Artistic Stylization of Images and Video

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Abstract

The half-day tutorial provides an introduction to Non- Photorealistic Rendering (NPR), targeted at both students and experienced researchers of Computer Graphics who have not previously explored NPR in their work. The tutorial focuses on two-dimensional (2D) NPR, specifically the transformation of photos or videos into synthetic artwork (e.g. paintings or cartoons). Consequently the course will touch not only on computer graphics topics, but also on the image processing and computer vision techniques that drive such algorithms. However the latter concepts will be introduced gently and no prior knowledge is assumed beyond a working knowledge of filtering and convolution operations. Some elements of the course will touch upon GPU implementation, but GPU concepts will be described at a high level of abstraction without need for detailed working knowledge of GPU programming.

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Eurographics 2011

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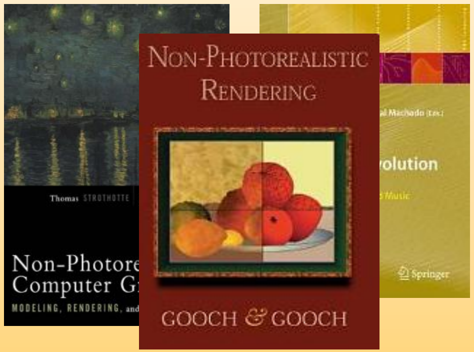
Artistic Stylization Resources

Texts



Strothotte & Schlechtweg
ISBN: 1558607870

Gooch & Gooch
ISBN: 1568811330

Romero & Machado
ISBN: 3540728767

Web Bibliographies

http://video3d.ims.tuwien.ac.at/%7Estathis/nprlib/index.php

http://isgwww.cs.uni-magdeburg.de/~stefans/npr/nprpapers.html

http://www.red3d.com/cwr/npr/ (dated)

Tutorials

SIGGRAPH 99 (Green et al.) – 2D/3D NPR
SIGGRAPH 02 (Hertzmann) – 2D NPR
SIGGRAPH 03 (Sousa et al.) – 2D/3D NPR
Eurographics 05,06 and...
SIGGRAPH 06 (Sousa et al) – 3D NPR
SIGGRAPH 10 (McGuire) – 3D NPR for Games

Main Publication Forums

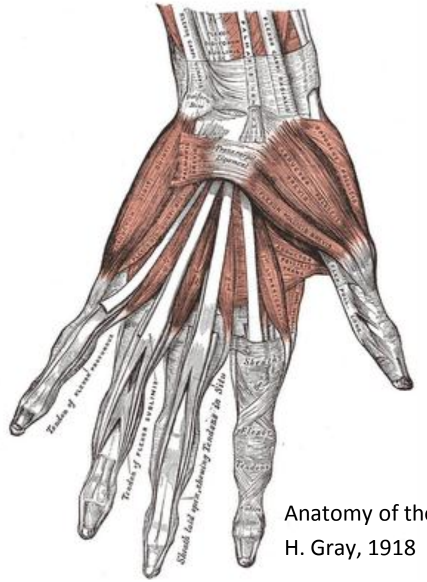
NPAR (Symposium on Non-photorealistic Animation)
Held in Annecy even years, at SIGGRAPH odd years.

IEEE Trans Visualization and Comp. Graphics (**TVCG**)
IEEE Computer Graphics and Applications (**CG&A**)
Eurographics and **Computer Graphics Forum**
SIGGRAPH, SIGGRAPH Asia and **ACM ToG**
EG Symposium on Rendering (**EGSR**)
ACM/EG Symposium on Computer Animation (**EGSA**)

Artistic Stylization

Non-Photorealistic Rendering (NPR)
Coined by Salesin et al., 1994

- **Stylized Rendering**
- **Aesthetic Rendering**
- **Artistic Stylization**
- **Artistic Rendering**



Anatomy of the Human Body
H. Gray, 1918

Motivation

Artistic Stylization

- **Why?**

Comprehension

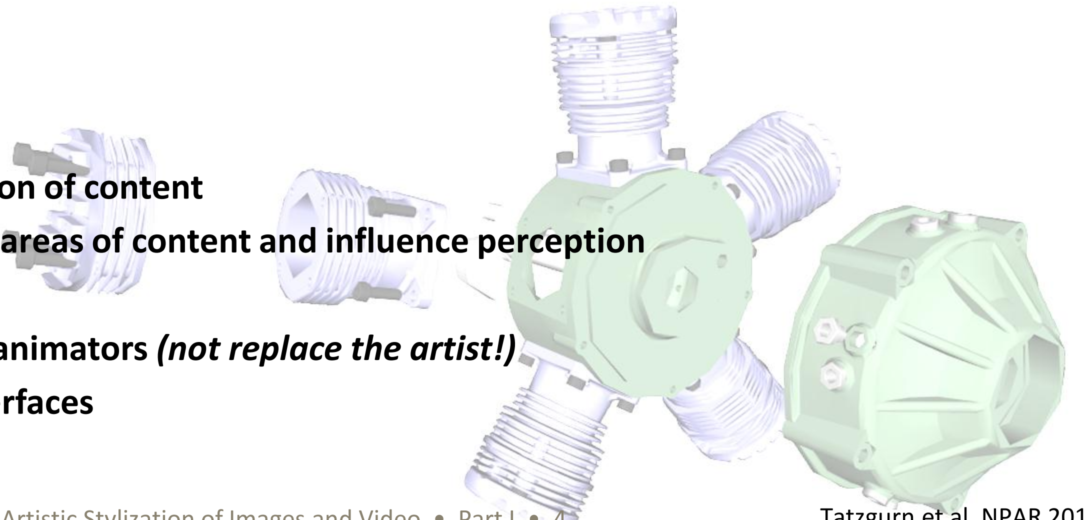
Communication

Visualization

Aesthetics

Animation

- **Artistic Stylization can**
  - **Simplify and structure the presentation of content**
  - **Selectively guide attention to salient areas of content and influence perception**
  - **Learn and emulate artistic styles**
  - **Provide assistive tools to artists and animators *(not replace the artist!)***
  - **Help us to design effective visual interfaces**

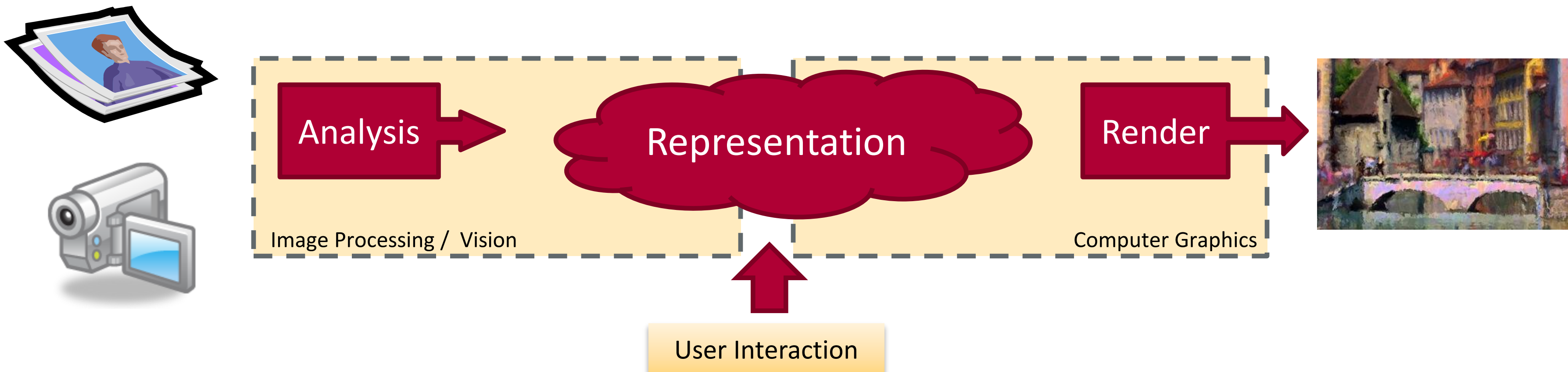


Tatzgurn et al. NPAR 2010

Motivation

Artistic Stylization

- **Rendering real images/video footage in to pseudo-artistic styles**
- **Convergence of Computer Vision, Graphics (and HCI)**



- **Visual analysis enables new graphics. Graphical needs motivate new vision.**

Chronology

Late 1980s
Advances in media emulation

D. Strassman (SIGGRAPH 86)

Video painting

P. Litwinowicz (SIGGRAPH 97)

Perceptual UI & segmentation

D. Decarlo [SIGGRAPH 02]

Space-time video

J. Wang [SIGGRAPH 04]
J. Collomosse [TVCG 05]

Anisotropy / filters

H. Winnemoeller [SIGGRAPH 06]
J. Kyprianidis [TPCG 08]

1990 1997 1998 2000 2002 2005 2006 2010

Semi-automatic painting systems

P. Haeberli (SIGGRAPH 90)

Fully automatic painting

A. Hertzmann (SIGGRAPH 98)
Treveatt/Chen [EGUK 97]
P. Litwinowicz [SIGGRAPH 97]

Automatic perceptual

J. Collomosse [EvoMUSART 05]

NPAR 2010
Grand challenges

User evaluation

T. Isenberg [NPAR 06]

Interactions with Vision

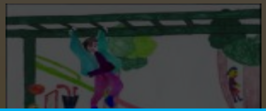
Rendering process is guided by...

emulation

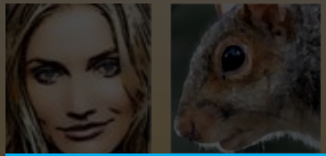
Perceptual UI &

User subconscious interaction

Space-time video



Anisotropy / filters



User concious interaction

Low-level image processing

Higher level computer vision

Direct Anisotropic filtering

1990 1997 1998 2000 2002 2005 2006 2010

Semi-automatic painting systems

P. Haeberli (SIGGRAPH 90)

Fully automatic painting

A. Hertzmann (SIGGRAPH 98)
Treveatt/Chen [EGUK 97]
P. Litwinowicz [SIGGRAPH 97]

Automatic perceptual

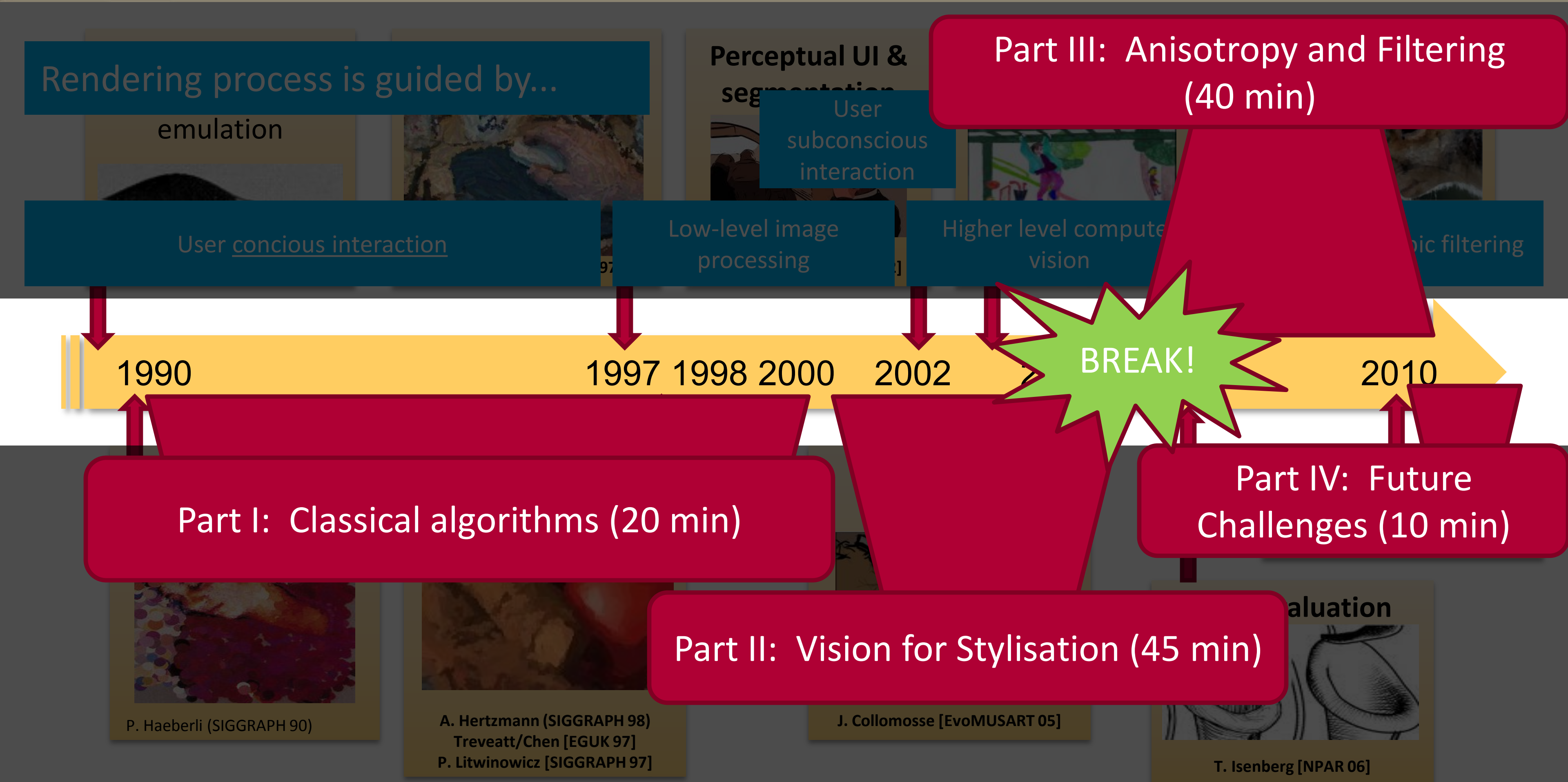
J. Collomosse [EvoMUSART 05]

NPAR 2010
Grand challenges

User evaluation

T. Isenberg [NPAR 06]

Tutorial Structure



Artistic Stylization of Images and Video

Part I – Classical Algorithms / Stroke Based Rendering

Eurographics 2011

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References

- **Paint by numbers: Abstract image representations**
  P. Haeberli, SIGGRAPH 1990
- **Almost Automatic Computer Painting**
  P. Haggerty, IEEE CG & A 1991
- **Orientable Textures for Image based Pen-and-Ink Illustration**
  D. Salisbury et al., SIGGRAPH 1997
- **Processing images and video for an impressionist effect**
  P. Litwinowicz, SIGGRAPH 1997
- **Statistical techniques for the automated synthesis of non-photorealistic images**
  S. Treavett and M. Chen, Eurographics UK 1997.
- **Automatic Painting based on Local Source Image Approximation**
  Shiraishi and Yamaguchi, NPAR 2000.
- **Painterly Rendering with Curved Strokes of Multiple Sizes**
  A. Hertzmann, SIGGRAPH 1998.
- **Paint by Relaxation**
  A. Hertzmann, CGI 2001
- **Fast Paint Texture**
  A. Hertzmann, NPAR 2002

Paint by numbers: Abstract Image Representations

Haeberli. (1990)

- **Stroke based rendering (SBR)**
- **Painting is a manually ordered list of strokes, placed interactively.**
- **Stroke attributes sampled from the photo.**

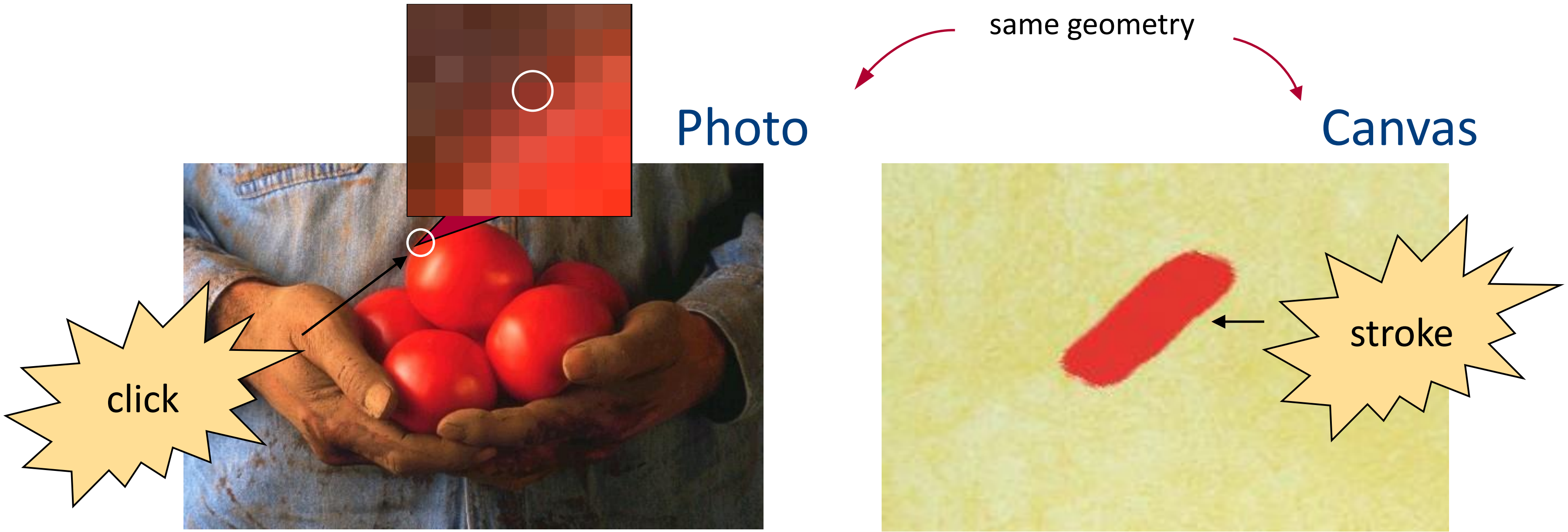


Photo credit. Hertzmann '98

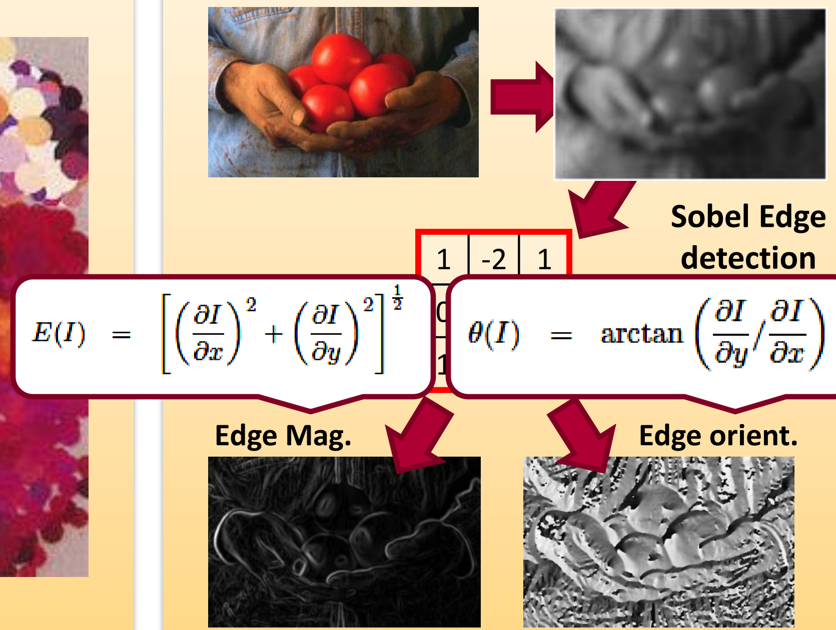
Paint by numbers: Abstract Image Representations

Haeberli. (1990)

- **Stroke <u>colour</u> and <u>orientation</u> are sampled from the source image**
- **Stroke <u>order</u> and <u>scale</u> are user-selected**
- **Addition of RGB noise generates an impressionist effect**

Photo credit: Haeberl '90.

