

Video processing



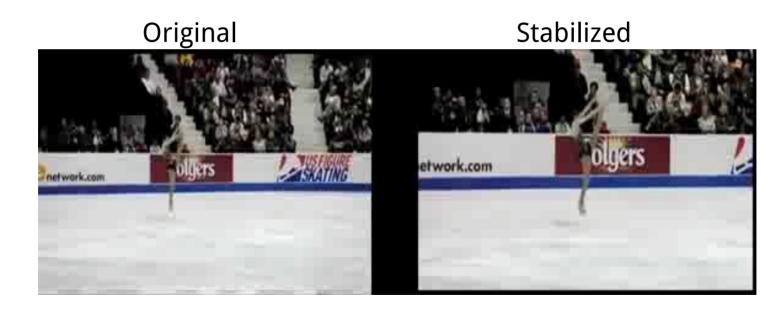
Overview

- Processing video frames
 - One-by-one (image processing)
 - Multiple frames at once
- Video stabilization
- Virtual background
- Shot separation



Video stabilization

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



M. Grundmann and V. Kwatra and I. Essa , "Auto-Directed Video Stabilization with Robust L1 Optimal Camera Paths", CVPR2011



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



Digital stabilization types

- Global
 - Making camera motion smooth
 - Can be fully automatic or initialized manually
- Object-centric
 - Object's position does not change significantly in the camera frame
 - Manual object selection





Stabilization by alignment

Two consecutive images, aligned by shifting one of them



Color composite (frame A = red, frame B = cyan)





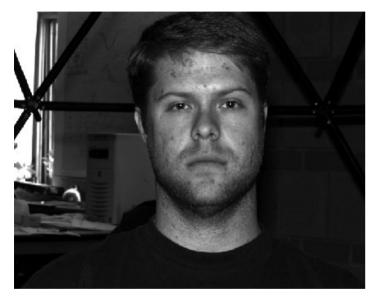


Stabilization by feature tracking

- 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).

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

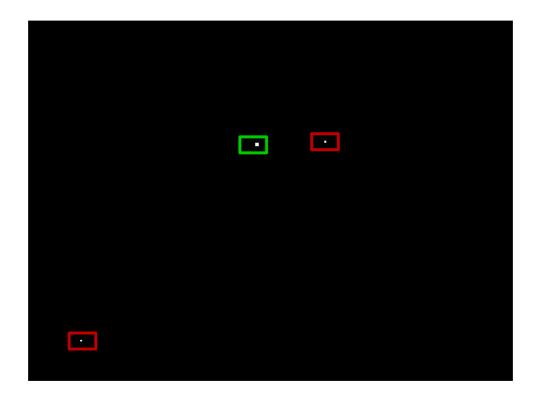
 \hat{h} ... average brightness of \pmb{H} \hat{f}_{ij} ... average brightness of \pmb{F}_{ij}

Normalized cross correlation:

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



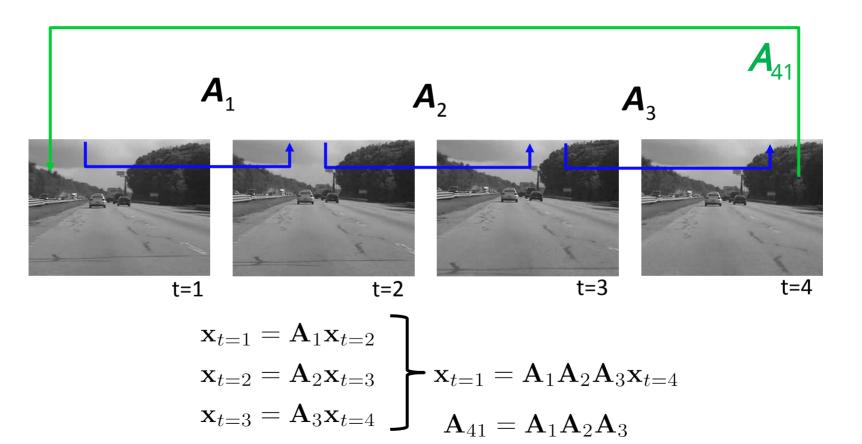
Example



More positions are equally suitable according to NCC



Transformation chain





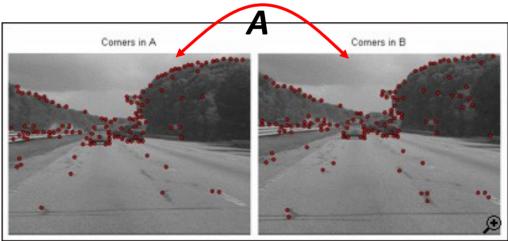
Number of features

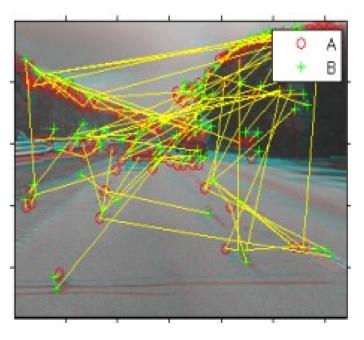
- One feature translation
- Two features translation + rotation or scale
- Three features affine transformation
 - Only planar motion
- Four features perspective transform
 - Assumes planar scene
 - Can lead to destroyed illusion of depth



