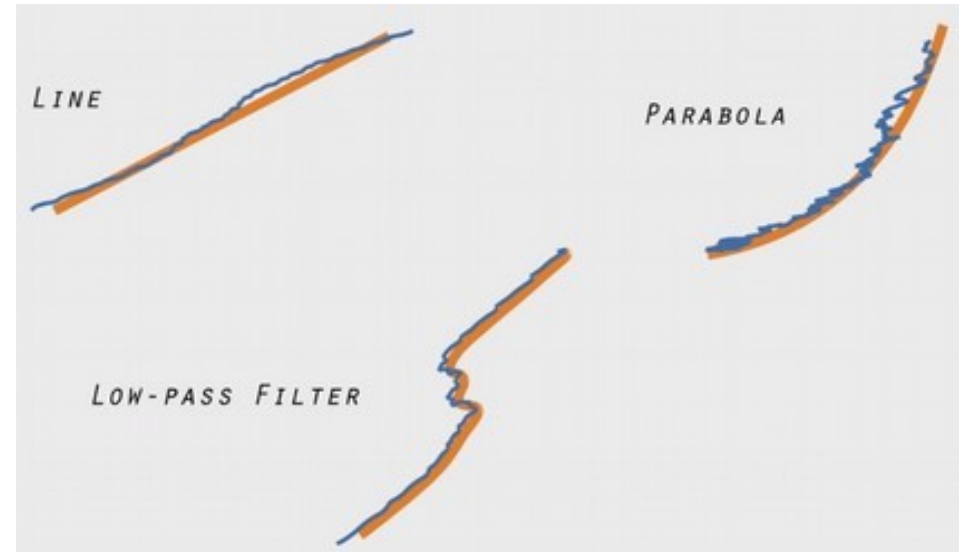
Stabilization in space

- Reconstruct 3D geometry using Structure from Motion
 - Reconstruction also gives us camera location and translation
- Filter camera path to get smooth path
- Compute warps for modified camera positions and apply them to frames



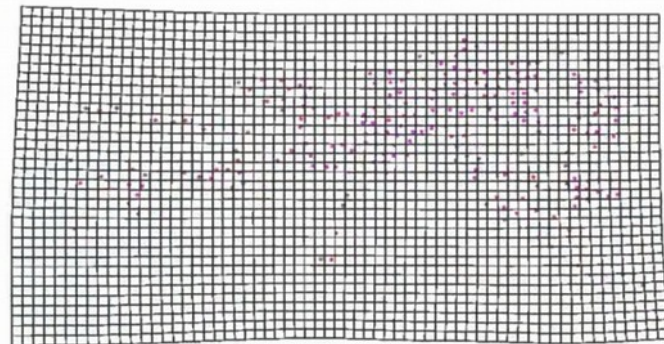
Camera motion types

- 2D stabilization is only removing image motion
- 3D camera path can be used to fit a parametric behaviour



Content-preserving warps

- Non-linear transform
 - 3D points from SFM algorithm
 - Transformation quad-mesh
- Fake small content shifts
 - Small displacements
 - Preserves illusion of depth