Paintings with / without orientable strokes



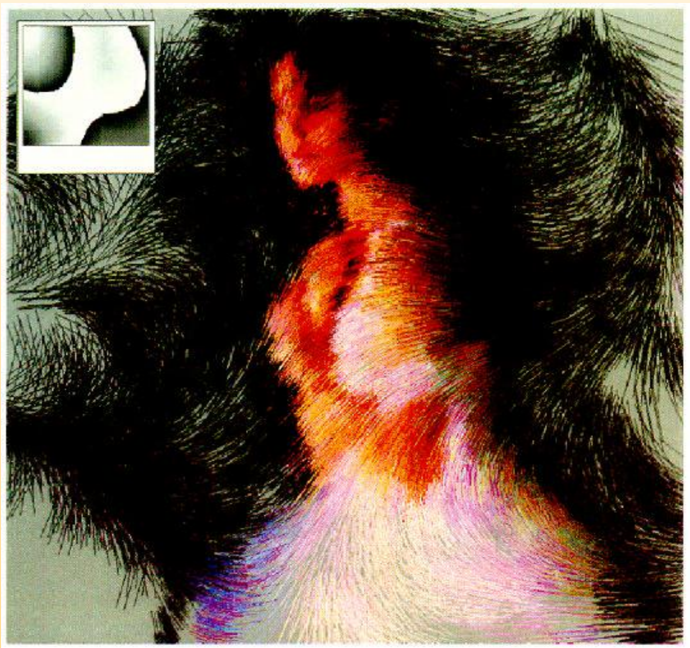
Orientation

Paint by numbers: Abstract Image Representations

Haeberli. (1990)

- **More stylised orientation effects with a manually defined orientation field**

Orientation field

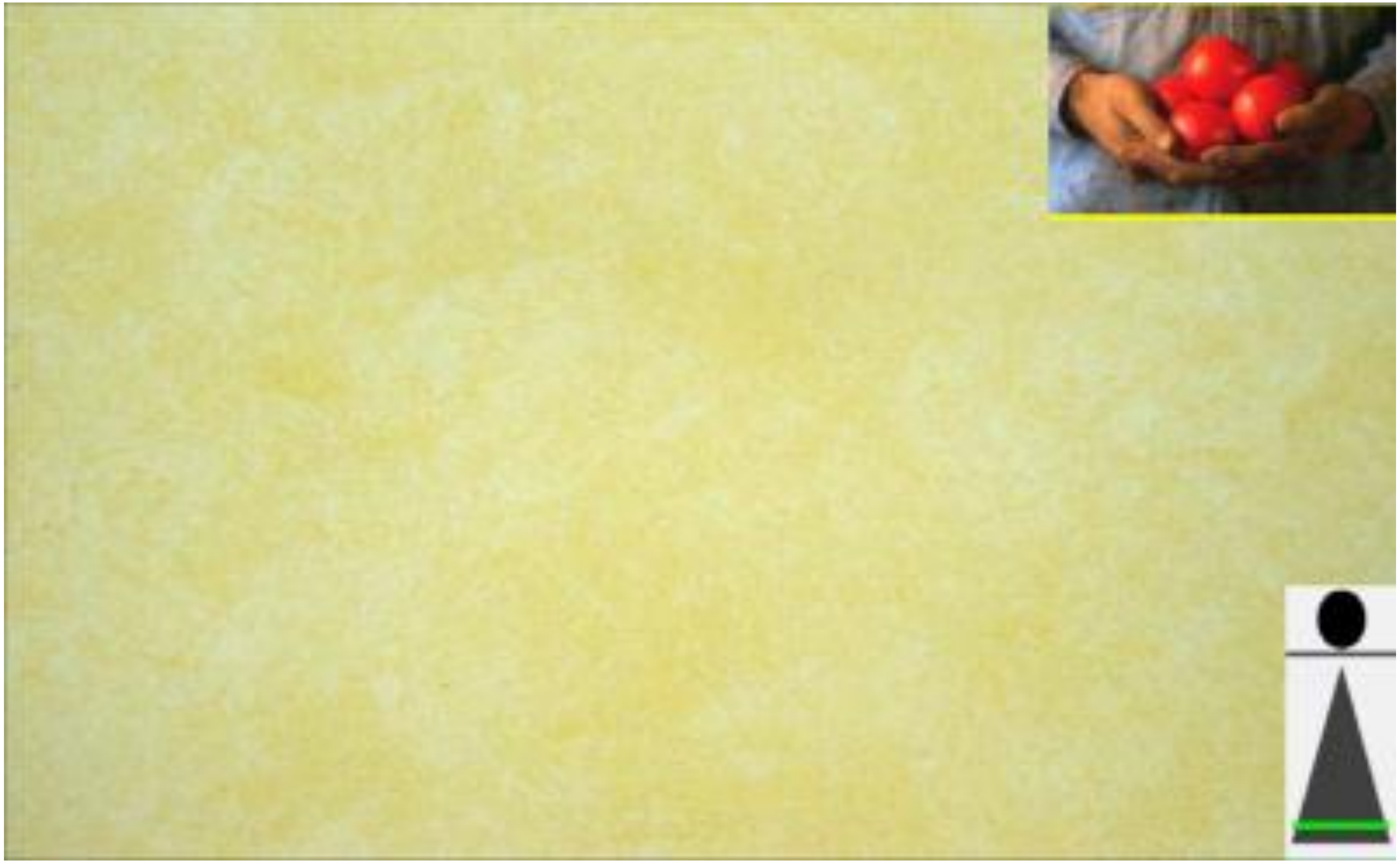


Painterly Rendering

Photo credit: Haeberl ’90.

Paint by numbers: Abstract Image Representations

Haeberli. (1990)

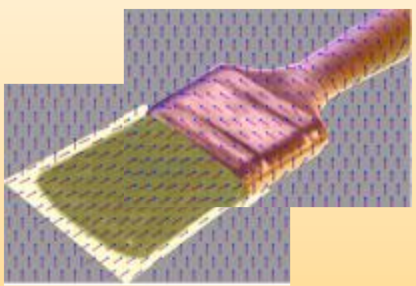


Code at http://www.collomosse.com/EG2011tut/haeberlidemo.zip

Orientable Textures for Image-based Pen-and-Ink Illustration

Salisbury et al. (1997)

- **Very similar system for pen-and-ink rendering of photos**
- **User defined orientation field.**
  - **Regions manually drawn and marked up with orientation**
- **Stroke (line) placement automatic. Strokes clipped to keep within regions.**



Manually defining regions of the orientation field

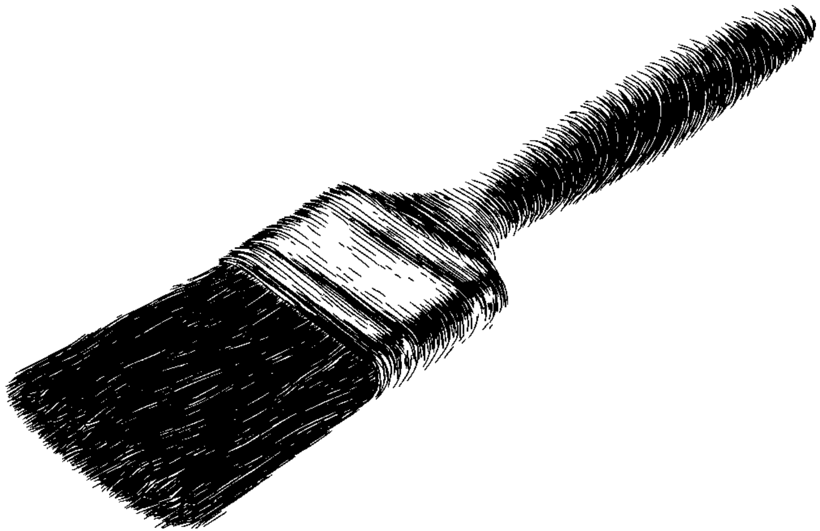


Photo credit: Salisbury'97.

Almost automatic computer painting

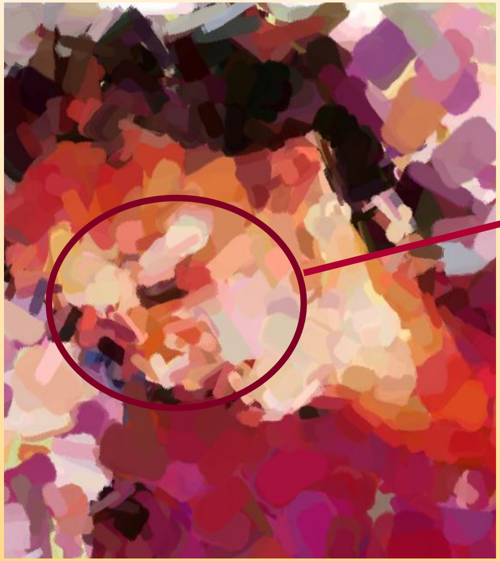
Haggerty (1991)

- Stroke colour and orientation are sampled from the source image
- Stroke order and scale ~~are user selected~~
- Scale sampled from Sobel edge magnitude
- Regularly place strokes. Order of strokes randomly generated

Fully automated

Photo credit: Haeberl '90.

Interactive (Haeberli)

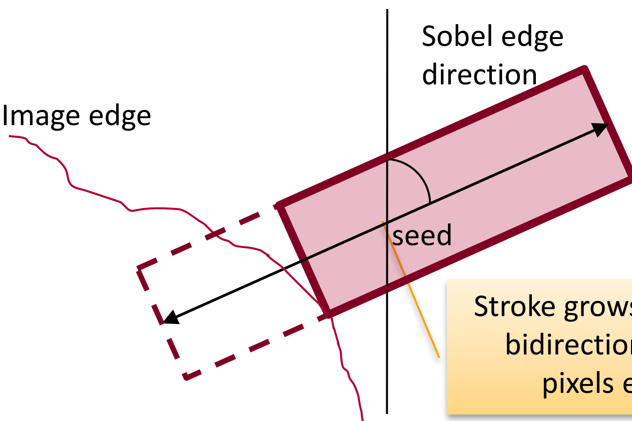


Pseudo-random (as Haggerty)

Loss of detail in important regions

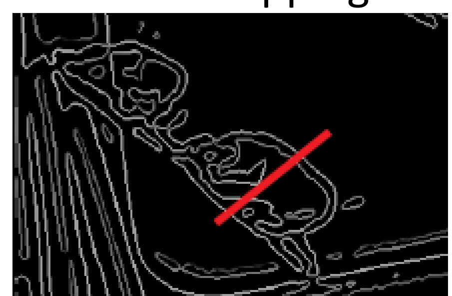
Processing Images & Video for Impressionist Effect

Litwinowicz (1997)



Stroke grows from seed point bidirectionally until edge pixels encountered

No clipping



Clipping

Photo credit: Litwinowicz '97

Statistical techniques for automated synthesis of NPR

Treavett and Chen (1997)

- **Common recipe for SBR in the 1990s**
  - **Sobel edge detection on blurred image**
  - **Regular seeding of strokes on canvas**
  - **Scale strokes inverse to edge magnitude**
  - **Orient strokes along edge tangent**
  - **Place strokes in a specific way using this data**

- **An interesting alternative uses 2nd order moments with local window to orient strokes.**
  - **Extended to multi-scale strokes by Shiraishi and Yamaguchi (NPAR 2000)**

Photo credit: Shiraishi / Yamaguchi '00

Automatic Painting based on Local Source Image Approximation

Shiraishi and Yamaguchi (2000)

- **2D zero-moments for greyscale image I(x,y)**

$$M_{lm} = \sum_x \sum_y x^l y^m I(x,y).$$

- **1st order moments provide centre of mass.**

$$x_c = \frac{M_{10}}{M_{00}} \qquad y_c = \frac{M_{01}}{M_{00}}$$

- **2nd order moments describe grey variance.**

$$a = \frac{M_{20}}{M_{00}} - x_c^2,$$

$$b = 2\left(\frac{M_{11}}{M_{00}} - x_c y_c\right)$$

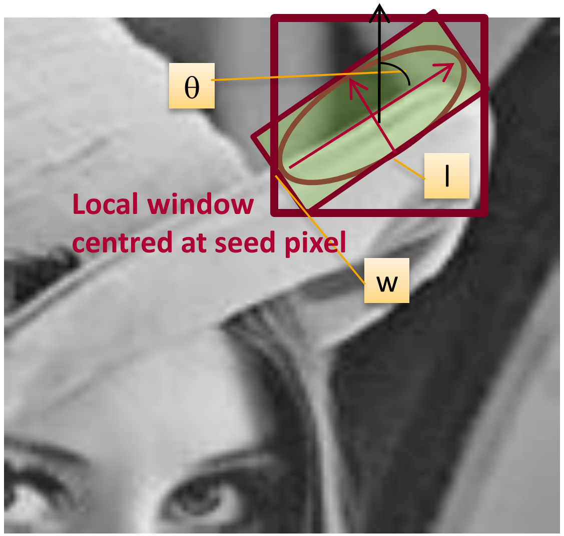
$$c = \frac{M_{02}}{M_{00}} - y_c^2.$$

- **Orient strokes orthogonal to the direction of greatest variance about the centre of mass.**

$$\theta = \frac{\tan^{-1}\left(\frac{b}{a-c}\right)}{2}$$

$$w = \sqrt{6\left(a+c-\sqrt{b^2+(a-c)^2}\right)}$$

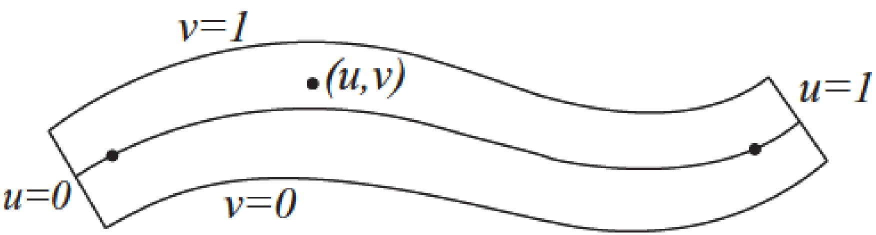
$$l = \sqrt{6\left(a+c+\sqrt{b^2+(a-c)^2}\right)}$$

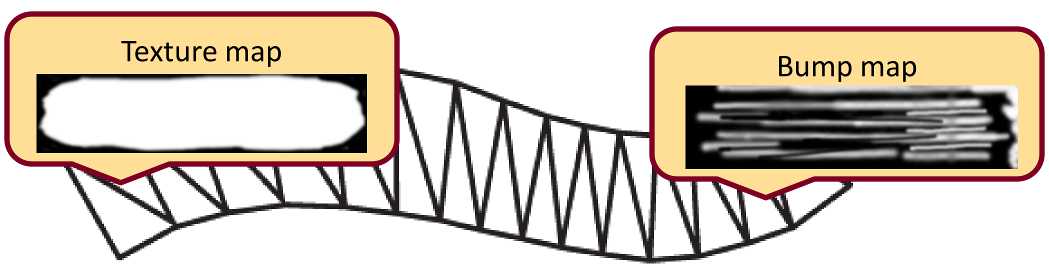


Painterly Rendering With Curved Brush Strokes

Hertzmann (1998)

- Artists do not paint with uniformly shaped short strokes (pointillism excepted!)
- Two key contributions (1998)
  - Multi-layer (coarse to fine) painting
  - Painting using β-spline strokes
- Spline strokes can be bump mapped for an improved painterly look (NPAR 2002)





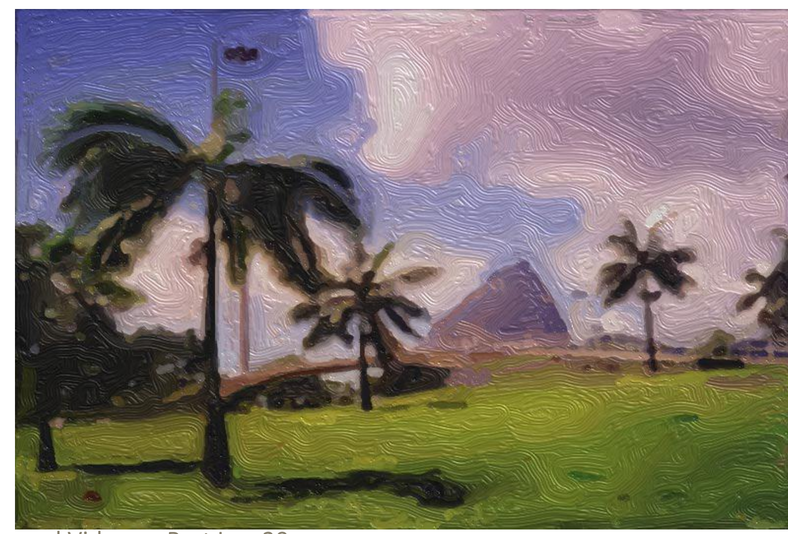


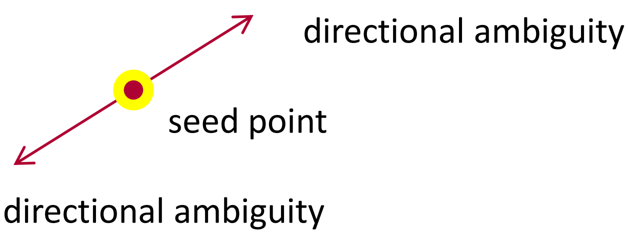
Photo credit: Hertzman '02

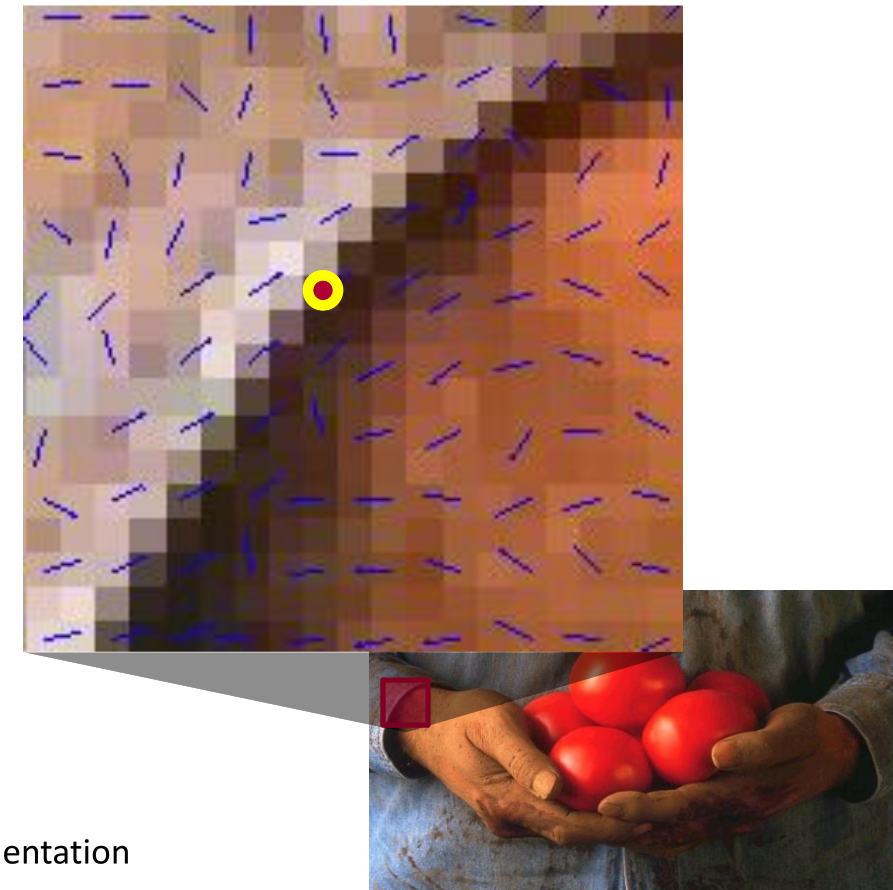
Painterly Rendering With Curved Brush Strokes

Hertzmann (1998)

- Greedy algorithm for stroke placement
- Regularly sample the canvas to seed strokes
- Build a list of control point for each stroke by “hopping” between pixels*

1) Pick a direction arbitrarily
   (some implementations explore both)





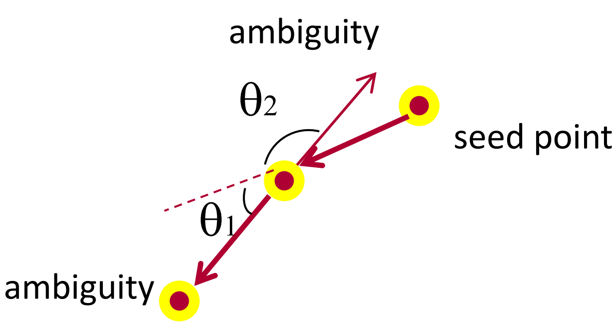
* In practice, best to use float coordinates and interpolate edge orientation