Stabilization using keypoints

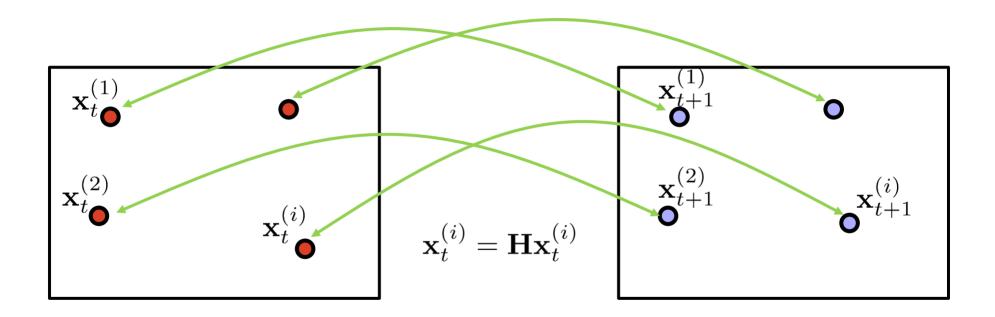
- Detect keypoints in both images, compute correspondences, estimate transformation
 - How to find best matches
 - How to estimate transformation







Deformation model





Algorithm

- Detect key-points in each image
- Search for correspondences between key-points in image pairs
 - If we are not sure which matches between first and second image are correct we have to use robust estimation methods (RANSAC)
- Compute transformations
- Align images to each other



Global stabilization example



What to do with black border?



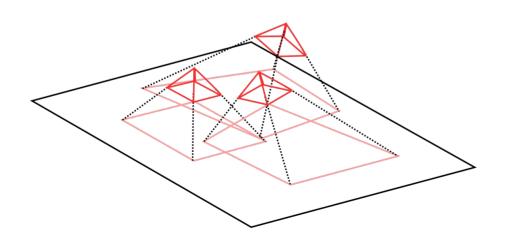
Filling in missing information

- Cropping viewport
 - Only focusing on always visible part of video
 - Can be problematic with large shifts
- Smoothing trajectory
 - Transfromation filtered with low-pass filter
 - Only jerky motion removed, camera still moves
- Mosaicking



Video mosaicking

- Find transformation between frames
- Assume planarity (expect distortion if not planar)
- Re-project images to a common image plane

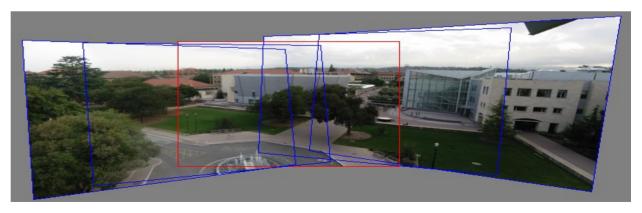






Video mosaicking algorithm

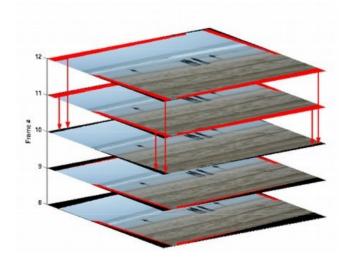
- For each N-th image in video (N fixed or dynamic)
 - Search for keypoints in image and determine correspondences to previous image
 - Estimate homography based on correspondences (RANSAC)
- Determine reference image and recalculate transformations
- Merge images (with blending)





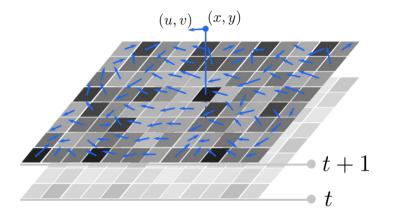
Mosaicking in video stabilization

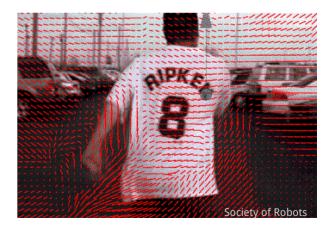
- Warp each frame to match smoothed motion
- Fill in missing regions from nearby frames
 - Single frame
 - Averaging