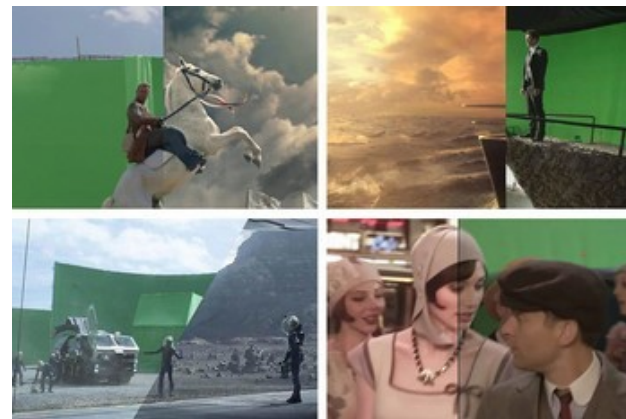


3D Stabilization Result



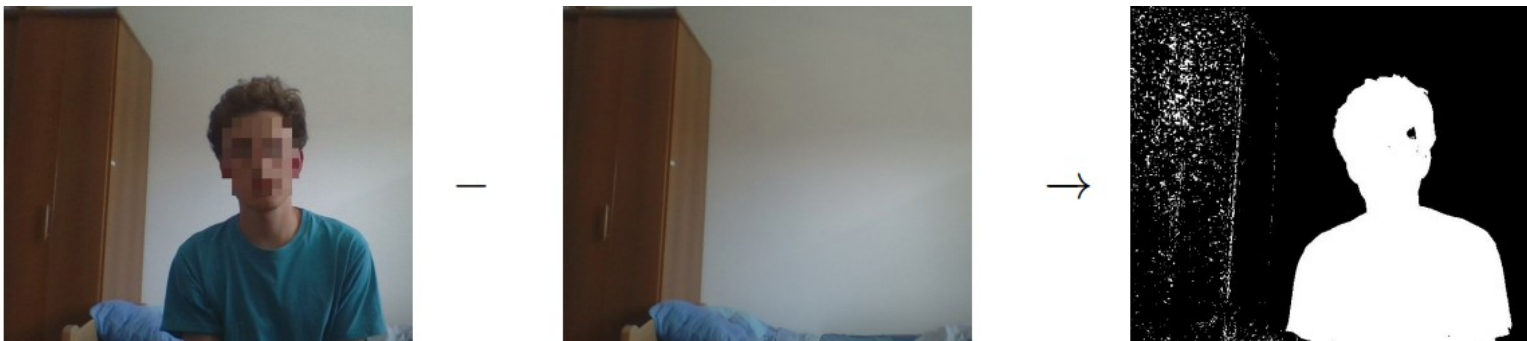
Compositing in video

- Replace background
 - Movies
 - Live shows
- Techniques
 - Rotoscoping
 - Background subtraction
 - Chroma key
 - Semantic matting



Background subtraction

- Known background
 - Model per-pixel statistics
 - One or more warm-up frames
 - Compute distance
- Simple implementation
 - Noisy output
 - Static scene
 - Video surveillance



Chroma key

- Monotonous background color
 - Green screen
 - Blue screen
- Reference color distance
 - Threshold
 - Postprocessing



Chroma key algorithm

- Input: $\{I_1 \dots I_N\}$, reference color, threshold, background image (B)
- For $i := 1 \dots N$
 - $D :=$ distance of all pixels in I_i to reference color
 - $M := D < \text{threshold}$
 - $I_i[M] = B[M]$

Chroma key issues

- Limits foreground
 - Wardrobe issues
 - Reflective surfaces
- Color bleed/spill



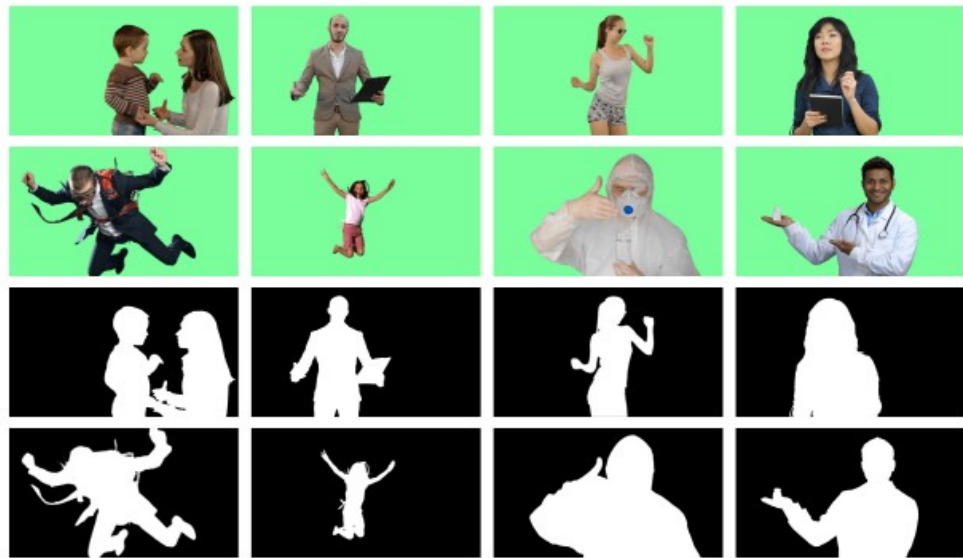
Virtual sets

- Projected backgrounds
 - Pre-recorded video
- LED screens
 - Camera tracking
 - Real-time rendering



Data-driven segmentation

- Use deep learning to predict mask
 - Foreground separation
 - Matting
- Training
 - Green-screen videos
 - Focus on borders



Video as sequence of shots

- Shots are useful start to detect scenes
 - Grouping shots into semantic units
 - Enable semantic retrieval in video
 - Easier navigation, understanding
- Manual segmentation of video into shots is slow
 - About 10 hours per 1 hour of video (for a movie)
 - Easier if edit decision list is available (unreliable)
- Automatic detection of shots
 - Detecting boundaries - transitions