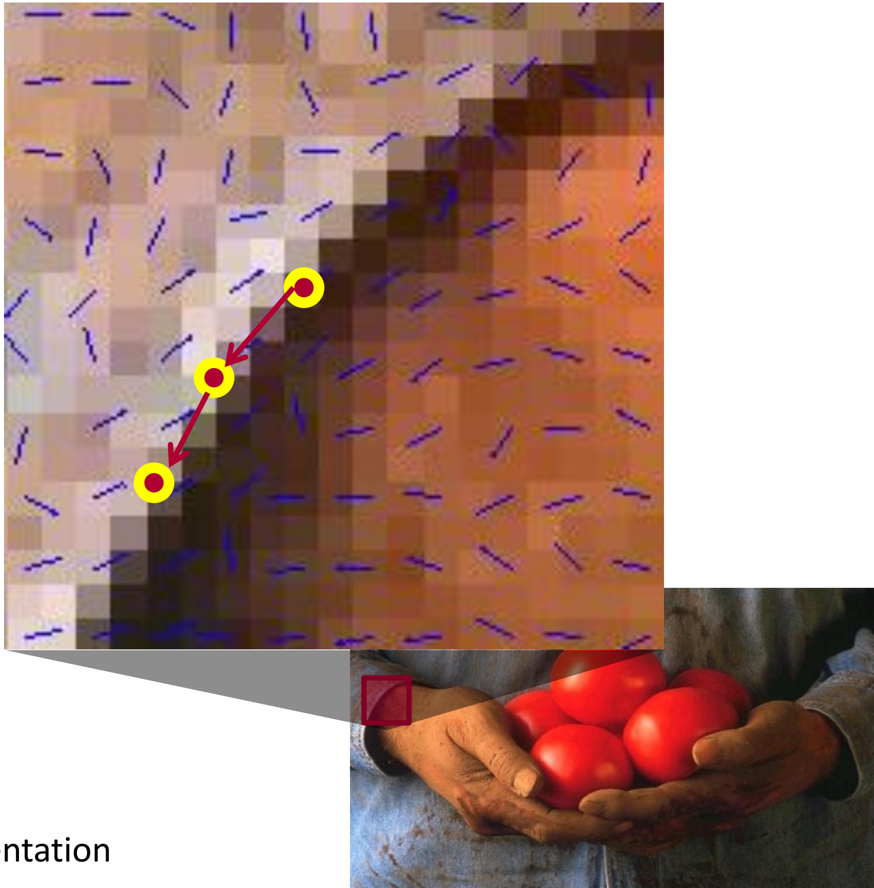
Painterly Rendering With Curved Brush Strokes

Hertzmann (1998)

- Greedy algorithm for stroke placement
- Regularly sample the canvas to seed strokes
- Build a list of control point for each stroke by “hopping” between pixels*

2) Make another hop, resolving directional ambiguity by hopping in the direction of min θ





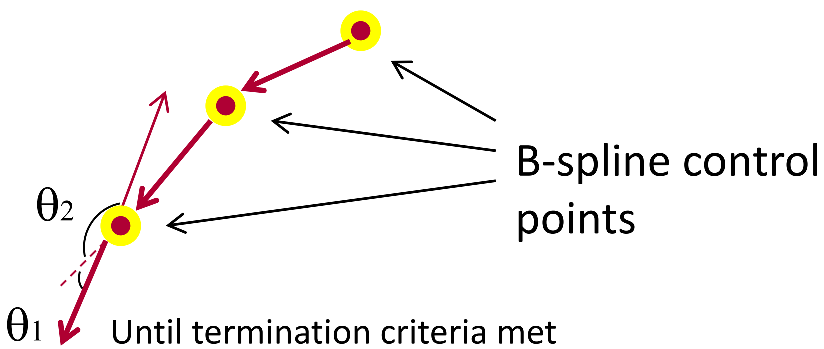
* In practice, best to use float coordinates and interpolate edge orientation

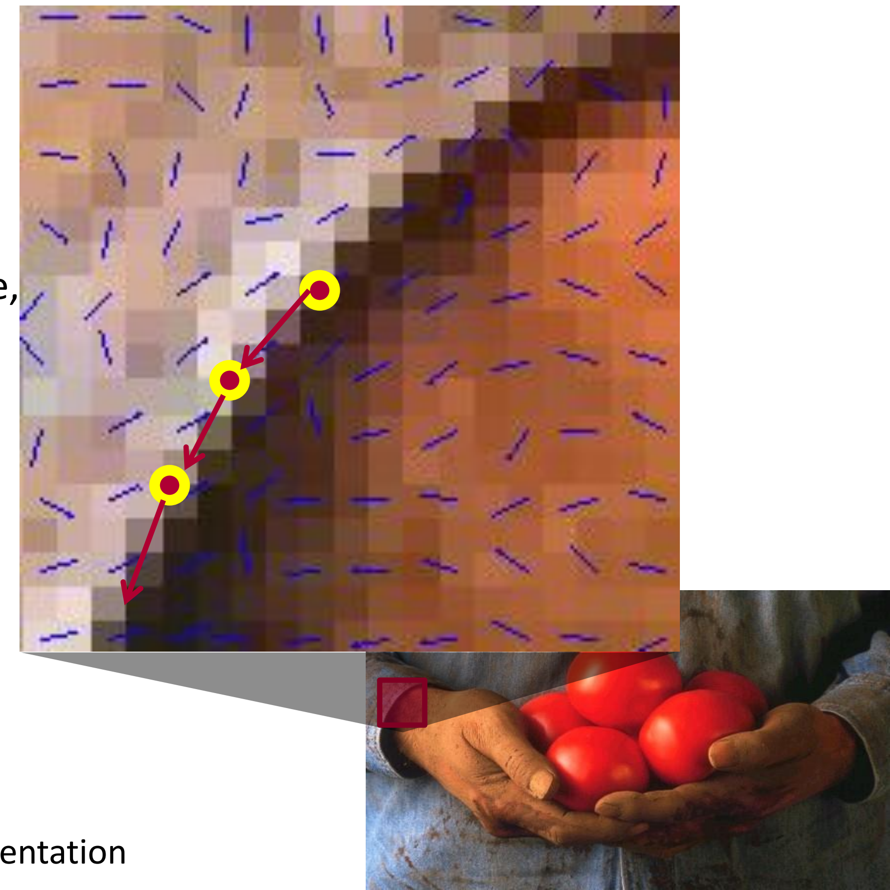
Painterly Rendering With Curved Brush Strokes

Hertzmann (1998)

- Greedy algorithm for stroke placement
- Regularly sample the canvas to seed strokes
- Build a list of control point for each stroke by “hopping” between pixels*

3) Keep hopping until end land on a pixel whose RGB colour differs (> threshold) from mean colour of stroke, or the stroke length is > a second threshold.





* In practice, best to use float coordinates and interpolate edge orientation

Painterly Rendering With Curved Brush Strokes

Hertzmann (1998)

- Painting is laid down in multiple layers (coarse to fine)
- Band-pass pyramid (= differenced layers of low-pass)
- Strokes from early layers are visible in final layer

- Paint coarsest layer with large strokes
- Paint next layer with smaller strokes
  - Only paint regions that differ between the layers
  - Use RGB difference

Painterly Rendering With Curved Brush Strokes

Hertzmann (1998)

- Tips and tricks
  - Non-linear diffusion* instead of Gaussian blur sharpens the painting – preserves edges and accuracy of edge orientation.
  - Build Gaussian pyramid at octave intervals, σ=(1,2,4,8). 4 layers sufficient.
  - Stroke thickness also at octave intervals
  - Low-pass filter the hop direction θ

* "Scale-Space and Edge Detection using Anisotropic Diffusion". P. Perona and J. Malik. *PAMI 12:629–639.* 1990.

Paint by Relaxation
Hertzmann. (2001)

- Global Optimization to Iteratively Produce “Better” Paintings

Photo credit: Hertzman ’01

Paint by Relaxation

Hertzmann. (2001)

- How to define the optimality of a painting ‘P’ derived from a photo ‘G’

$$
\begin{aligned}
E(P) &= E_{app}(P) + E_{area}(P) + E_{nstr}(P) + E_{cov}(P) \\
E_{app}(P) &= \sum_{(x,y)\in I} w_{app}(x,y) \|P(x,y) - G(x,y)\| \\
E_{area}(P) &= w_{area} \sum_{S \in P} \text{Area}(S) \\
E_{nstr}(P) &= w_{nstr} \cdot (\text{number of strokes in } P) \\
E_{cov}(P) &= w_{cov} \cdot (\text{number of empty pixels in } P)
\end{aligned}
$$

Weighted sum of Heuristics

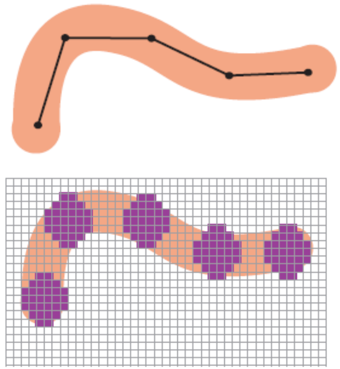
- **Painting similar to photo - weighted**
- **Stroke area (“paint used by artist”)**
- **Number of strokes**
- **Fraction of canvas covered by strokes**

- Weighting ω_{app} is derived from a Sobel edge magnitude (or user defined)
- The right strokes in the right place will minimize the energy function E(P)

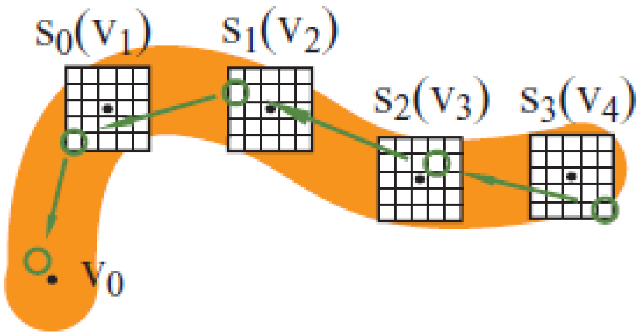
Paint by Relaxation

Hertzmann. (2001)

- Strokes selected at random and modified by local optimization to minimize E(P)
- Strokes modelled as active contours (“snakes”)
  - … but energy is ~E(P) no $1^{st}/2^{nd}$ order derivative terms
  - E(P) is approximated under control points
- Dynamic programming solution
  - move each control point to obtain locally optimal position (5x5)
  - E(P) at control point dependent only on current and previous



$$
\begin{aligned}
s_0(v_1) &= \min_{v_0} e_0(v_0) + e_0(v_1) + e_1(v_0, v_1) \\
s_1(v_2) &= \min_{v_1} s_0(v_1) + e_0(v_2) + e_1(v_1, v_2) \\
&\vdots \\
s_{i-1}(v_i) &= \min_{v_{i-1}} s_{i-2}(v_{i-1}) + e_0(v_i) + e_1(v_{i-1}, v_i)
\end{aligned}
$$



Paint by Relaxation

Hertzmann. (2001)

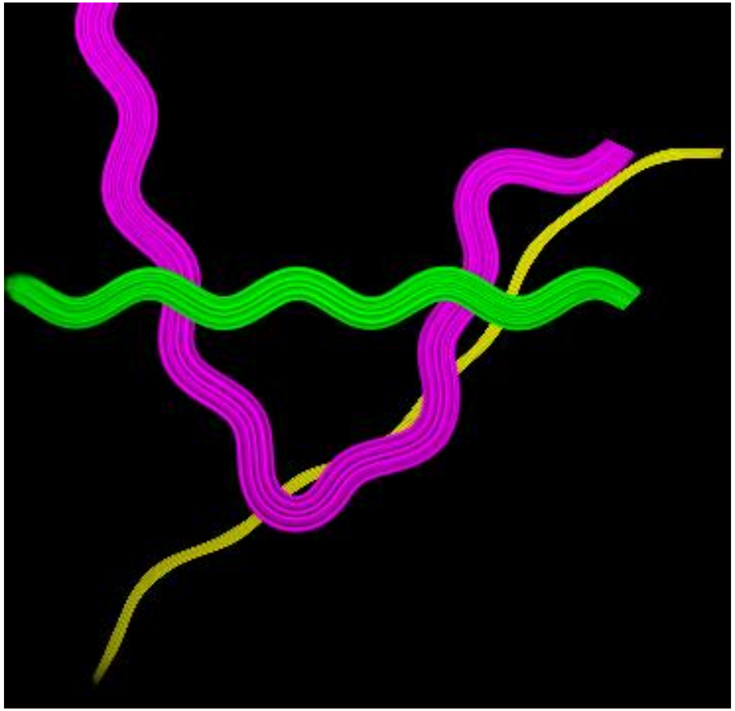
- Sobel magnitude can be replaced with a manually sketched mask to alter emphasis

Photo credit: Hertzman '01

Paint by Relaxation

Hertzmann. (2001)

- Quick Start: OpenGL **research code** for bump-mapped paint strokes
  - Strokes as Catmull-Rom (interpolating) splines
  - Bump mapping via Multi-texturing (can be disabled)
  - Dependency on OpenCV to load images (can substitute this trivially)
  - Code used in “Empathic Painting” Collomosse et al. NPAR 2006



http://www.collomosse.com/EG2011tut/sbr_opengl.zip

Artistic Stylization of Images and Video

Part II – Vision for Stylisation

Eurographics 2011

John Collomosse

Centre for Vision Speech and Signal Processing (CVSSP),
University of Surrey, United Kingdom

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Higher Level Visual Analysis

- **Artistic Stylization pre-2000**
  - **Dependent on low-level image processing (e.g. Sobel) to drive preservation of local edge and high frequency content.**
- **An Artist does not paint a stroke by looking only at the image content under that stroke**
- **A higher level of visual analysis is needed:**

Consider more than local edge information

Global analysis vs. greedy placement

- **Computer Vision and Optimisation are solutions**

Region-based discrimination

Around the Cake (Thiebaud'62). Markup (Kolliopoulos '06)

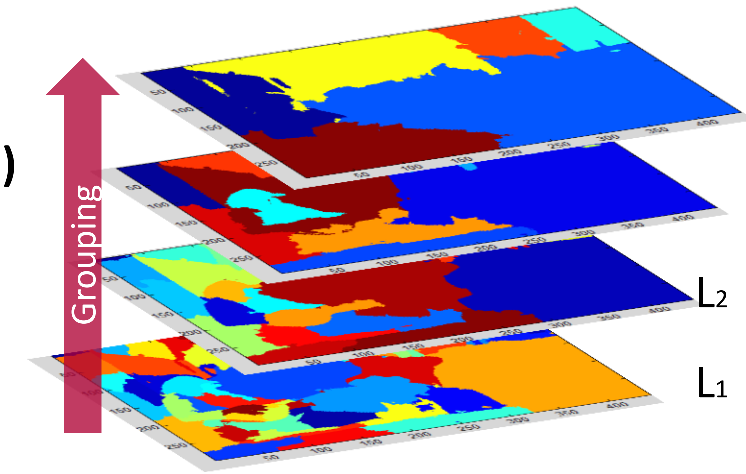
Stylization and Abstraction of Photographs

Decarlo and Santella. (2002)

- **Segmentation (EDISON / Mean-Shift)** [Christoudias et al, ICPR 2002]
  - **Create a spatial hierarchy of regions**
    - **Strokes painted in a region have same prominence**
    - **Or render regions flat with black edges to create ‘toon effect**
  - **Determine prominence of regions interactively**
    - **…using an eye tracker**

Stylization and Abstraction of Photographs
Implementation Steps

- **Segment levels of low-pass (Gaussian) pyramid**
  - **DeCarlo uses factor of $\sqrt{2}\sigma$ between layers**
  - **Discard regions < 500 pixels (on 640x480 image)**
- **Segments grouped into hierarchy from fine to coarse based on overlap and common colour**



1. For each* region A at the current level e.g. L_1
2. Find the region B_i in level above e.g. L_2 maximising:

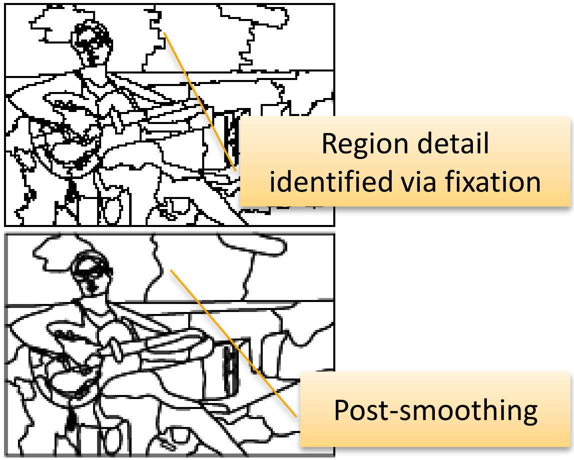
$$\text{overlap}(A, B_i) = \frac{\text{area}(A \cap B_i)}{\|\text{color}(A) - \text{color}(B_i)\| + 1}$$

3. Assign A's parent to Bi, providing $A \cap B_i$ is contiguous+

*At step 1, iterate through regions in order of increasing area.
+ After all levels are processed, any orphan regions become children of root note.

Stylization and Abstraction of Photographs

Decarlo and Santella. (2002)



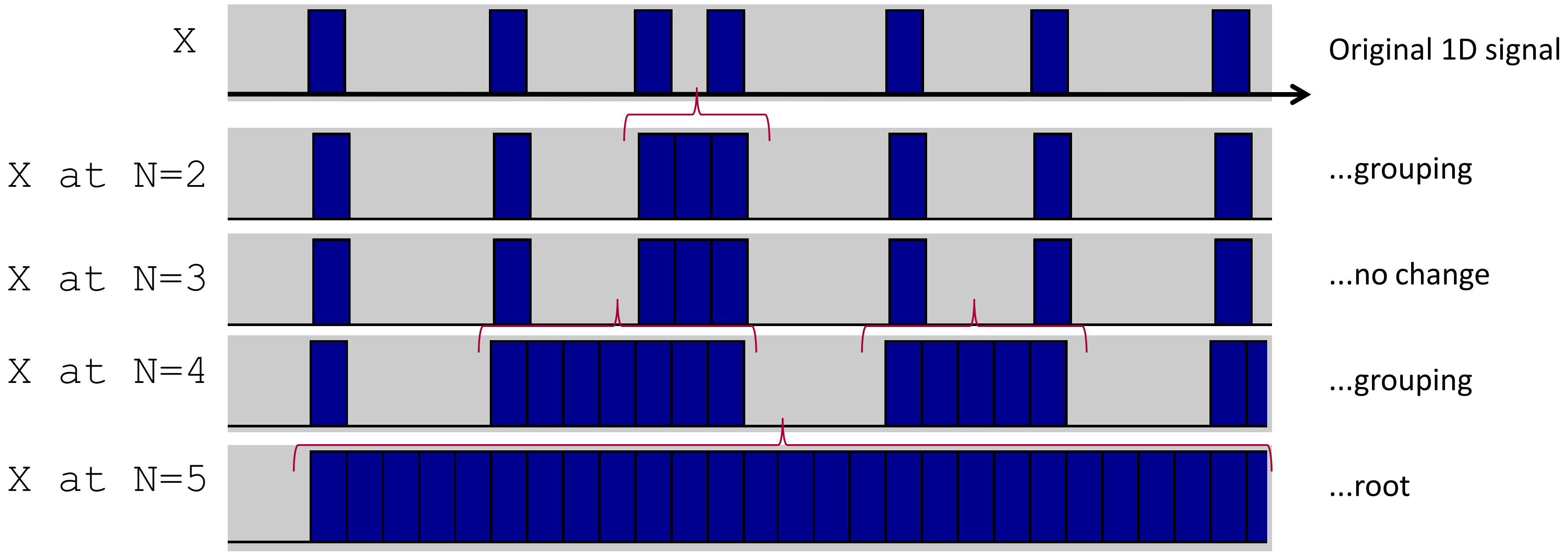
- **Painting starts at the coarsest level of region detail**
- **A region is split if more than half its children are fixated upon**
- **The resulting region map is noisy, but aesthetics improve after smoothing and vectorisation**

Sieves

Bangham et al. (2003)

- **Alternative scale-space hierarchy using sieves**
  - **Morphological operations (closure followed by opening)**

```
X=imerode(imdilate(X,ones(1,N)),ones(1,N));
```



The Art of Scale Space (Sieves)

Bangham et al. (2003)

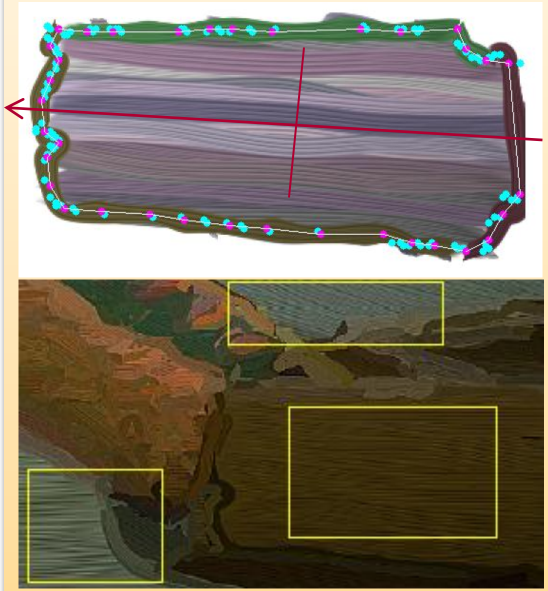
- **Sieves better preserve edges/corners vs. Gaussian**
  - Extended to 2D in [Bangham '99], NPR application [Bangham '03]. Colour sieves (Harvey '04)

- Similar level of detail strategy to Decarlo/Santella can be applied to scale-space tree

Region based Painting

- **Painting the regions**

Paint via 3rd party algorithm e.g. Hertzmann with constant stroke size [Santella /DeCarlo NPAR'02]



Fill region with strokes in direction of principal axis [Shugrina et al, NPAR '06]

Fill with strokes in directions derived from region exterior contour [Wang et al, NPAR '10]

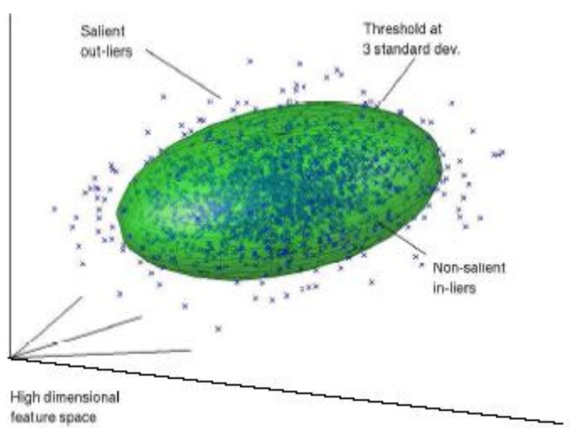
c.f. video painting...