Optical flow stabilization

- Use optical flow instead of keypoints, more dense
 - Lucas & Kanade fast, local
 - Horn & Schunk slow, global
 - RAFT deep learning
- For each pixel compute its most likely translation in the next image
- Fit global transformation to multiple optical flow vectors



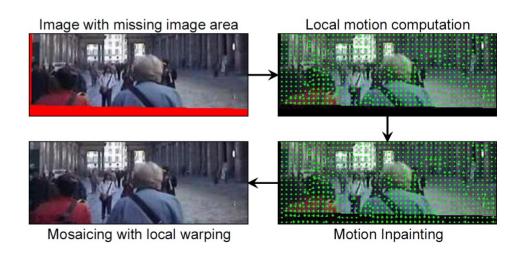






Motion inpainting

- Use optical flow to predict which pixels will move where
- Improve mosaicking using these predictions
 - Warp images
 - Inpaint missing information





2D stabilization result



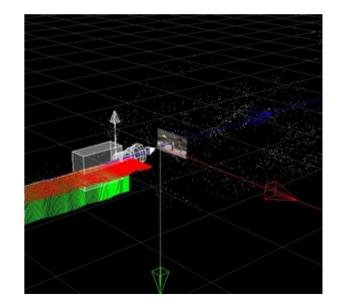
Raw video



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

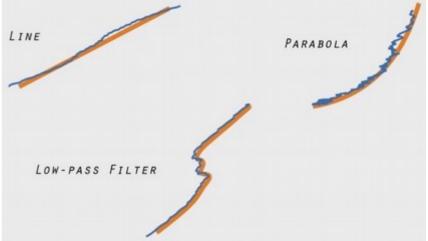






Camera motion types

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

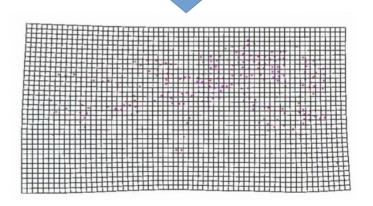




Content-preserving warps

- 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 issues

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







Virtual sets

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





Semantic segmentation

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

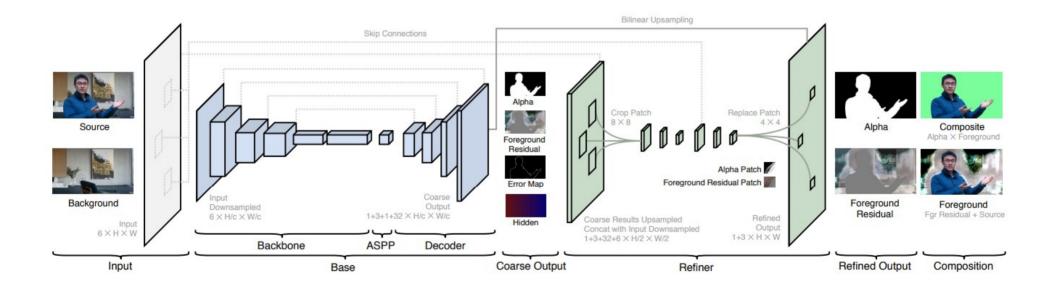




Shanchuan Lin et al., Real-Time High-Resolution Background Matting, CVPR 2021



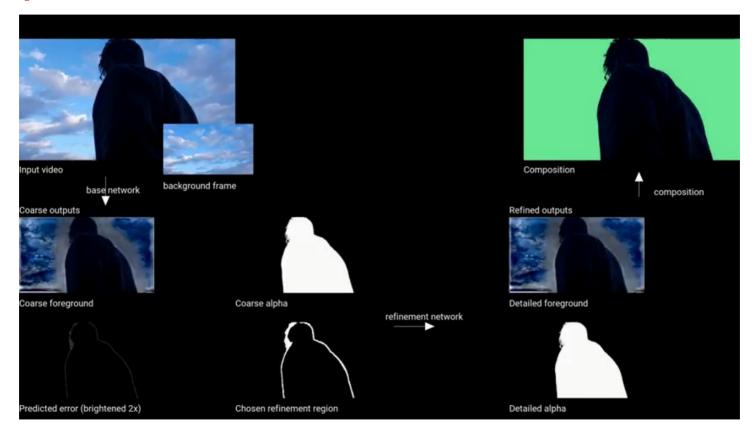
Model pipeline