Video structure

Video/movie - sequence of scenes



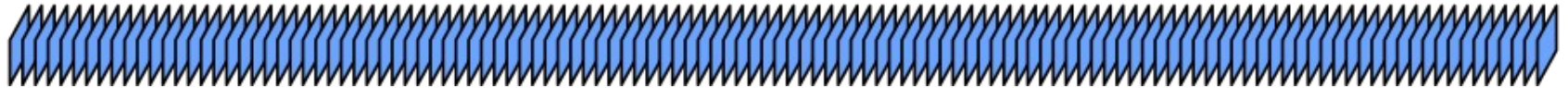
Scene - sequence of shots that form a semantic unit



Shot - sequence of frames from beginning to the end of camera recording



Frame - single image



Transition types

- Cut
 - Sharp transitions between shots
 - Sudden change of all pixels in the frame
- Fade
 - Fade-out – gradual transition to color
 - Fade-in – gradual transition from color
 - Dissolve – gradual transition between shots
 - Wipe – gradual erase

Cut



Fade



Dissolve



Wipe

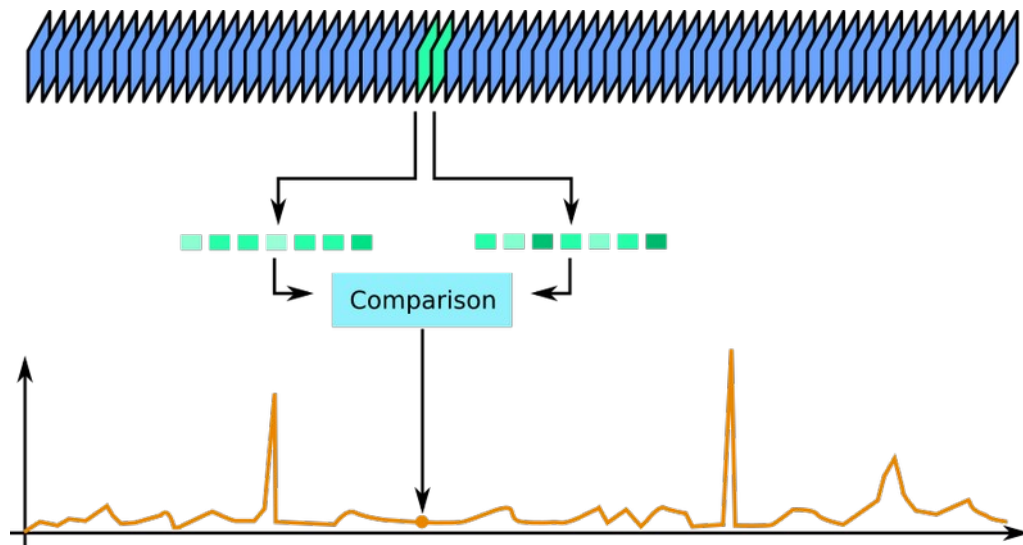


Detecting transitions

- Describe frame content
 - Features: color, texture, edges, etc.
- Measure difference
 - Two frames
 - Multiple frames
- Difference large enough
 - Threshold
 - Adaptive measures

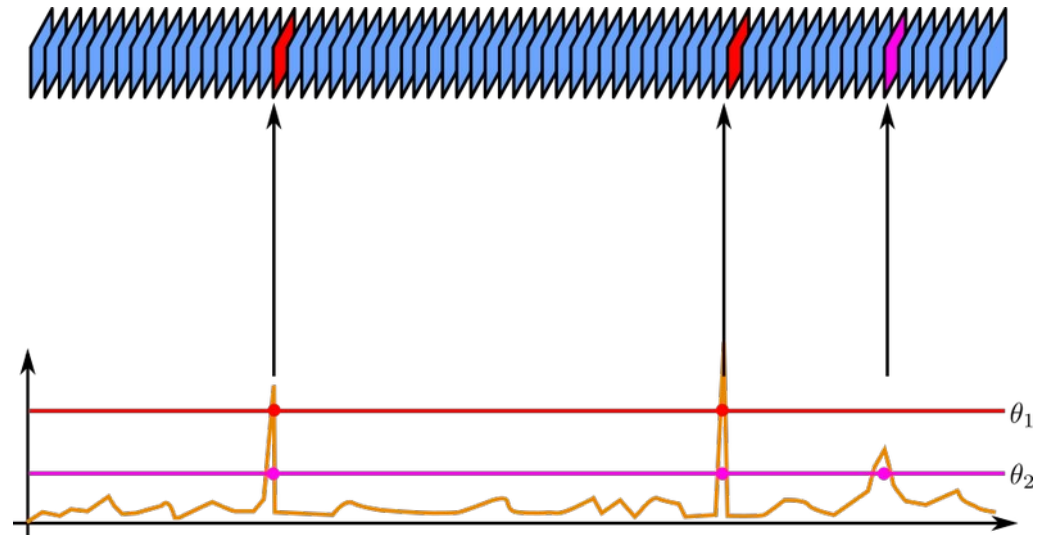
Detecting cuts

- Assumptions
 - Almost stationary
 - Almost constant scene
 - Constant illumination
- Representations
 - Gaussian model
 - Histograms
 - Deep-learning