Genetic Paint: Search for Salient Paintings

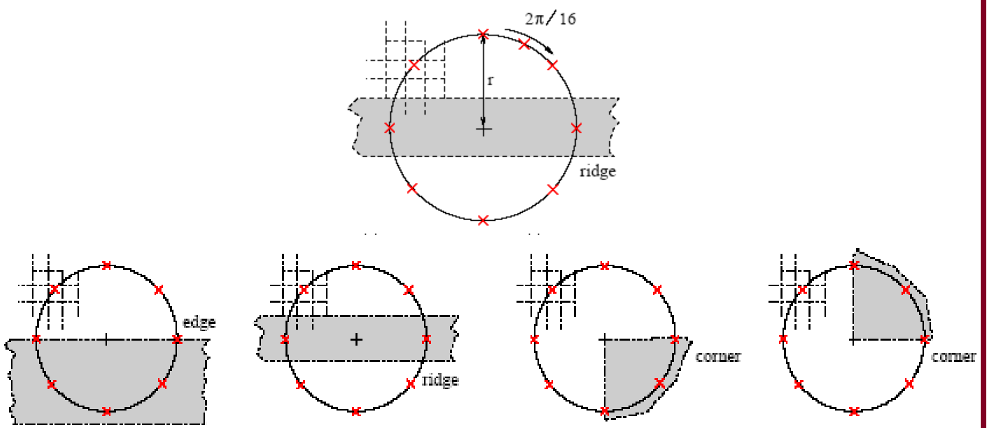
Collomosse et al. 2005.

- **Automated Differential Emphasis in Painting**
  - **Prescriptive salience measures [Itti & Koch]**
    - **Not closely correlated to human behaviour [Santella/DeCarlo NPAR'04]**
    - **Salience is subjective and task dependent**
  - **Trainable measure of salience (GMM of radial features)**

Rarity & Visibility



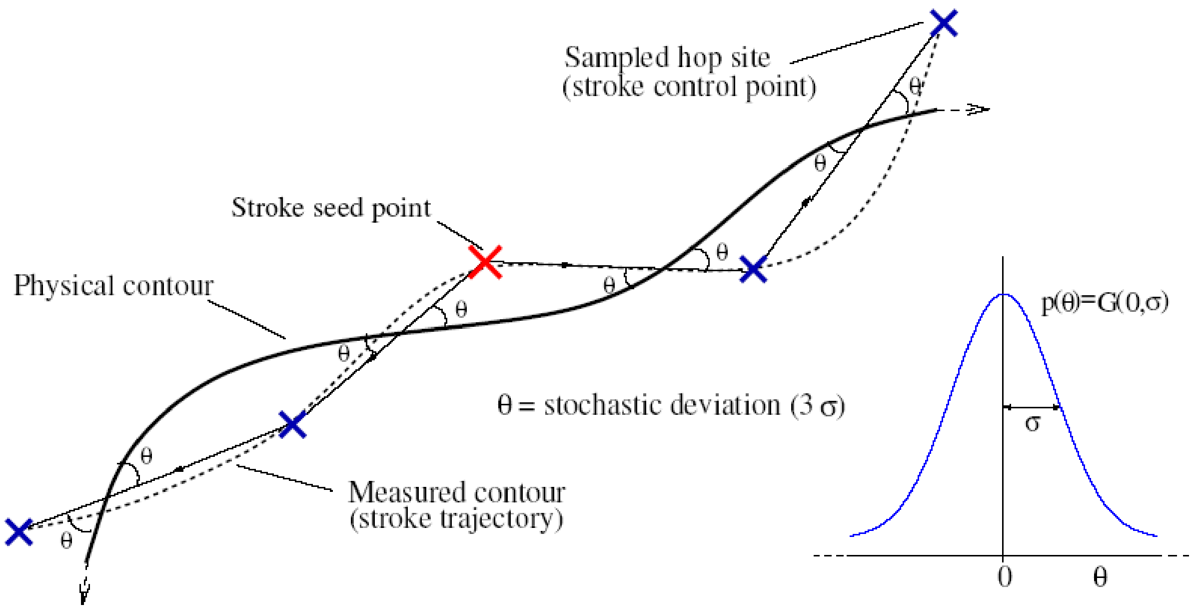
Radial Features

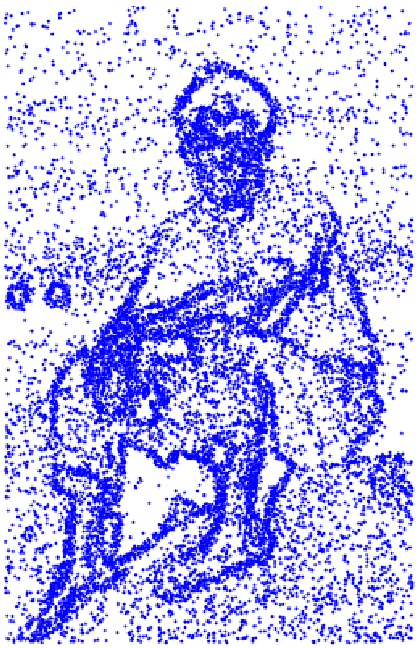


Genetic Paint: Search for Salient Paintings

Collomosse et al. 2005.

- **Genetic Optimizaton to find “best” painting**
  - **<u>The optimal painting preserves detail in salient areas, and removes non-salient detail</u>**
  - **MSE between salience map and Sobel edge detail in the painting (c.f. Hertzmann ‘01)**

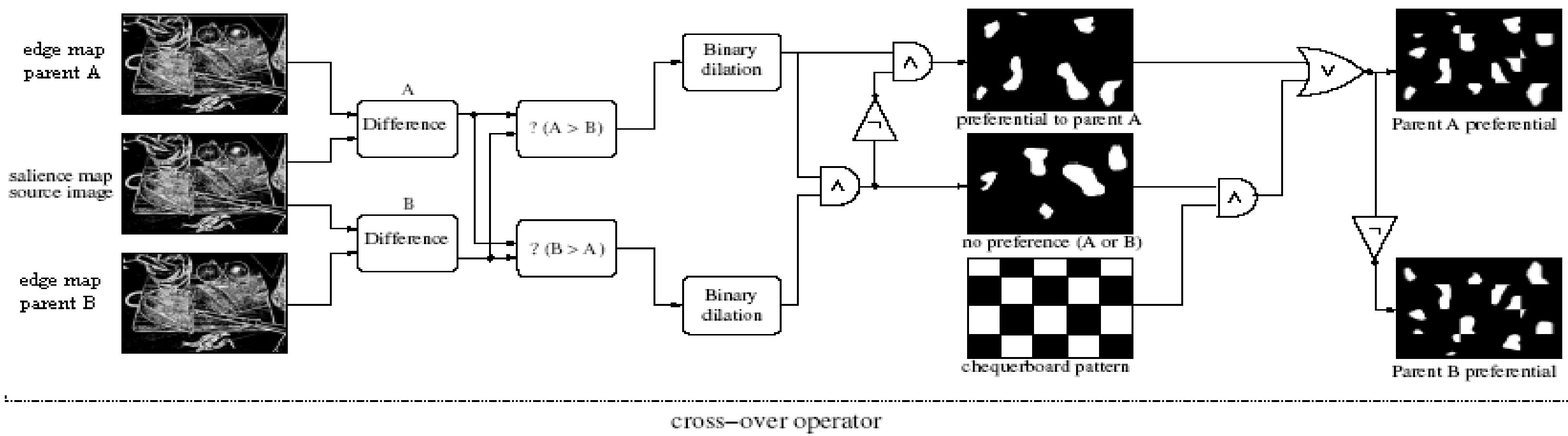




Genetic Paint: Search for Salient Paintings

Collomosse et al. 2005.

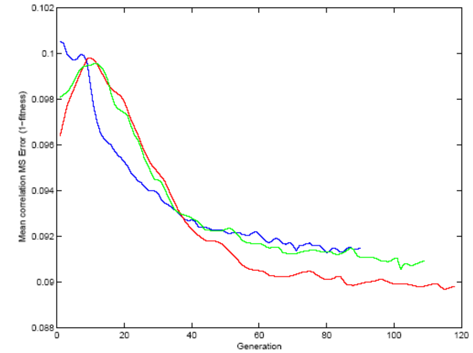
- Paintings are bred by cloning strokes from two individuals
- (Two parent cross-over)
  - fitness proportionate selection with replacement
- Promotion of rapid convergence
  - Top 10% carried over to next gen. automatically
  - Bottom 10% culled



Genetic Paint: Search for Salient Paintings

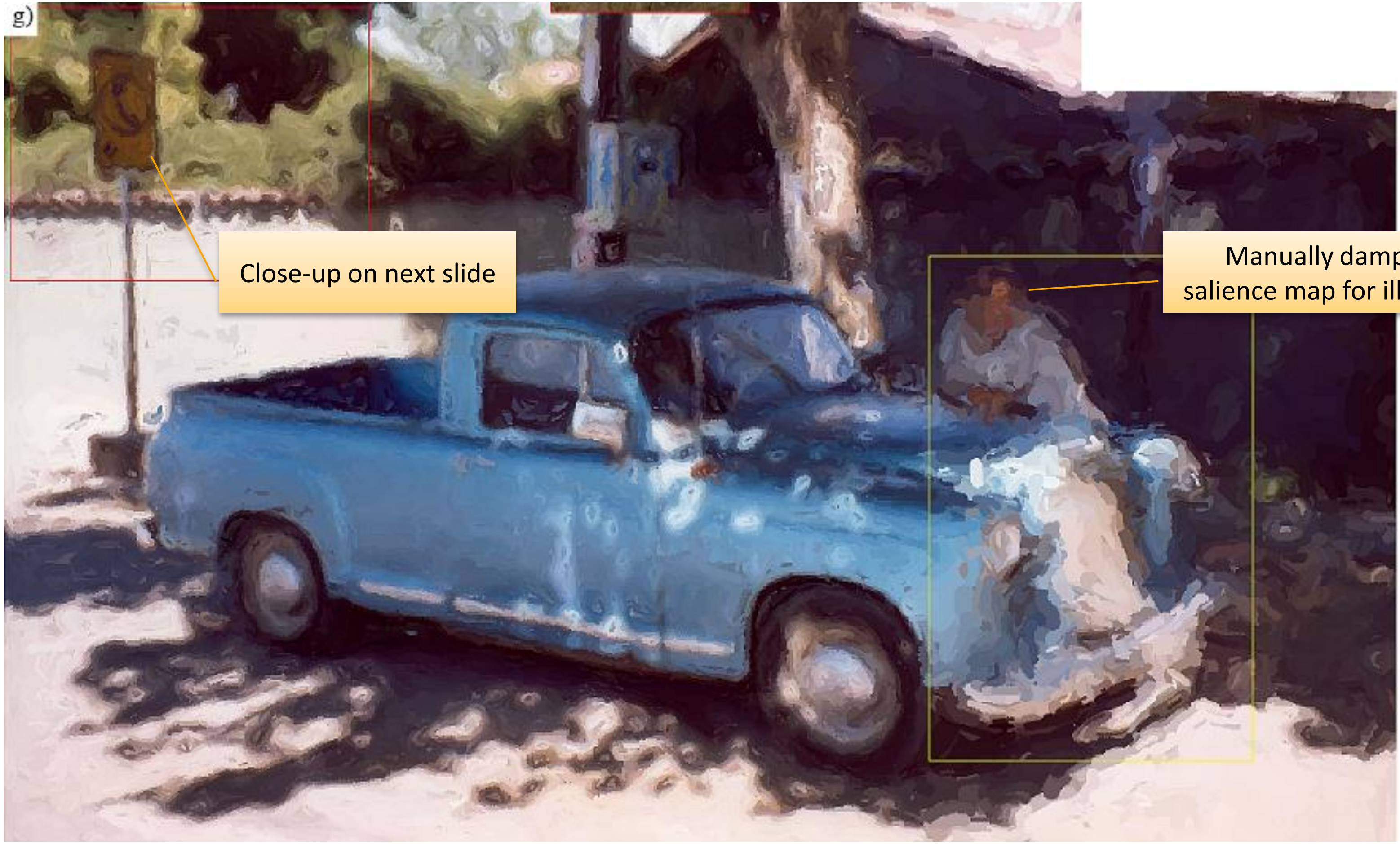
Collomosse et al. 2005.

- **Iterative optimization improves detail in salient regions**
  - **Population of ~50 paintings**
  - **Convergence in ~200 iterations**
  - **Stochastic variation in stroke attributes creates diversity**
  - **GA combines favourable regions of parent paintings**



Genetic Paint: Search for Salient Paintings

Collomosse et al. 2005.



Close-up on next slide

Manually dampened salience map for illustration

Comparison of Salience vs. Edge based Painting

- **Comparison of Sobel-driven and Salience-driven painting**
  - **Detail on the sign is preferentially retained (wrt. Leaves of the tree)**
  - **Not all edges / high frequency texture are salient**

Original

Litwinowicz ‘97

Salience driven

Painting Code

- **Painting research code available**
  - **http://www.collomosse.com/EG2011tut/summerschool.zip**

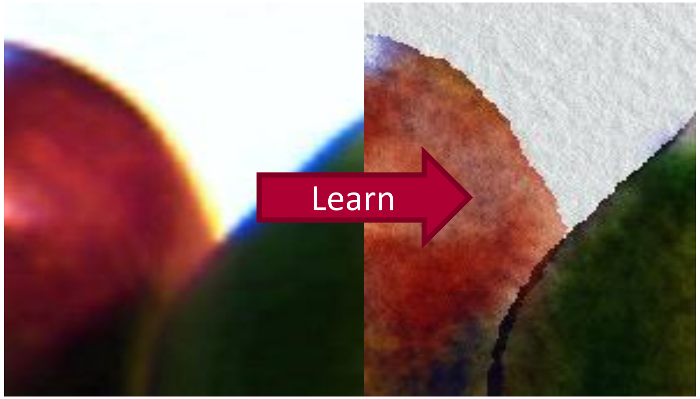
- **MATLAB based (experiment with different salience maps)**
- **Code adapted from Collomosse et al. 2005 – single iteration, spline strokes.**
- **Previously released as lab exercise at EPSRC VVG Summer School (2007)**

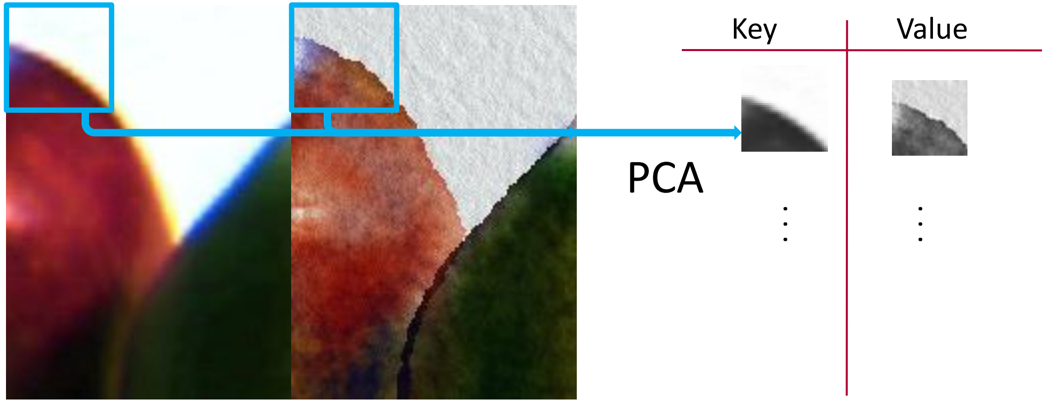
Image Analogies
Hertzmann et al. (2001)

- **Style Transfer**
  - **Learning vs Heuristic approach to stylise photos**
  - **Patch based lookup (luminance only)**

$$Y(p) \leftarrow \frac{\sigma_B}{\sigma_A}(Y(p) - \mu_A) + \mu_B$$

    - **Similar to Freeman texture synthesis but using external collection of patches**
    - **Learned as lookup table**





- **Style Transfer**
  - **Synthesis has ‘data’ and ‘smoothness’ terms**
    - **Data (patch lookup)**
      - **Pixel-wise luminance comparison (after PCA)**
    - **Smoothness (derived from Ashikhmin)**
      - **Minimise MSE between proposed patch and existing neighbours**
      - **Gaussian weighted distance function (avoids discontinuity)**

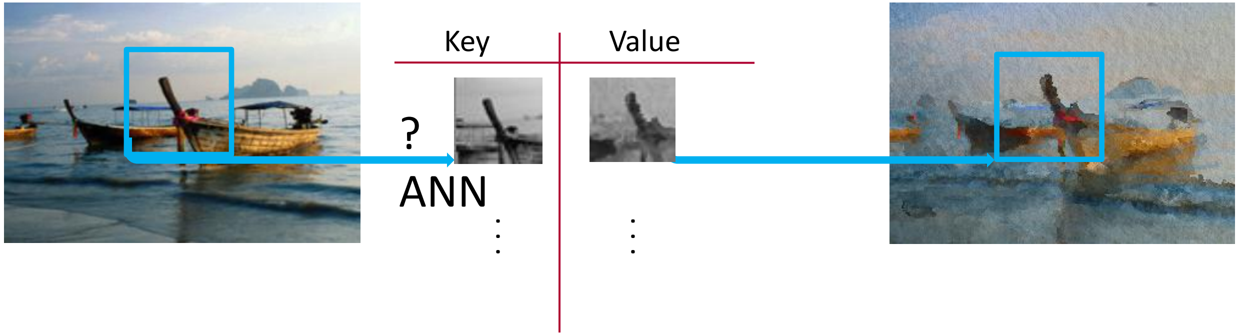
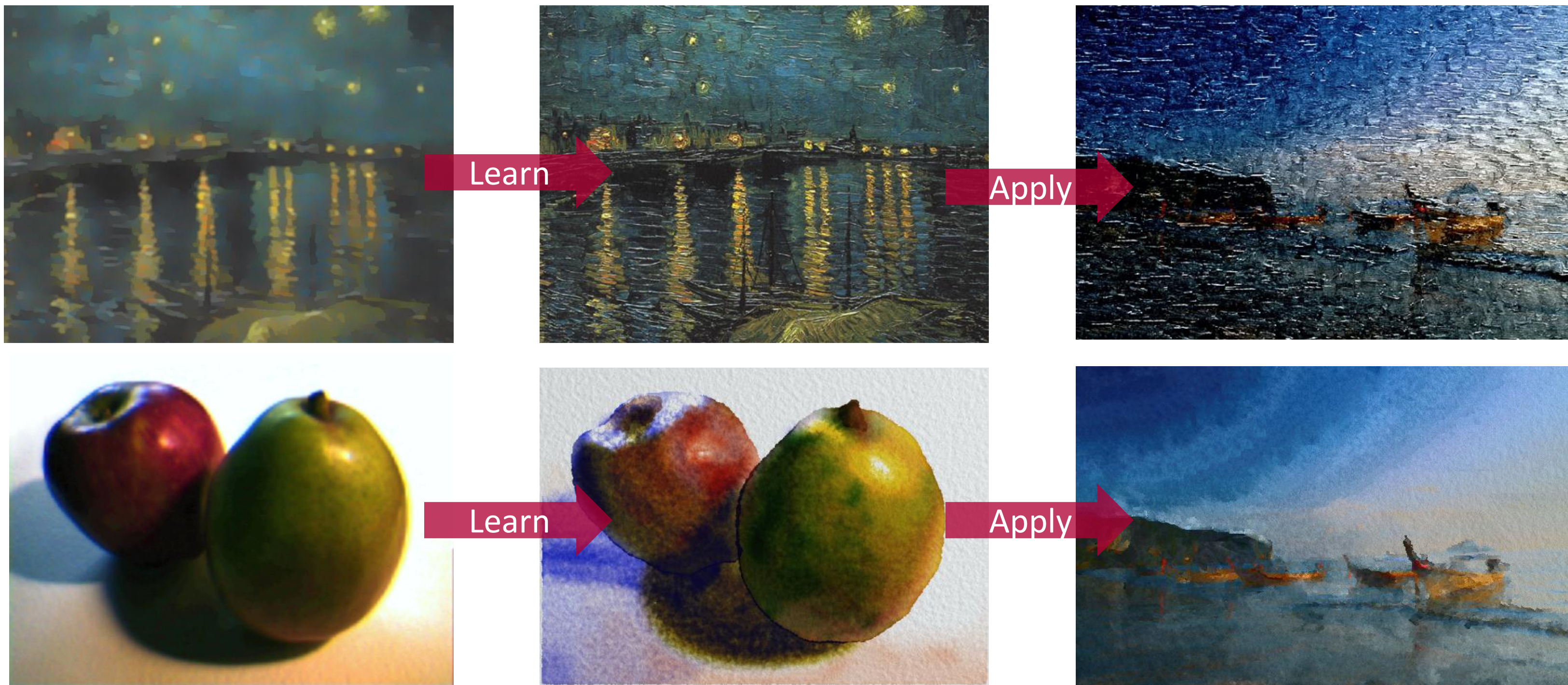