Shanchuan Lin et al., Real-Time High-Resolution Background Matting, CVPR 2021



Examples



Shanchuan Lin et al., Real-Time High-Resolution Background Matting, CVPR 2021



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



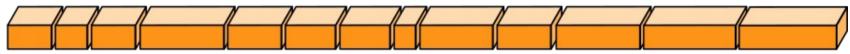
Video structure

Video/movie - sequence of scenes

Scene - sequence of shots that form a semantic unit



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



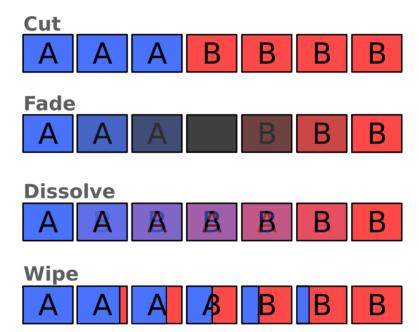
vicos sualgnitive ystemslab

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





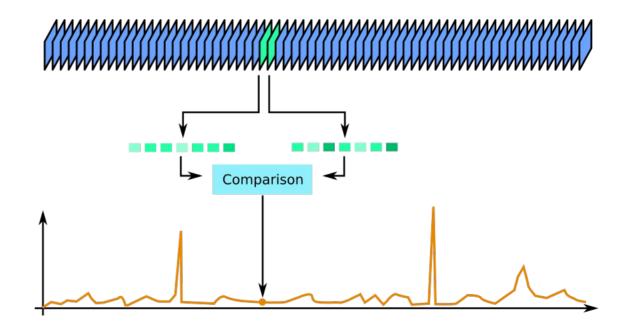
Detecting transitions

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



Detecting cuts

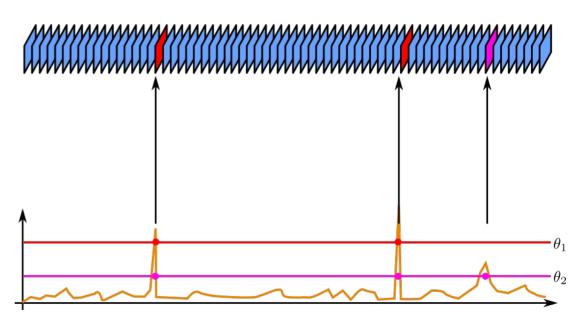
- Assumptions
 - Almost stationary
 - Almost constant scene
 - Constant illumination
- Cut if significant change
 - Color
 - Intensity
- Descriptors
 - Gaussian model
 - Histograms





Setting a threshold

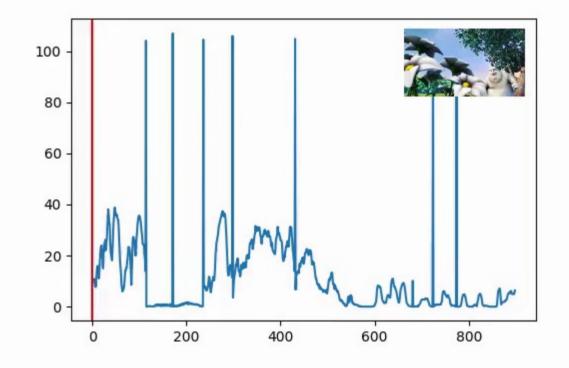
- Distance between consecutive frames
- How to set cut detection threshold?
 - Global methods
 - Adaptive methods





Detecting cuts with MSE

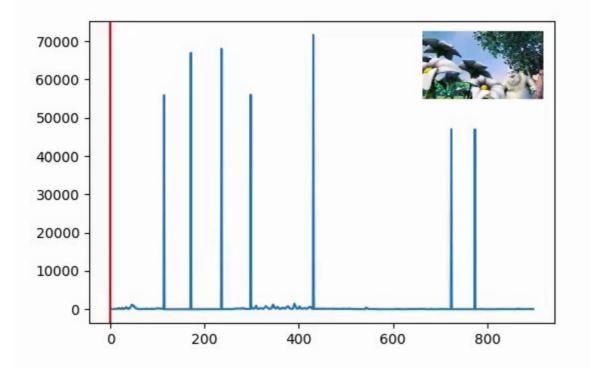
$$MSE = \frac{1}{N} \sum_{i=1}^{N} (Xi - Yi)^2$$





Detecting cuts with histograms

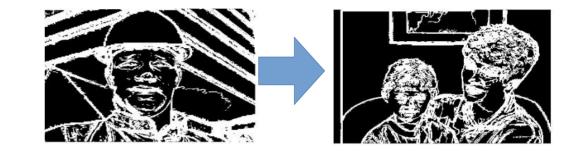
$$X^{2} = \frac{1}{2} \sum_{i=1}^{B} \frac{(x_{i} - y_{i})^{2}}{(x_{i} + y_{i})}$$