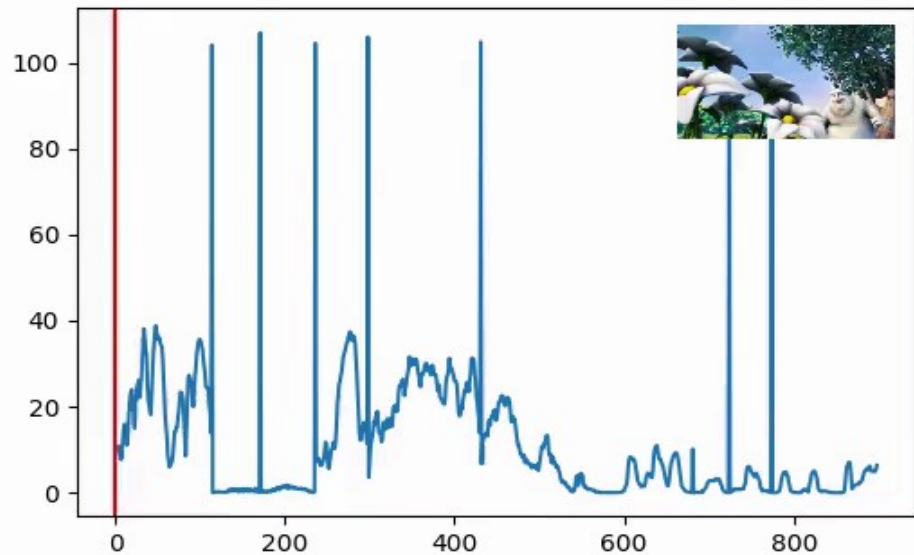
Setting a threshold

- Distance between consecutive frames
- How to set cut detection threshold?
 - Global methods
 - Adaptive methods