Image Analogies
Hertzmann et al. (2001)

- **Style Transfer Examples**

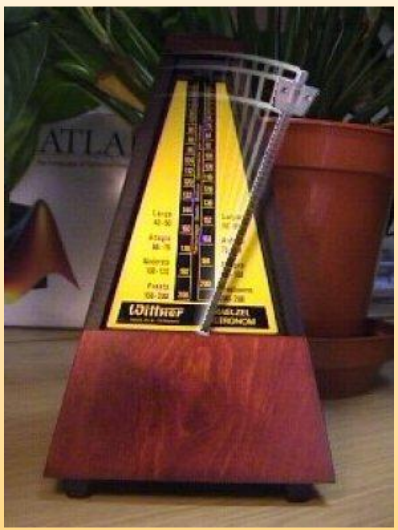


- **Other extensions to video [Hors & Essa '02] and to take orientation into account [Lee et al. '10]**

Video Painting

- **Video Stylisation**
  - **Techniques to create painterly animations or cartoons from video**
  - **Enabled by automated techniques for image stylization**

Stylised Appearance



Stylised Motion

Temporal Coherence

- **Goal of video stylization**
  - **Create the desired aesthetic exhibiting good <u>temporal coherence</u>**
- **Temporal coherence is here defined as:**
  1. **Absence of distracting flicker**
  2. **Motion of brush strokes (or other component marks) is in agreement with the motion of content**
- **Naïve approaches**
  - **Repaint every frame independently**

    = *Flicker (violates 1.)*
  - **Fix strokes in place and change attributes e.g. colour according to video content**

    = *Motion unmatched (violates 2.)*

    "the shower door effect" – Barb Meier

Meier '96

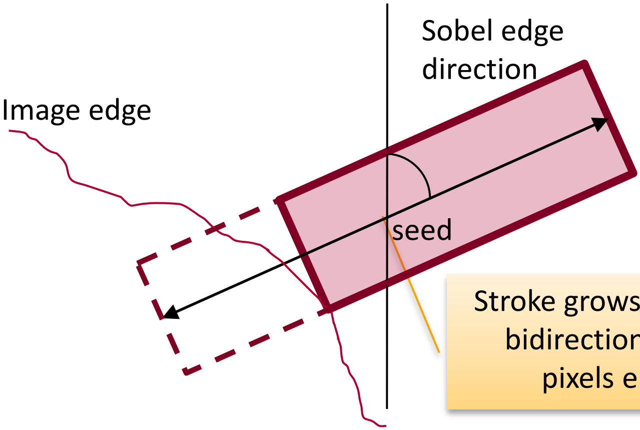
Processing Images & Video for Impressionist Effect

Litwinowicz (1997)

- **Painterly animation using Optical Flow**
  - **Brush strokes are pushed from frame to frame using flow estimate**
  - **Oscar winning visual effects in movie “What Dreams May Come” (1998)**
    - **Manual correction of flow estimate (~1000 person-hours [Green’99])**

Processing Images & Video for Impressionist Effect

Litwinowicz (1997)



Stroke grows from seed point bidirectionally until edge pixels encountered

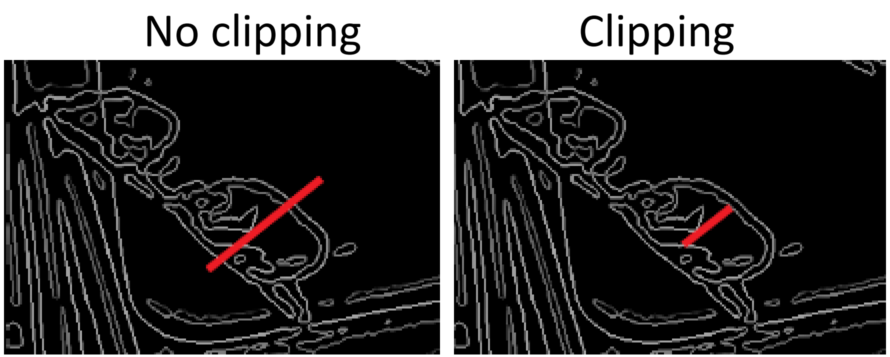


Photo credit: Litwinowicz '97

Processing Images & Video for Impressionist Effect

Litwinowicz (1997)

- **Initialisation as per single image (regular seeding)**
  - Randomise rendering order of strokes
- **Strokes translated to next frame via flow field**
- **Greedy approximation to avoid irregular coverage**
  - Delaunay triangulation of seeds (and image corners)
  - **Death.** Seeds too close together are deleted
    - Tested in random order
  - **Birth.** Triangles with area > threshold are subdivided
    - New seeds are randomly place rendering order

Photo credit: Litwinowicz '97

Processing Images & Video for Impressionist Effect

Litwinowicz (1997)

- **Stroke Birth**

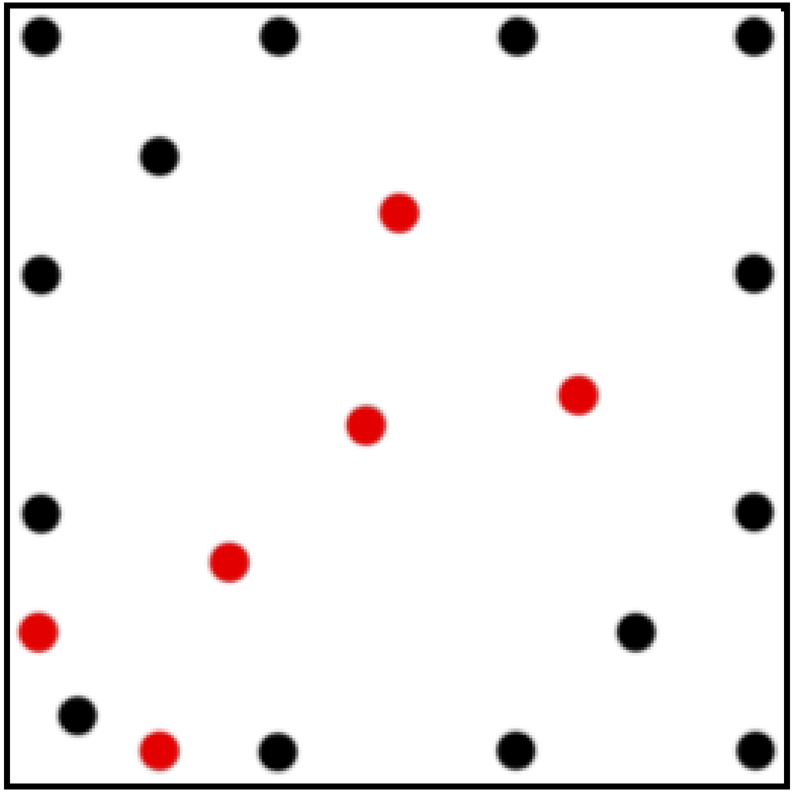
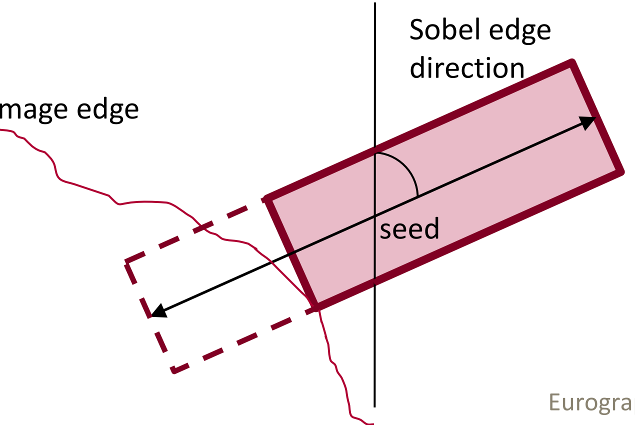


Photo credit: Litwinowicz '97

Processing Images & Video for Impressionist Effect

Litwinowicz (1997)

- **Tips on reducing flicker**
  - **Detect your own scene cuts and reinitialise**
  - **Use a robust Optical Flow algorithm (!)**
    - **e.g. SIFTFlow or Brox**
  - **Pre-filter heavily (Gaussian). Care with interlaced content.**
  - **Interpolate orientations from strong edges only**
    - **Smooths out codec noise**
    - **Litwinowicz uses thin-plate spline (expensive) but can use Poisson filling (fast on GPU) to good effect**



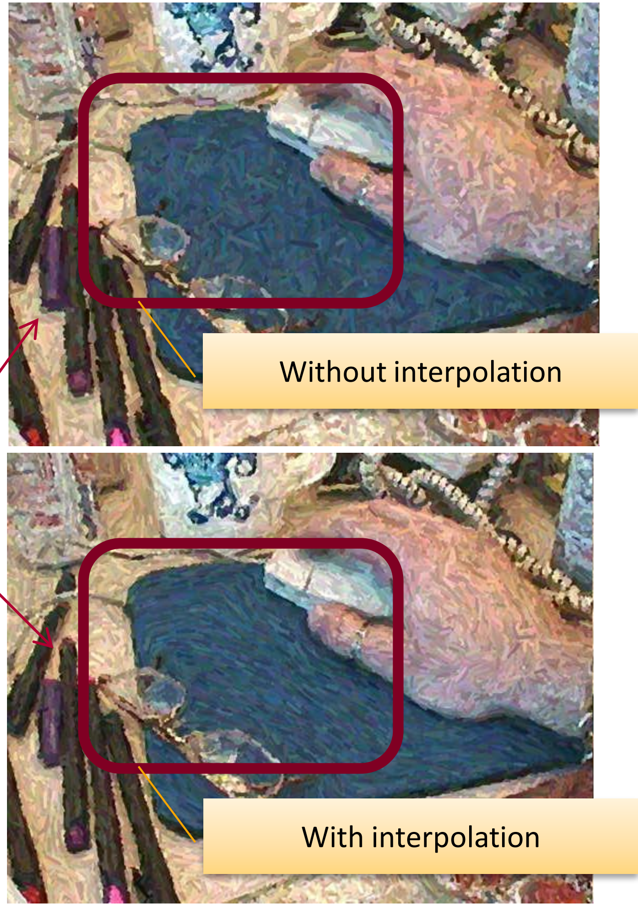


Photo credit: Litwinowicz '97

Processing Images & Video for Impressionist Effect

Litwinowicz (1997)

- **Main sources of temporal incoherence**
- **Motion matching**
  - **Optical Flow = visual correspondence problem**
  - **Inevitable inaccuracies in estimate are cumulative**
  - **Content appears to slip below strokes = shower door effect**
    - **Manual correction of OF mitigates this but is expensive**
- **Flicker**
  - **Random order of new strokes disguises regularity**
    - **…but the noise generates flicker**
  - **Sudden disappearance of strokes exposes others = popping**
  - **Sobel edges are noisy at moderate scales**
    - **Strokes are clipped against flicking edge map**

Improving the Coherence of Flow-based Schemes

- **Main sources of temporal incoherence**
- **Motion matching**
  - **Optical Flow = visual correspondence problem**
  - **Inevitable inaccuracies in estimate are cumulative**
  - **Content appears to slip below strokes = shower door effect**
    - **Manual correction of OF mitigates this but is expensive**
- **Flicker**
  - **Random order of new strokes disguises regularity**
    - **…but the noise generates flicker**
  - **Sudden disappearance of strokes exposes others = popping**
  - **Sobel edges are noisy at moderate scales**
    - **Strokes are clipped against flicking edge map**

<u>Addressed by</u>

Hertzmann and Perlin
NPAR 2000

Hays and Essa
NPAR 2004

Painterly Rendering for Video and Interaction

Hertzmann and Perlin (2000)

- **Repaint only the areas that change significantly**
  - **Fast – enables realtime interaction**
  - **Limits shower-door by repainting limited regions of canvas (“paint-over”)**
- **RGB Difference to detect regions**
  - **Optical flow *optionally* used to translate strokes**

$$\frac{1}{|M|}\sum_{(i,j)\in M} ||I_{t+1}(i,j) - I_t(i,j)|| > T_V$$

- **Control points shifted under flow**

Paint-Over

Hertzmann '00

Paint-Over and Optical Flow

Hertzmann '00

Image and Video-based Painterly Animation

Hayes & Essa (2004)

- **Key Innovation**
  - **Temporal smoothing of stroke attributes**
- **Stroke Opacity for birth/death**
- **Orientation**
  - **RBF interpolated field (similar to Litwinowicz)**
  - **But interpolated from strokes marked "strong"** ***not from per-frame orientation field***
    - **Strokes born on strong edges**
- **Length and orientation are also smoothed**

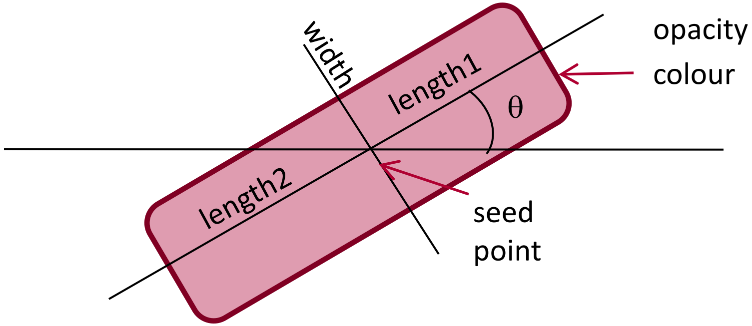


Image and Video-based Painterly Animation

Hayes & Essa (2004)

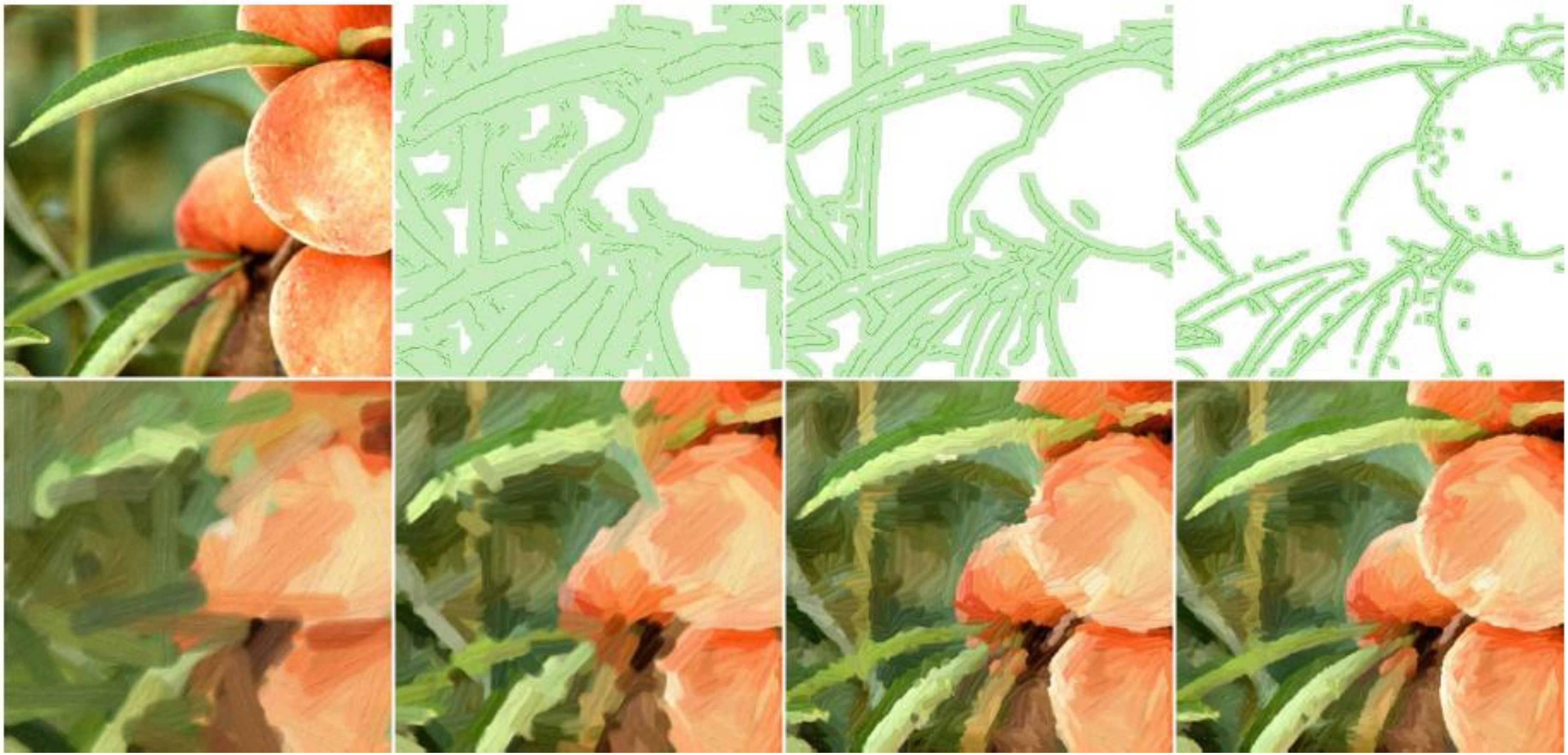


Image and Video-based Painterly Animation

Hayes & Essa (2004)

Video Watercolorization by bi-directional advecation

Boisseau et al. (2007)

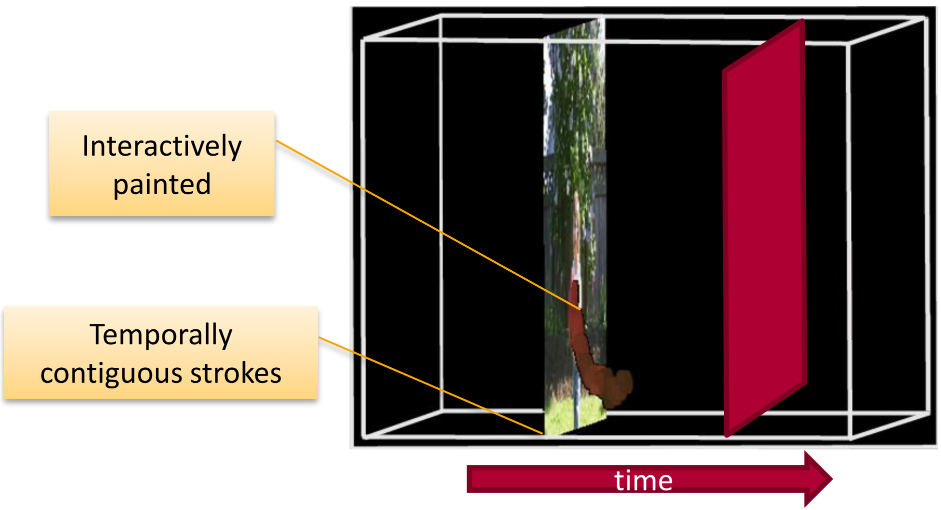
- **Bi-Directional Flow (of textures vs. strokes)**
  - **Adaptation of “Texture advection” from flow visualisation**
  - **Frequent occlusions in video motivated bi-directional flow**
    - **Two textures seeded – one flows forward, one back**