Detecting cuts with edges

- Color methods are not robust to illumination changes
- Compare edge pixels
 - How many appeared
 - How many vanished

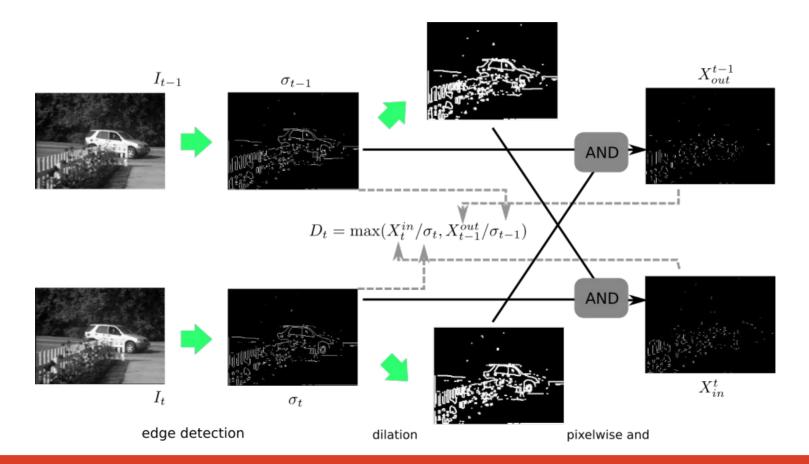


 $D_t = \max(X_t^{in} / \sigma_t, X_{t-1}^{out} / \sigma_{t-1})$

 $X_t^{in} \cdots$ number of new edges at time t $X_{t-1}^{out} \cdots$ number of vanished edges at time t-1 $\sigma_t \cdots$ number of all edges at time t $\sigma_{t-1} \cdots$ number of all edges at time t-1

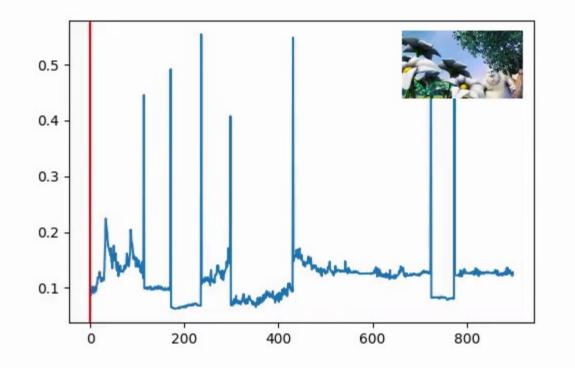


Algorithm





Detecting cuts with edges

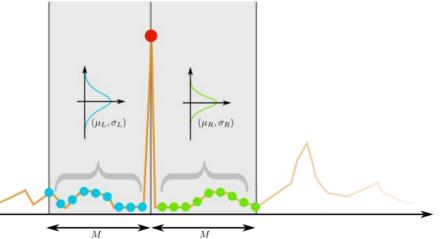




Adaptive threshold

- 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

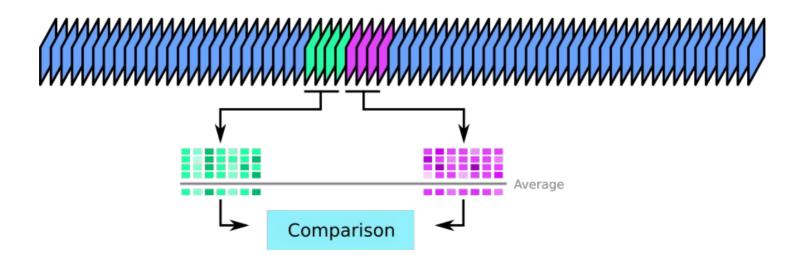
 $D_t > \max(\mu_L + \alpha \sigma_L, \mu_R + \alpha \sigma_R)$





Temporal averaging

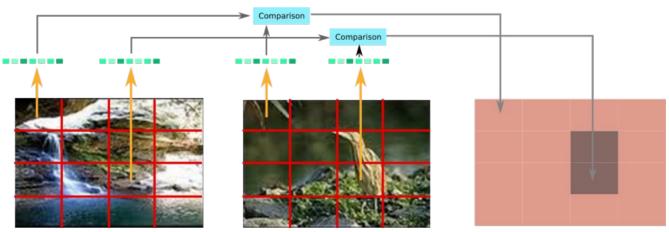
- Not enough or too much change between two frames
- Average several consecutive descriptors





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