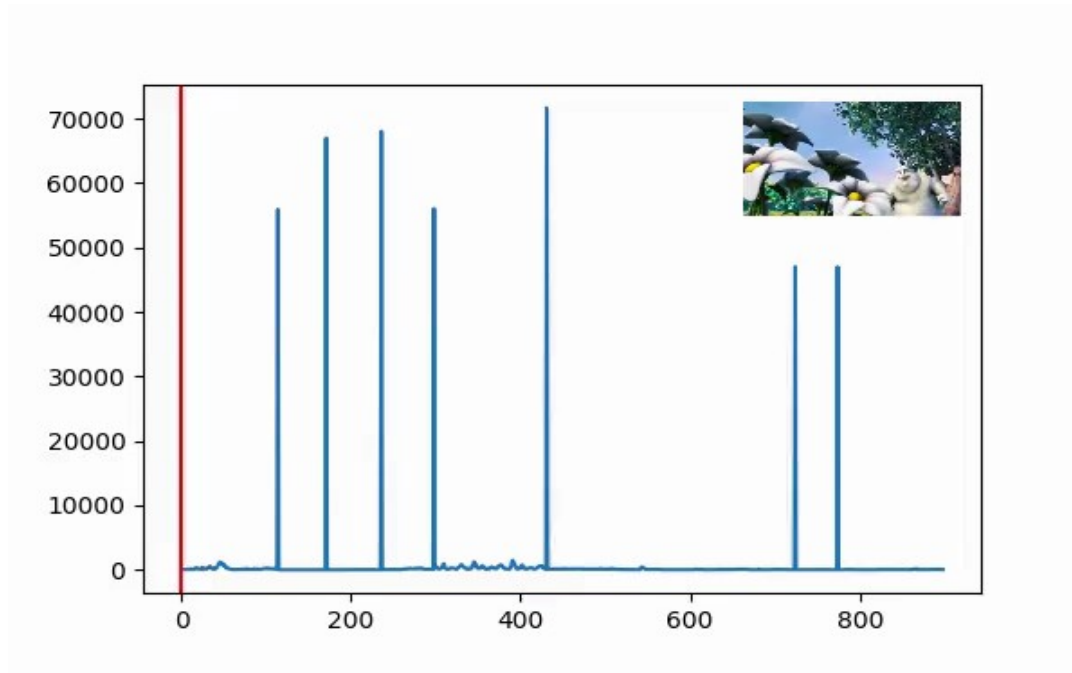
Detecting cuts with MSE

$$MSE = \frac{1}{N} \sum_{i=1}^N (X_i - Y_i)^2$$



Detecting cuts with histograms

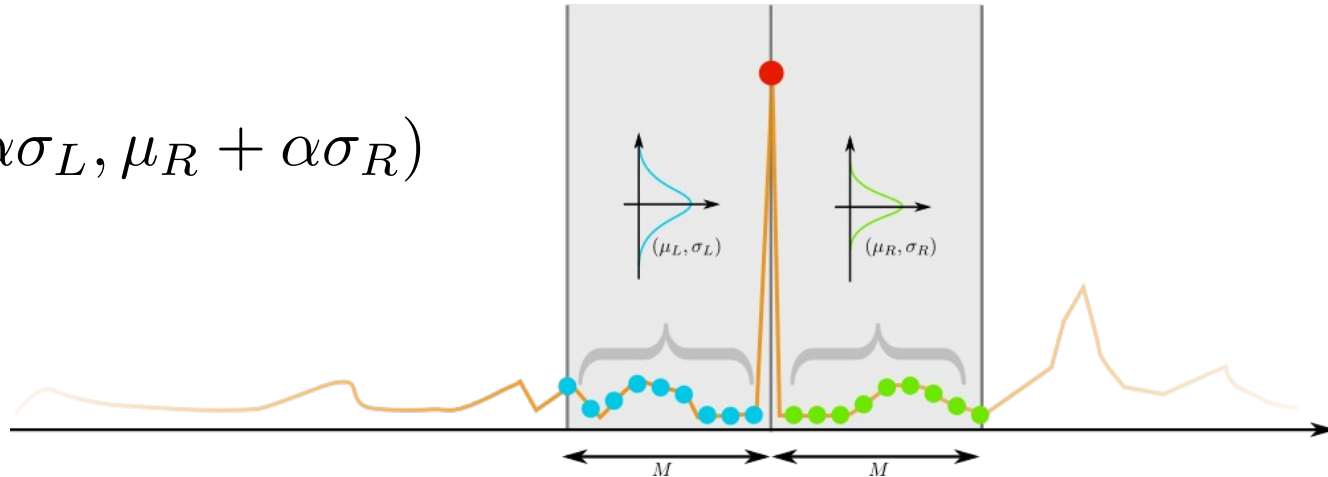
$$\chi^2 = \frac{1}{2} \sum_{i=1}^B \frac{(x_i - y_i)^2}{(x_i + y_i)}$$



Adaptive threshold

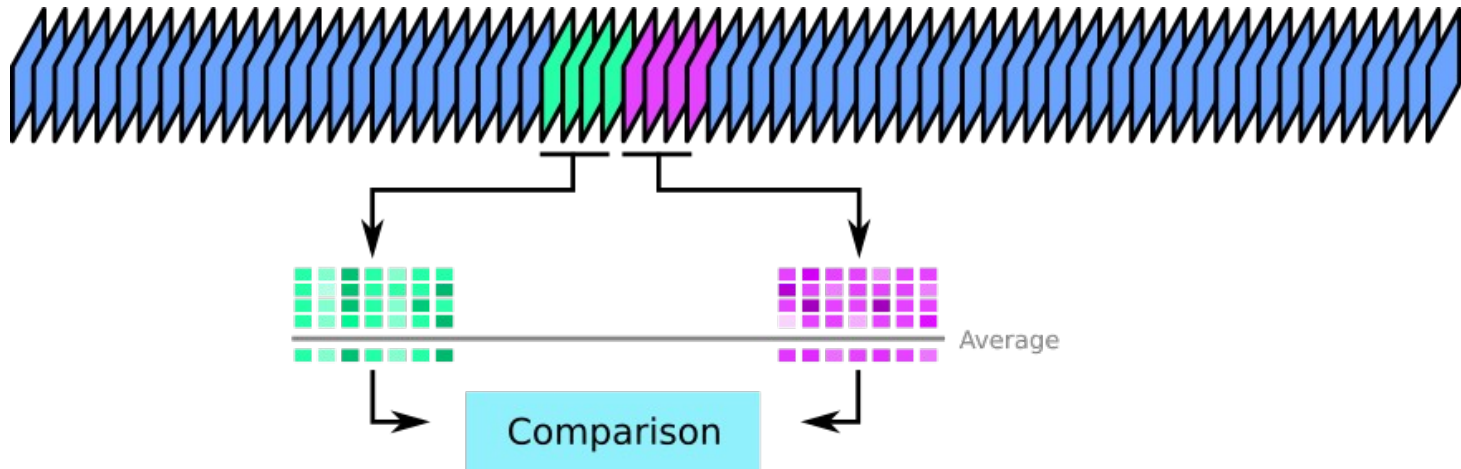
- Cut changes result in sharp peaks
- Frame t is a cut frame if D_t
 - is the largest in interval $[t - M, t + m]$
 - is larger than the maximum of scaled variance based on interval