- **Trend towards more global temporal analysis**

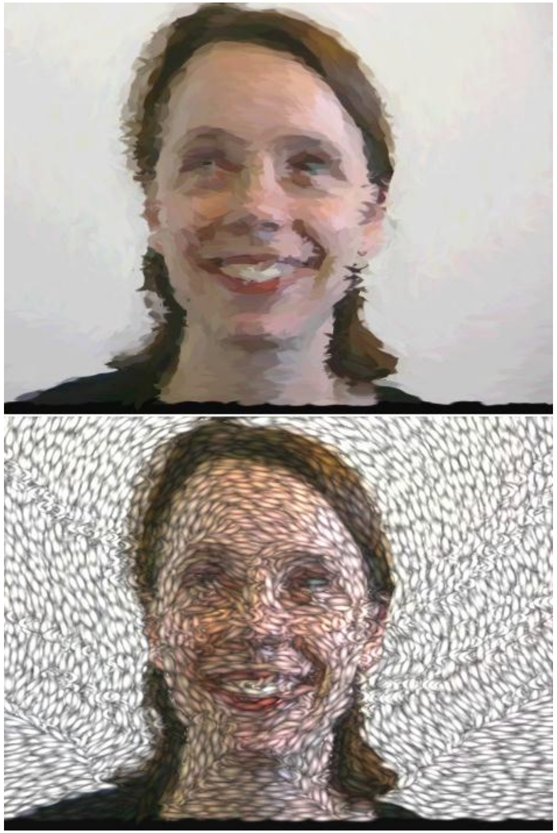
Video Cubism

Klein et al. (2002)

- **Temporally local (inter-frame) approaches**
  - No long-view of video structure
    - necessitates averaging of past information
    - Averaging mitigates flicker but exaggerates the shower door effect
- **Spatio-temporal primitives**



timeslice



Space-time Segmentation for Video Stylisation

- **Automated Space-time Analysis**
  - **Goal is coherent segmentation of video into semantic regions**
  - **Coherent space-time regions are smoothed then do not flicker**

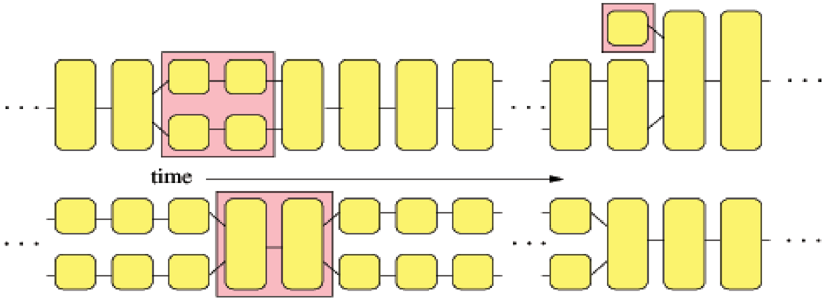
Extending Mean-shift to Space-time (3D)

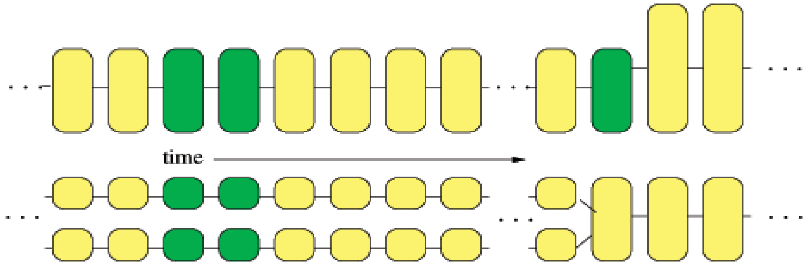
EDISON segment frames and associate (2D+t)

Stroke Surfaces: Coherent Artistic Animations from Video

Collomosse et al. (2005)

- **Region association (2D+t)**
  - **Based on a weighted blend of heuristics**
    - **Shape (Fourier Descriptors)**
    - **Colour**
    - **Overlap (as DeCarlo/Santella)**
  - **Associations are filtered by locating**
    - **Short-time branches**
    - **Short-time cycles**
  - **Surface voxels between volumes are identified**
  - **Surfaces fragmented into "stroke surfaces" that abut only two volumes**

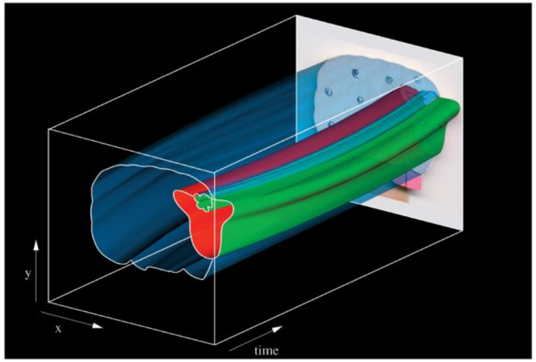




Stroke Surfaces: Coherent Artistic Animations from Video

Collomosse et al. (2005)

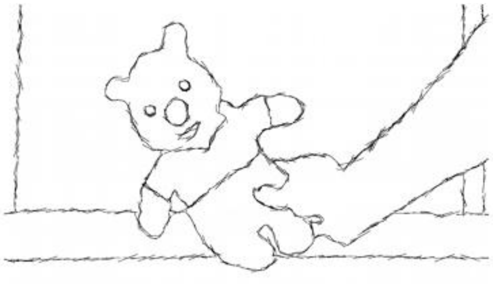
- **"Stroke Surfaces" separate volumes**
  - **Winged edge structure**
  - **Smoothing the surface smoothes the volumes**
    - **Generalisation of snakes to 2D surfaces**
    - **Separate terms for spatial and temporal constraint**



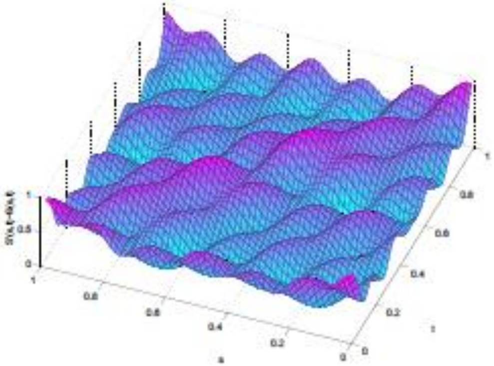
$$E = \int_0^1 \int_0^1 (E_{int}[\underline{Q}(s,t)] + E_{ext}[\underline{Q}(s,t)])\mathrm{d}s\mathrm{d}t$$

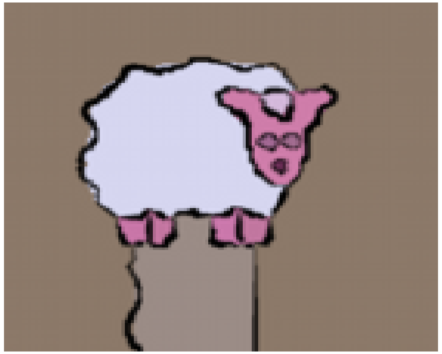
$$E_{int} = \alpha\left|\frac{\partial \underline{Q}(s,t)}{\partial s}\right|^2 + \beta\left|\frac{\partial \underline{Q}(s,t)}{\partial t}\right|^2 + \gamma\left|\frac{\partial^2 \underline{Q}(s,t)}{\partial s^2}\right|^2 + \delta\left|\frac{\partial^2 \underline{Q}(s,t)}{\partial t^2}\right|^2$$

$$E_{ext} = \eta f(\underline{Q}(s,t)).$$

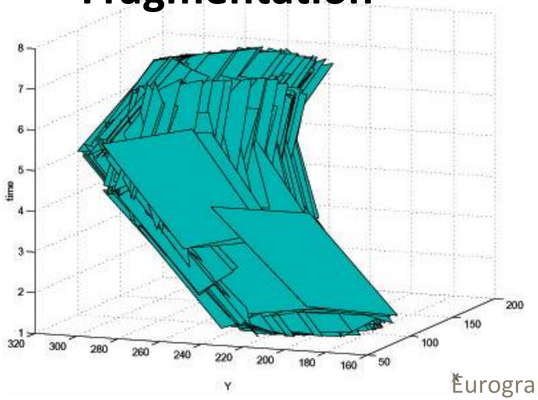


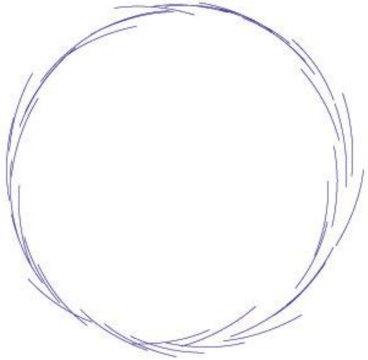
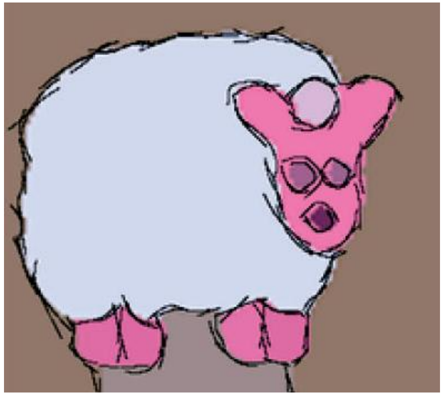
- **Surface Manipulation**
  - **Undulation**





  - **Fragmentation**



Stroke Surfaces: Coherent Artistic Animations from Video

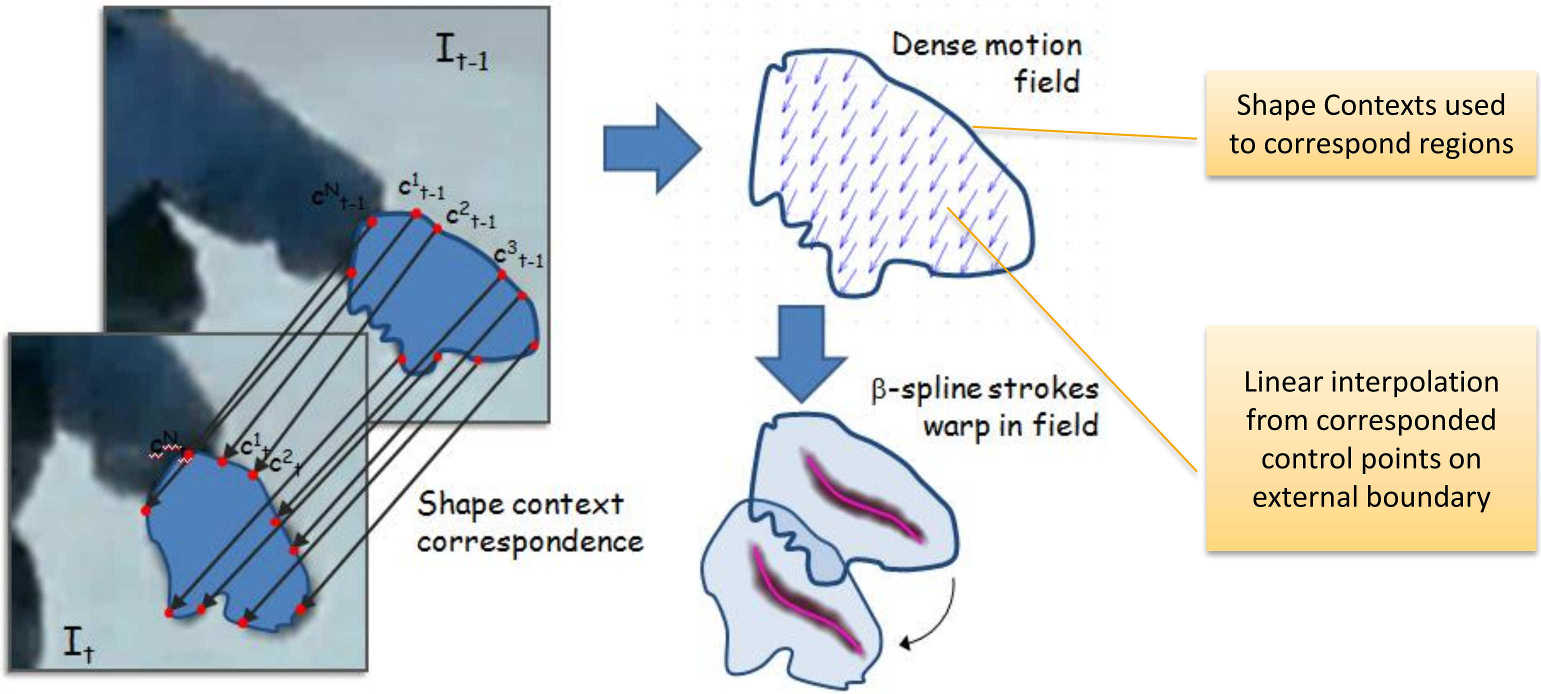
Collomosse et al. (2005)

- **Coherent Segmentation**

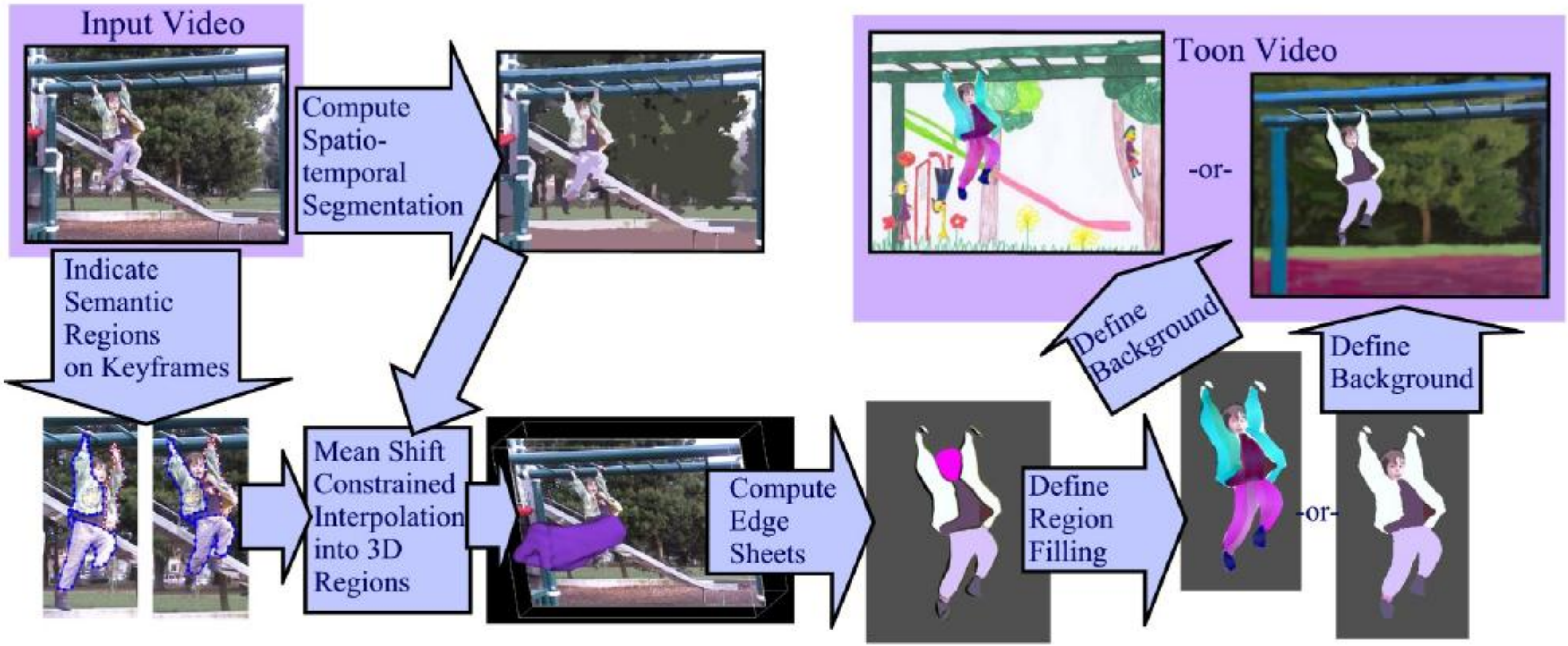
Rotoscoping for Painterly Rendering

Agarwala et al. (2004)

- **Rotoscoping**
  - **Coherent motion of (groups of) regions can be exploited to paint coherently**
  - **Interpolate internal points (e.g. stroke seeds) from region boundary**



- **Rotoscoping**



Video Tooning
Wang et al. (2004)

- **Rotoscoping**
  - **Coherent motion of (groups of) regions can be exploited to paint coherently**

Cartoon Style Rendering of Motion

Collomosse et al. (2003)

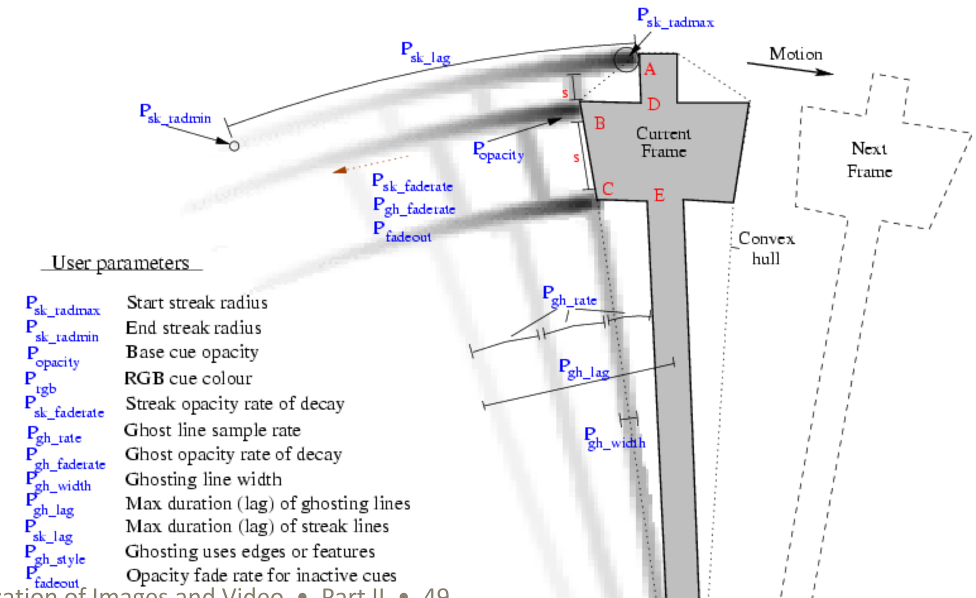
- **Motion Emphasis**
  - **Augmentation cue (Speed-lines, ghosting)**
  - **Deformation (Squash and stretch, general deformation)**
  - **Time warping (Anticipation/snap)**

- **Augmentation Cues**
  - **Segment trails of corresponded control points into smooth sections.**
  - **Iteratively select smooth sections to maximising:**

$$
\begin{aligned}
H(0) &= 0 \\
H(i+1) &= H(i) + (\alpha v(x) + \beta L(x) - \\
&\quad \gamma D(x) - \delta\omega(x,\sigma;w) + \zeta\rho(x))
\end{aligned}
$$

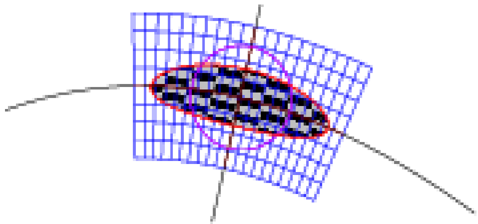
$\alpha, \beta, \gamma, \delta, \zeta$: user weights
σ selected sections

$v(x)$ mean velocity over x
$\rho(x)$ mean curvature at x
$L(x)$ temporal extent of x
$D(x)$ dist from convex hull at x
$\omega(x,\sigma;w)$ overlap of x and σ



Squash and Stretch

- **Deformation Cues**
  - A motion dependent curvilinear basis is formed using the trajectory of the region centroid, and its normal.



$$\underline{x} = \underline{G}_c(s) + r\underline{n}(s)$$

U(.) as the transformation from curvilinear space, keep the inverse as a lookup table.

$$\underline{x} = U(\underline{r}) \qquad \underline{r} = (s, r)^T$$

$$\underline{x} \leftarrow U\left(\begin{bmatrix} k & \mathbf{0} \\ \mathbf{0} & \frac{1}{k} \end{bmatrix} U^{-1}(\underline{x})\right)$$

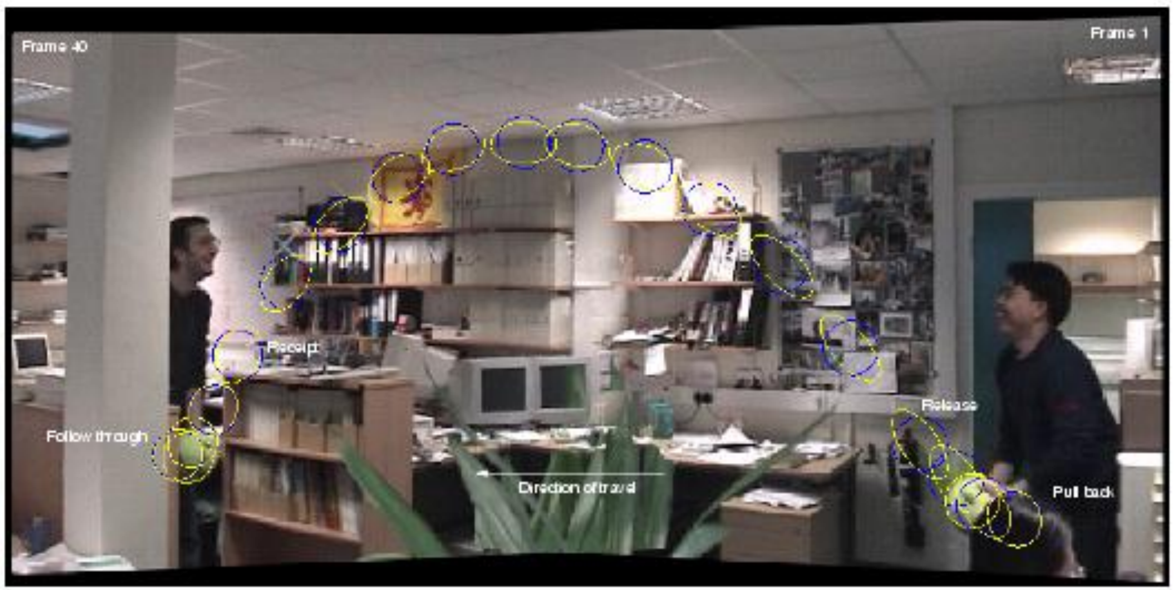
$$k = 1 + \frac{K}{2}\left(1 - cos\left(\pi \frac{v^2+1}{2}\right)\right)$$

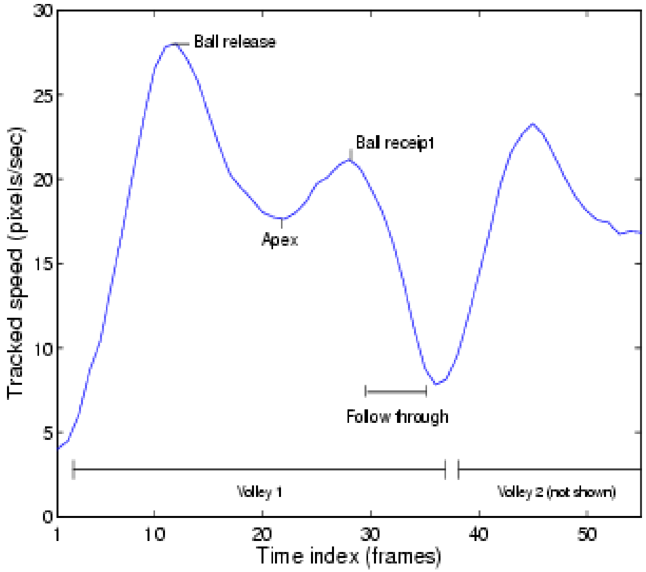
$$v = \begin{cases} 0 \text{ if } |\dot{\underline{\mu}}| < V_{min} \\ 1 \text{ if } |\dot{\underline{\mu}}| >= V_{max} \\ (|\dot{\mu}| - V_{min})/(V_{max} - V_{min}) \text{ otherwise} \end{cases}$$

Squash and stretch
(after Chenney et al '02)

Squash and Stretch

- **Deformation Cues**
  - **Squash and stretch in a camera motion compensated frame**





General Deformation

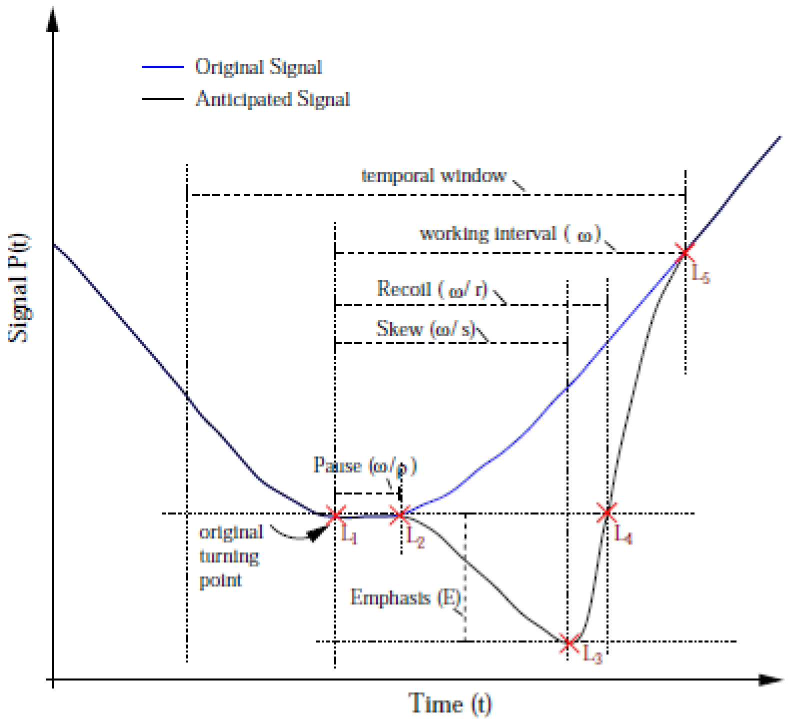
- **Deformation Cues**
  - **More general motion deformations can be created by specifying a transfer function dependent on a point's local acceleration and position, as well as its speed.**

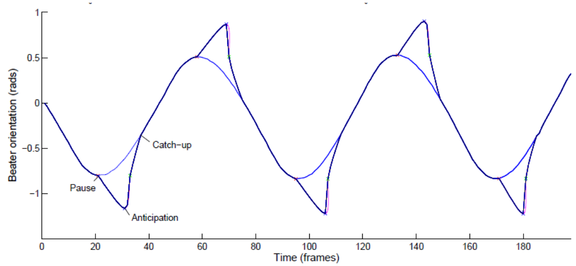
$$x' = U(T(U^{-1}(\underline{x}), \underline{\dot{x}}, \underline{\ddot{x}}))$$

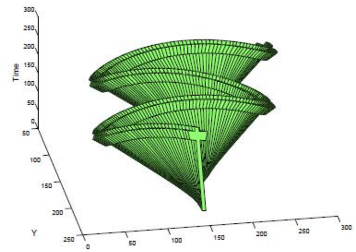
A function can operate on each component of $\underline{r} = (r_1, r_2)$ independently, to create effects suggesting drag we use...

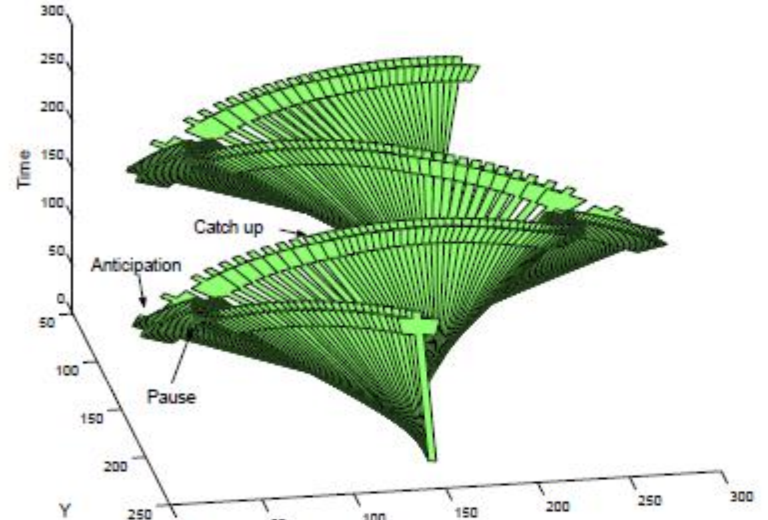
$$r_1 = r_1 - F(\frac{2}{\pi} atan(|\underline{\dot{x}}_i|))^P sign(\underline{\dot{x}}_i)$$

- **Anticipation (Snap)**
  - **Alter motion timing to introduce a lag then "catch up" prior to changes of motion**









Video Paintbox: The Fine Art of Video Painting

Collomosse and Hall (2006)

- **A Complete Video Paintbox**

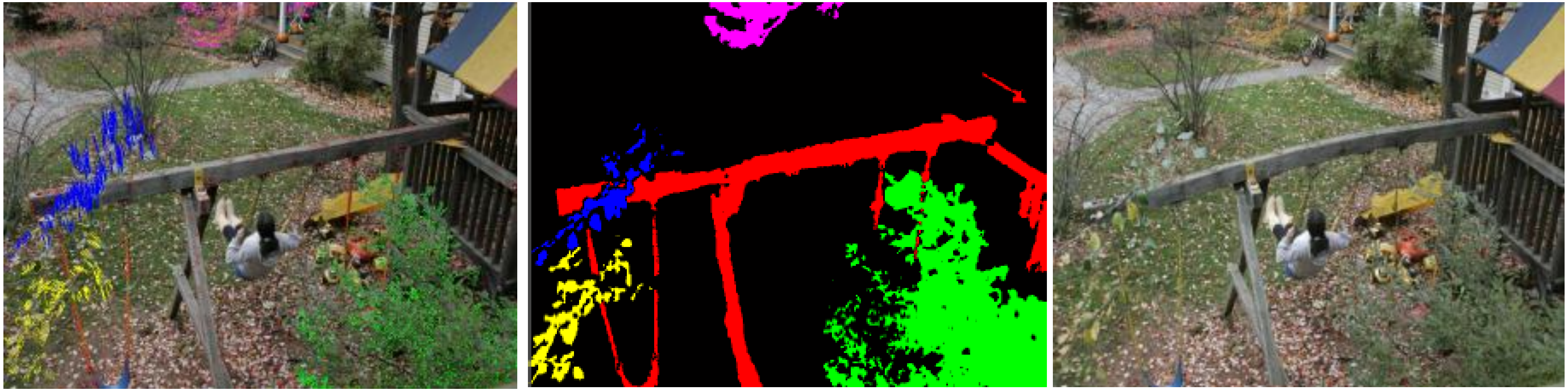
Segmentation + augmentation + deformation

Anticipation + deformation

Motion Magnification

Liu et al. (2005)

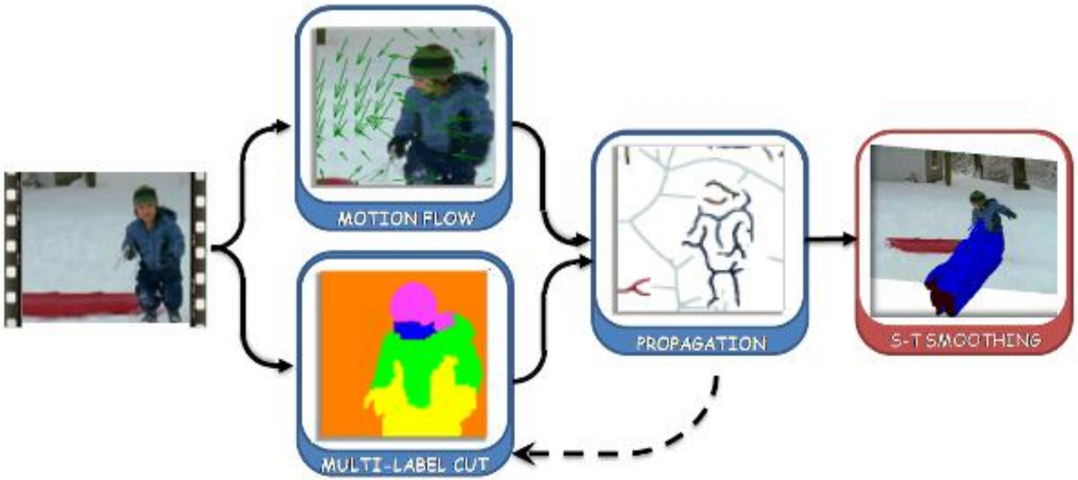
- **Deformation Cues**
  - **General deformation technique using motion vector clustering to layer video**
    - **User intervention needed to fix noisy segmentation maps**
  - **Per-pixel flow vector pushes pixels to exaggerate existing motion**
  - **Texture filling compensates for holes**

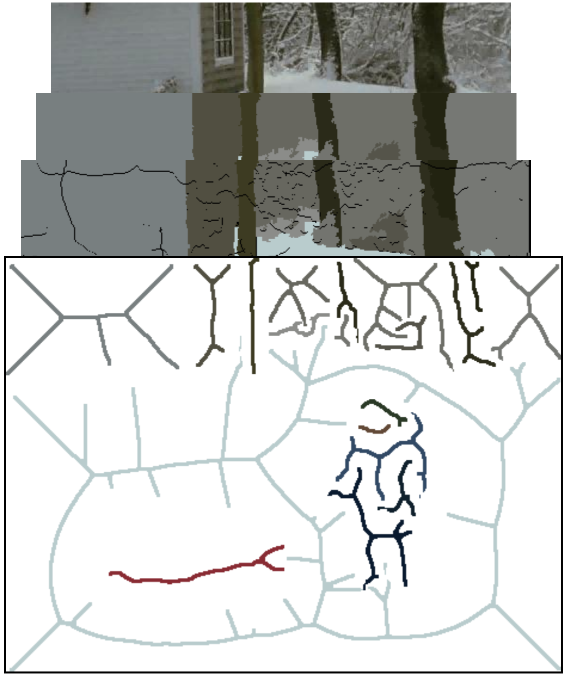


Liu et al. '05

Motion Magnification

- **Combining Segmentation and Optical Flow**
  - **Multi-label graph-cut segmentation with label prior propagated forward from previous frames**
  - **Region colour models are learned incrementally**





propagation to next...

Wang et al. '10

Motion Magnification

- **Combining Segmentation and Optical Flow**
  - **For each pixel** $p \in \mathcal{P}$ **within frame** $I_t(p)$
    - **Find best mapping** $l : \mathcal{P} \rightarrow \mathcal{L}$

      $\mathcal{L} = (l(1), \ldots, l(p), \ldots, l(|\mathcal{P}|))$
    - **Subset of** $\mathcal{L}$ **are carried from** t-1 **by flow**

$$E(\mathcal{L},\Theta,\mathcal{P}) = U(\mathcal{L},\Theta,\mathcal{P}) + V(\mathcal{L},\mathcal{P}).$$

Learned colour model

$$U(\mathcal{L},\Theta,\mathcal{P}) = \sum_{p \in \mathcal{P}} -\log P_g(I_t(p)|l(p);\Theta).$$

Contrast adaptive

$$P_g(I(p)|l(p) = l_i;\Theta) = \sum_{k=1}^{n_i} w_{ik} N(I(p);\mu_{ik},\Sigma_{ik})$$

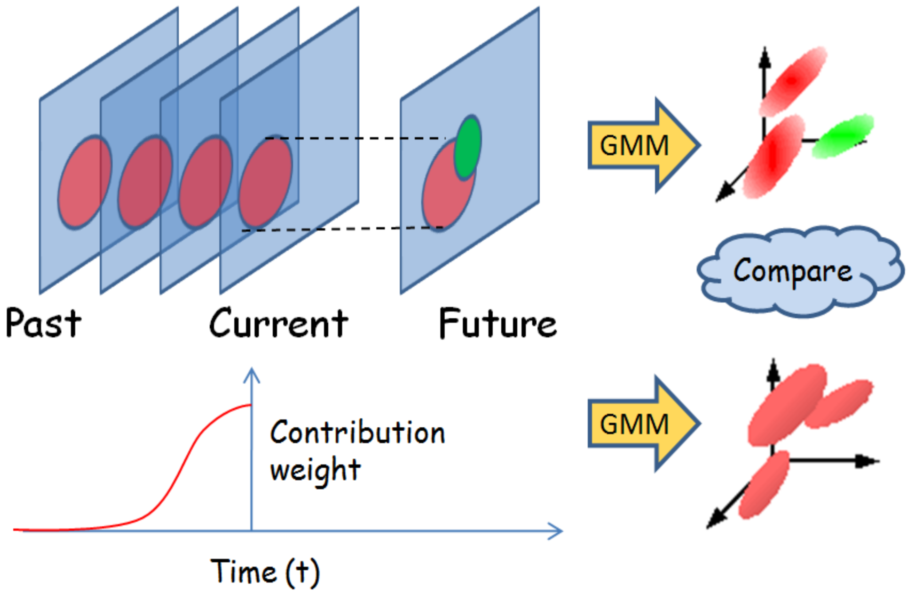
$$V(\mathcal{L},\mathcal{P}) = \gamma \sum_{(m,n) \in N} [l(m) \neq l(n)] e^{-\beta\|I(m)-I(n)\|^2}.$$

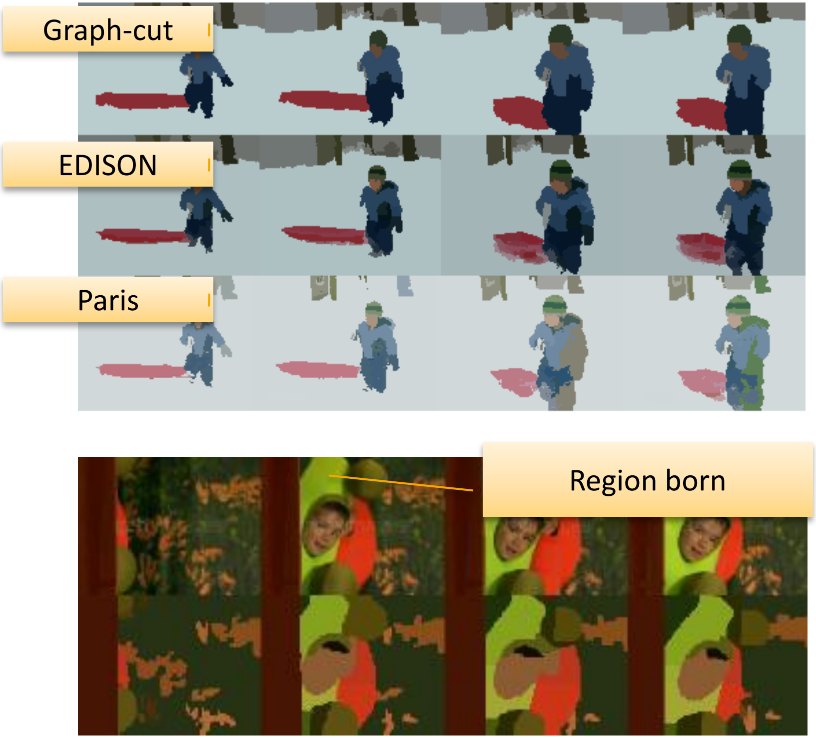
- **Colour models are learned over time incrementally via Gaussian Mixtures**

Wang et al. ‘10

Motion Magnification

- **Region colour distribution (GMM) updated with temporal weight**
  - **Comparison with historic model (Chi^2) can detect region birth**

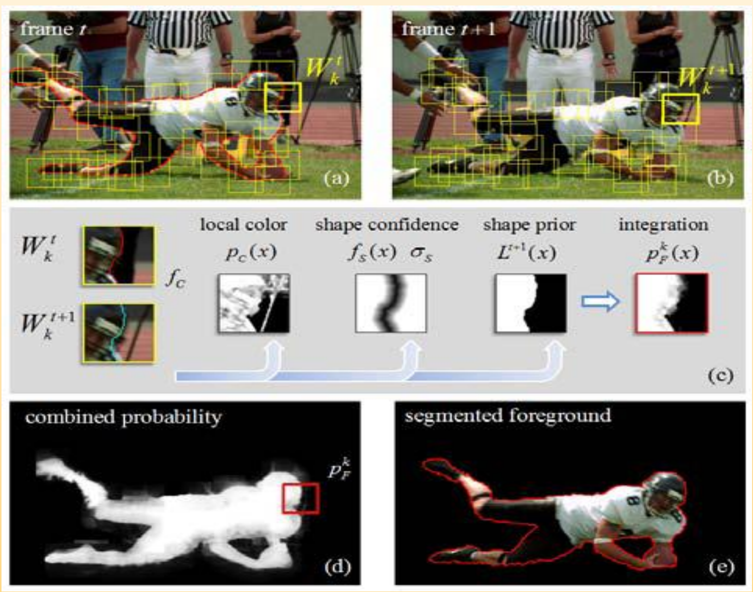




Wang et al. '10

Motion Magnification

- **Trends from automatic 'Tooning to interactive tools**
  - **The necessity of interaction to solve the general segmentation problem**



Video Snap-Cut

Bai et al. '09

Complex Interactive Painting Systems

Liang et al. '10

Yet many applications demand automation or real-time. Part III discusses solutions.