$$D_t > \max(\mu_L + \alpha\sigma_L, \mu_R + \alpha\sigma_R)$$



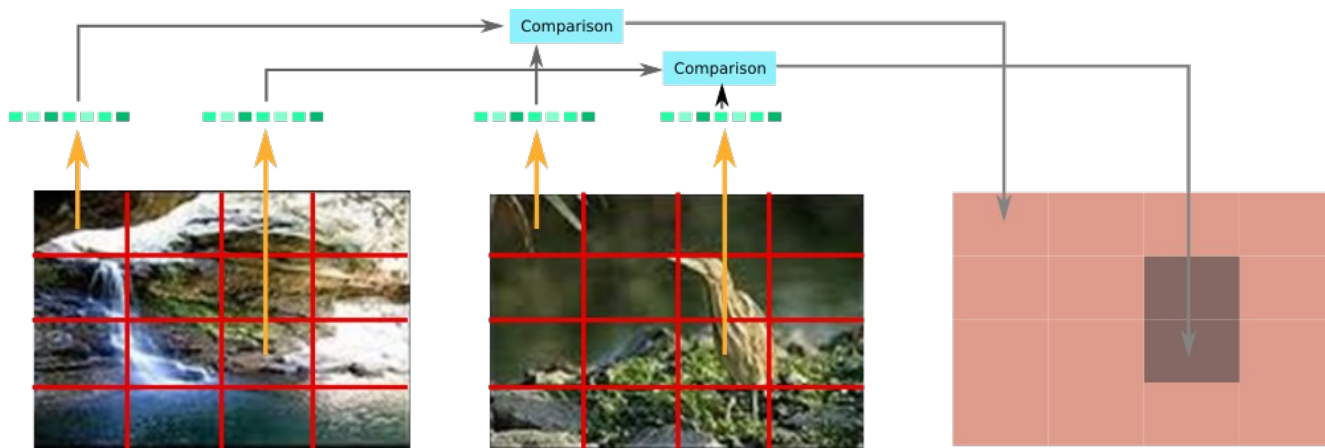
Temporal averaging

- Not enough or too much change between two frames
- Average several consecutive descriptors



Partial changes

- Global descriptors do not consider locality of changes
- Compute distances between frames for blocks
 - Ignore change if less than N blocks change
 - Compute overall distance



Detecting fades

- Not a lot of change between two frames
- Two stage threshold
 - Low threshold – potential fade start
 - Comparing to the start frame
 - Measure difference until it is increasing
 - Compare to the high threshold

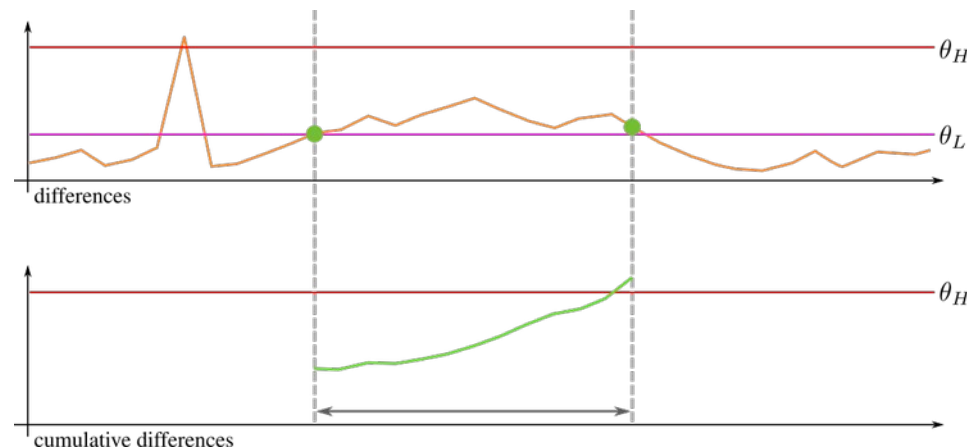
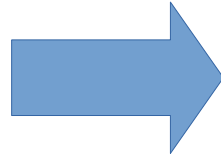


Image morphing



How to deform image A to image B?

Control points

Control points mark matching pixels in both images

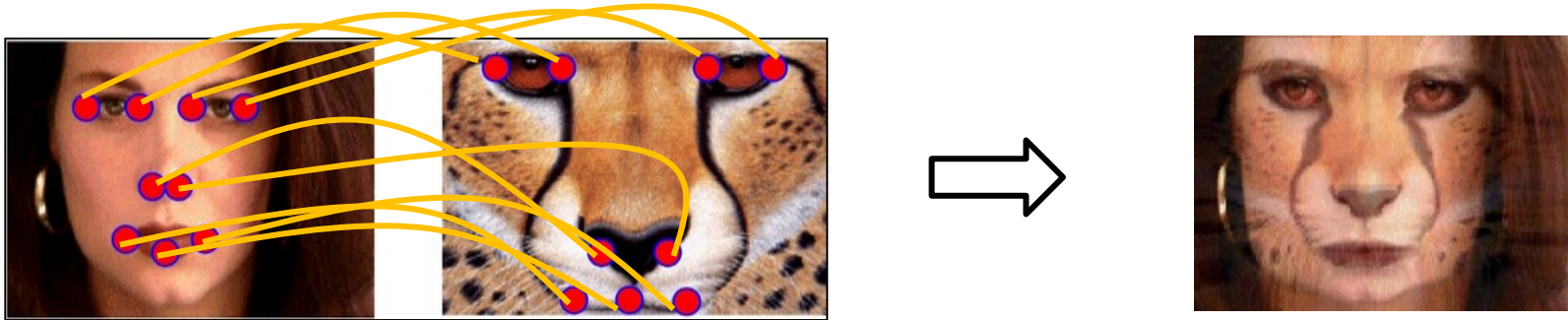
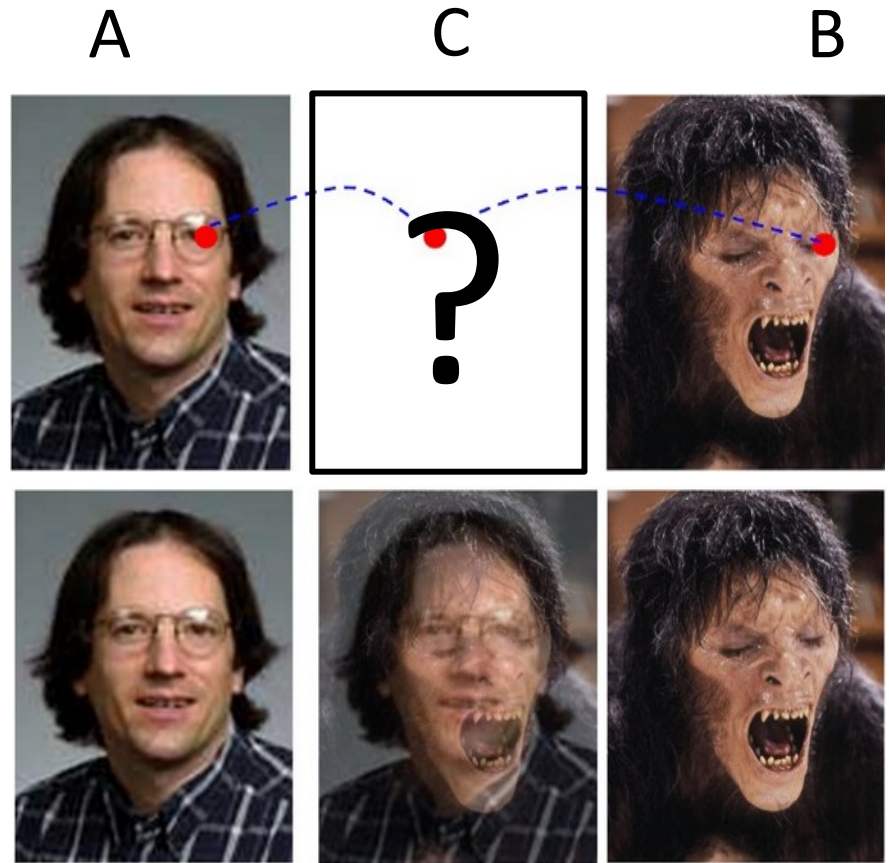


Image morphing

- How to compute intermediate image C
- Naive approach - weighted sum of pixels

$$C_t = \alpha_t A + (1 - \alpha_t) B$$
$$0 \leq \alpha_t \leq 1$$

- Not realistic - not combining semantic parts



Deformation field approximation

- Determining entire field is time-consuming
- Locally linear transformation
- Correspondences – control points
- Delaunay triangulation, interpolation

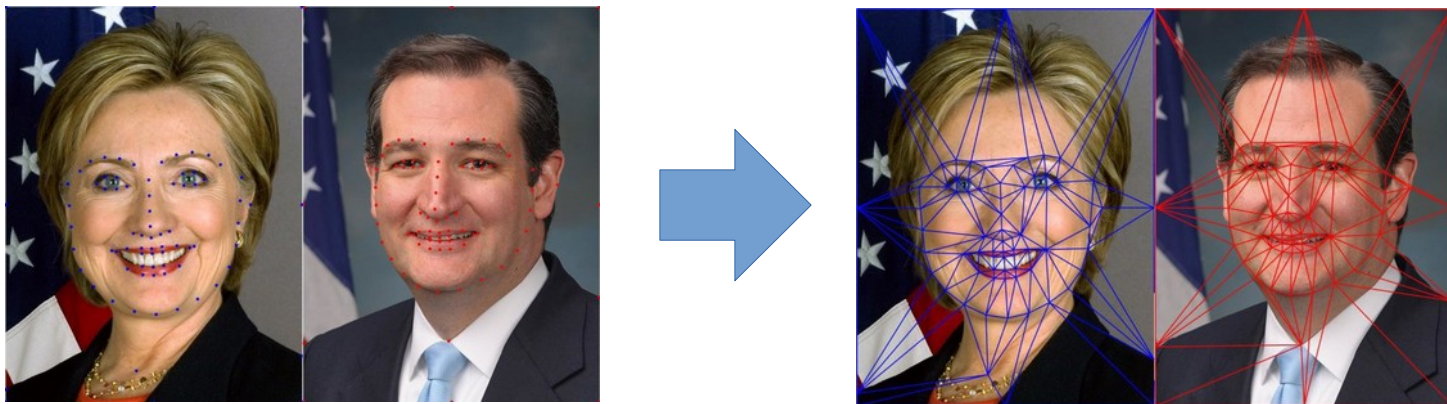
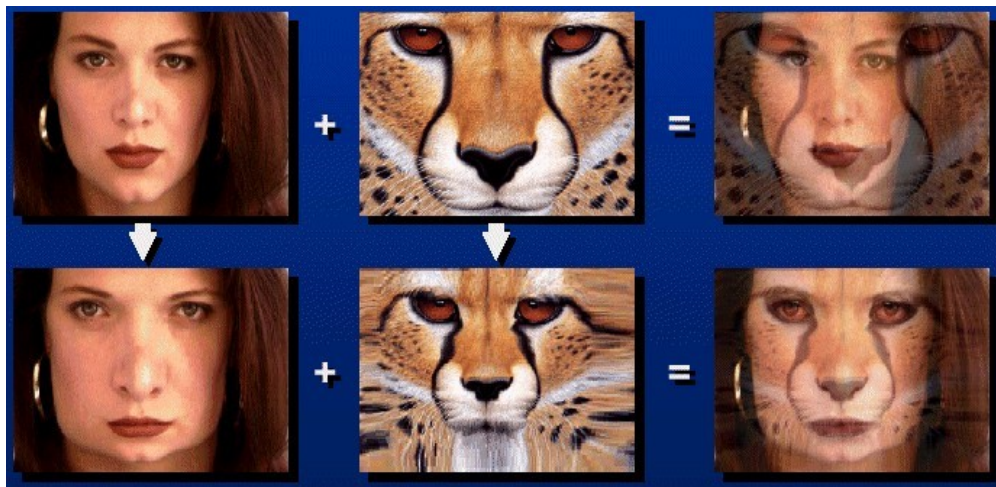


Image morphing overview

- For each image C_t compute ...
 - Interpolated position of control points
 - Two transformations: $dA = A - C_t$ and $dB = B - C_t$
 - Blend colors of interpolated images

$$\mathbf{x}_i^C = \alpha_t \mathbf{x}_i^A + (1 - \alpha_t) \mathbf{x}_i^B$$

$$C_t = \alpha_t dA + (1 - \alpha_t) dB$$



Naive

Correct

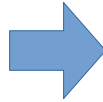
Morphing example



Input images



Control points



Warped images



Blended image



One more morphing example