Coffee Q & A

- **After the break!**
  - **Part III - Anisotropy and Diffusion**
  - **Part IV - Future Challenges in NPR**



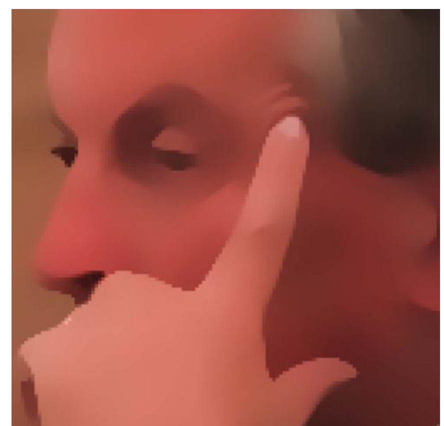



Photo credits as noted in Part III

Artistic Stylization of Images and Video

Part III – Anisotropy and Filtering

Eurographics 2011

Jan Eric Kyprianidis

Hasso-Plattner-Institut, University of Potsdam, Germany

Image/Video Abstraction

- **Stylized Augmented Reality for Improved Immersion**
  Fischer et al., 2005
- **Real-time Video Abstraction**
  Winnemöller et al., SIGGRAPH 2006
- **Coherent Line Drawings**
  Kang et al., NPAR 2007
- **Structure Adaptive Image Abstraction**
  Kyprianidis & Döllner, EG Theory and Practice of Computer Graphics 2008
- **Flow-based Image Abstraction**
  Kang et al., Transactions on Visualization and Computer Graphics 2009
- **Artistic Edge and Corner Preserving Smoothing**
  Papari et al., IEEE Transactions on Image Processing 2007
- **Image and Video Abstraction by Anisotropic Kuwahara Filtering**
  Kyprianidis et al., Pacific Graphics 2009
- **Shape-simplifying Image Abstraction**
  Kang & Lee, Pacific Graphics 2008

Stylized Augmented Reality for Improved Immersion

Fischer et al. (2005)

Non-photorealistic display of both the camera image and virtual objects:

- **Abstraction:** Bilateral filter applied to Gaussian pyramid and then upsampled
- **Edges:** Canny edge detector + morphological dilation

Conventional augmented reality

Stylized augmented reality

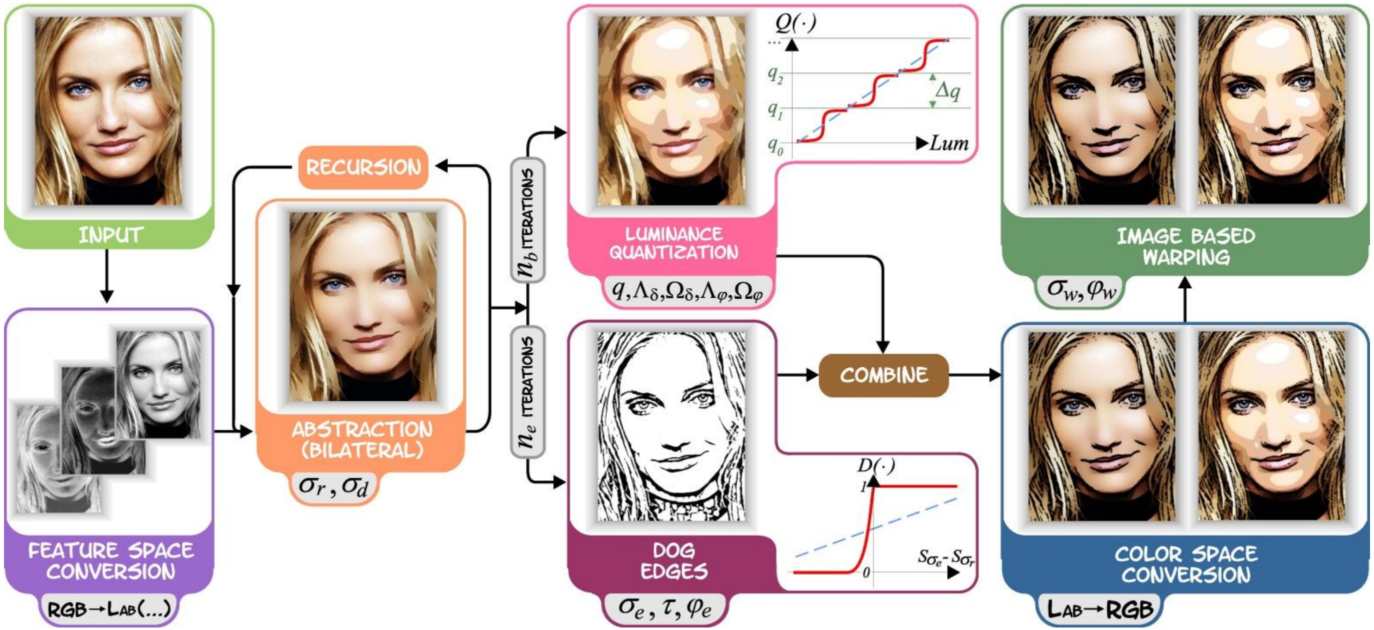
Image credit: Fischer et. al. (2005)

Real-time Video Abstraction

Winnemöller et al. (2006)

- **Abstraction:** Multiple iterations of xy-separable bilateral filter + color quantization
- **Edges:** Difference of Gaussians + thresholding

Image credit: Winnemöller et. al. (2006)



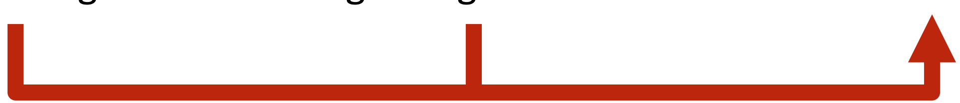
Coherent Line Drawings

Kang et al. (2007)

- **Edges:** 1D difference of Gaussians directed by flow field + flow-guided smoothing and thresholding.

Image credit: Kang et. al. (2007)

Input image   Edge Tangent Flow   Line drawing

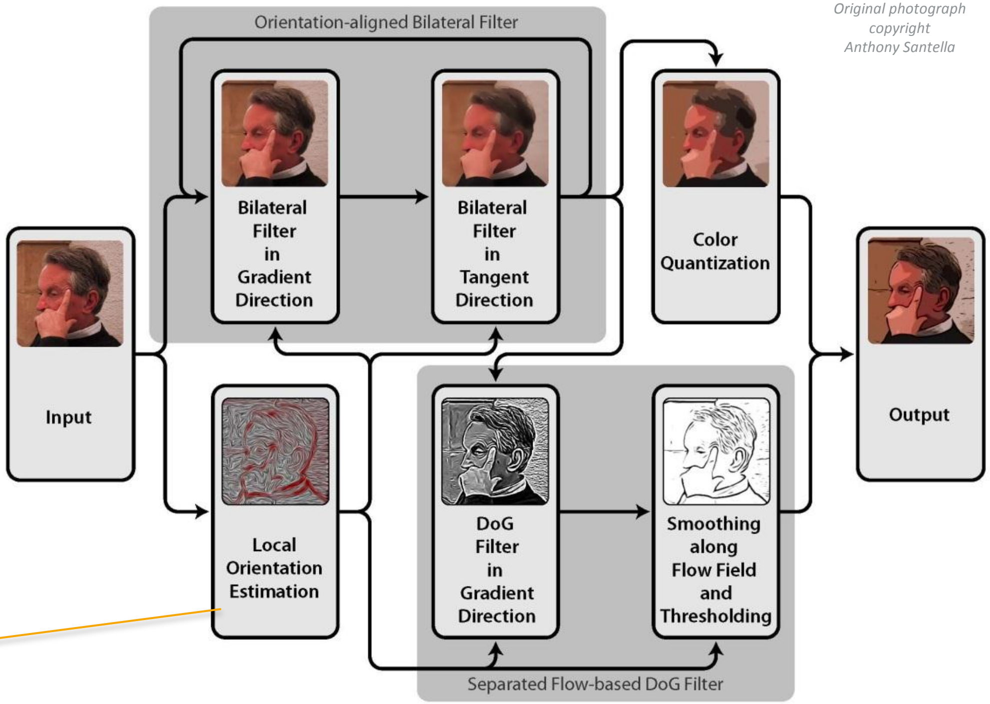


Flow-based filtering

Structure Adaptive Image Abstraction

Kyprianidis & Döllner (2008)

- **Abstraction:** Multiple iterations of orientation-aligned bilateral filter
- **Edges:** separable flow-based difference of Gaussians



Original photograph copyright Anthony Santella

Local orientation and an anisotropy measure derived from the smoothed structure tensor are used to guide the bilateral and difference of Gaussians filters

Flow-based Image Abstraction

Kang et al. (2009)

- **Abstraction:** Multiple iterations of flow-based bilateral filter
- **Edges:** (separable) flow-based difference of Gaussians
- Local orientation estimation of both techniques is based on the edge tangent flow (ETF)

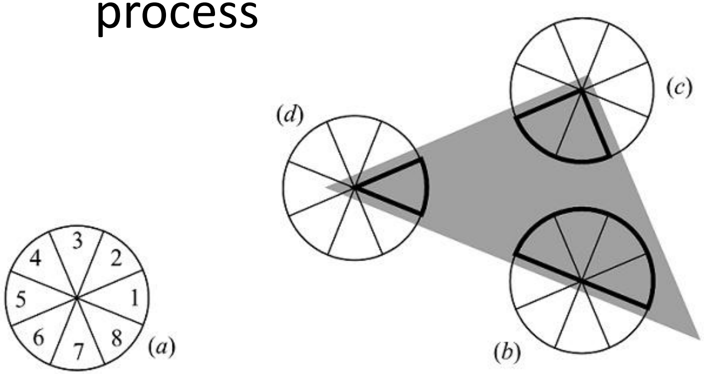
Image credit: Kang et. al. (2009)

Artistic Edge and Corner Preserving Smoothing

Papari et al. (2009)

- Generalization of the Kuwahara filter. Creates output with a painterly look.
- Addresses two key issues of the original Kuwahara filter:
  - Rectangular subregions
  - Unstable subregion selection process

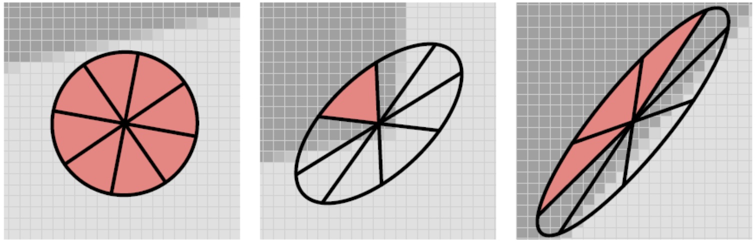
Credit for images: Papari et. al. (2009)



Anisotropic Kuwahara Filtering

Kyprianidis et al. (2009)

- Further generalization of the Kuwahara filter.
- Adaptation of the shape, scale and orientation of the filter to the local image structure.



Original image by Paulo Brandão@flickr.com

Shape-simplifying Image Abstraction

Kang & Lee (2008)

- PDE-based technique that simultaneous simplifies colors and shape:
  - Constrained mean curvature flow
  - Shock filter

Image credit: Kang & Lee (2008) / original image by Tambako the Jaguar@flickr.com

Input | 20 iterations | 40 iterations | 60 iterations

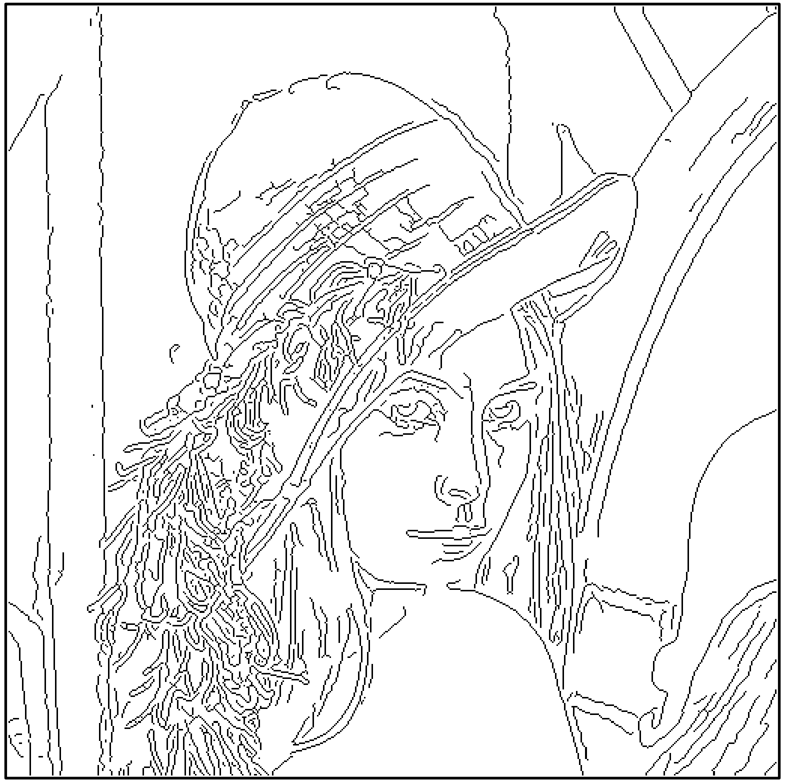
Difference of Gaussians

Difference of Gaussians:

- Laplacian of Gaussian (LoG)
- Isotropic Difference of Gaussians (DoG)
- Flow-based Difference of Gaussians
- Separable Flow-based Difference of Gaussians

DoG Edges vs Canny Edges

Original image from USC-SIPI Image Database



Canny Edges

Flow-based difference of Gaussians

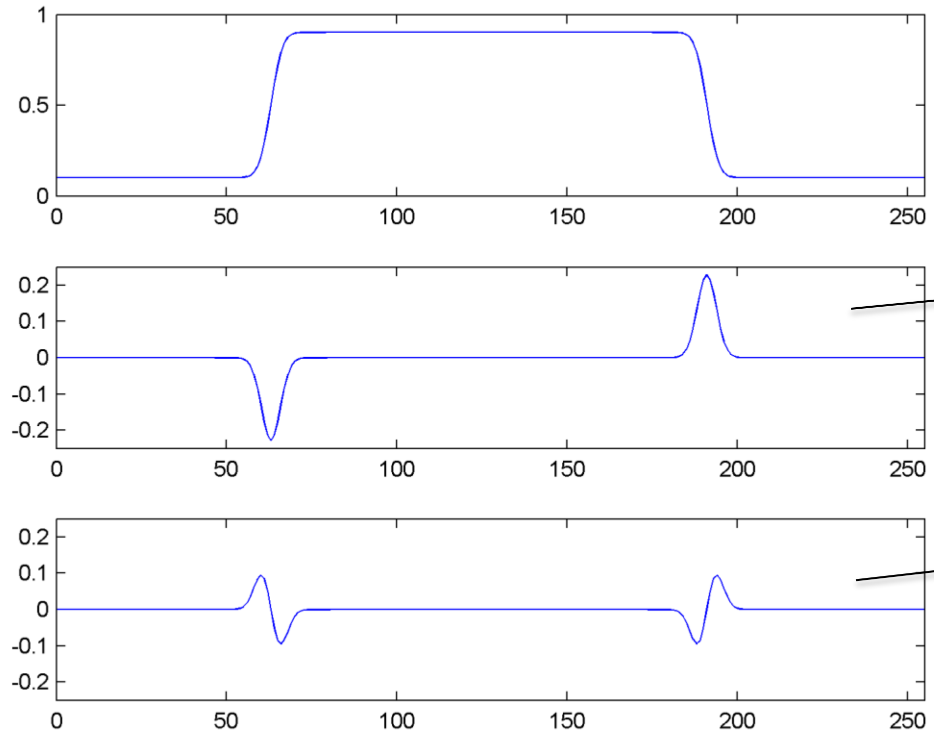
Edge Detection

Edge profile without noise:

Scanline of an image

First derivative of scanline

Second derivative of scanline



Edges are located at minima or maxima of the first derivative

Edges are located at zero crossings of the second derivative

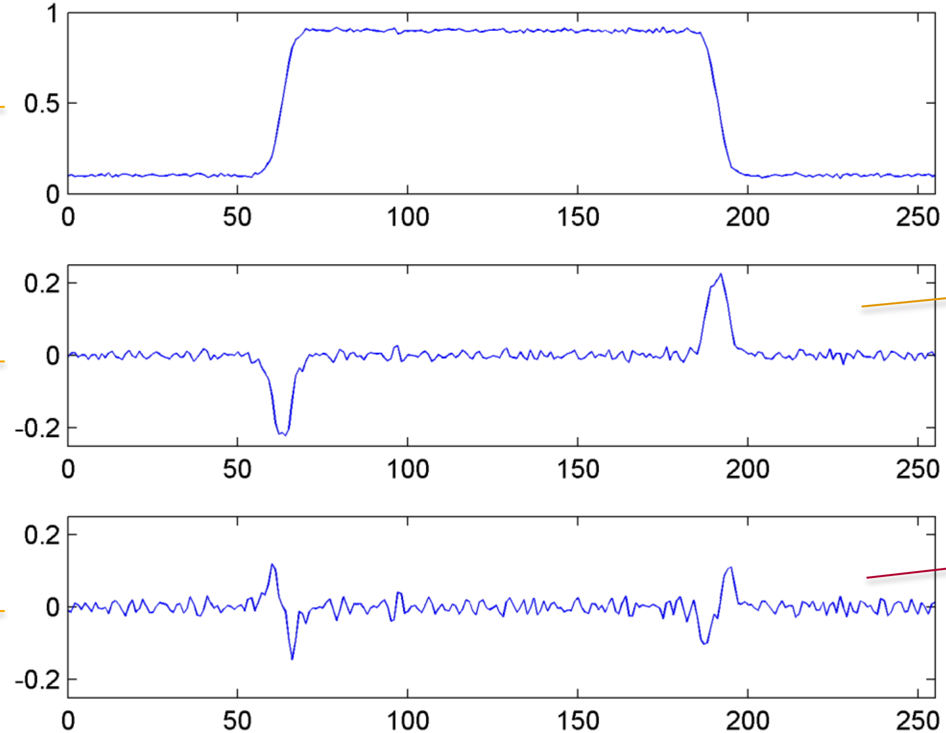
Edge Detection

Edge profile with noise:

Scanline of an image **with noise**

First derivative of scanline

Second derivative of scanline



First derivative sensitive to noise

Second derivative even more sensitive to noise

Laplacian of Gaussian (LoG)

Marr & Hildreth (1980)

In 2D the second derivative corresponds to the Laplacian:

$$L = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

Similar to the second derivative the Laplacian is sensitive to noise. To make the Laplacian less sensitive to noise, apply a Gaussian to the image first:

$$\mathrm{LoG} = L \star G_\sigma \ ,$$

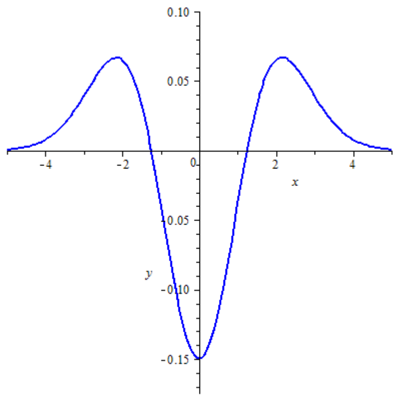
where G_σ is a 2D Gaussian with standard deviation σ:

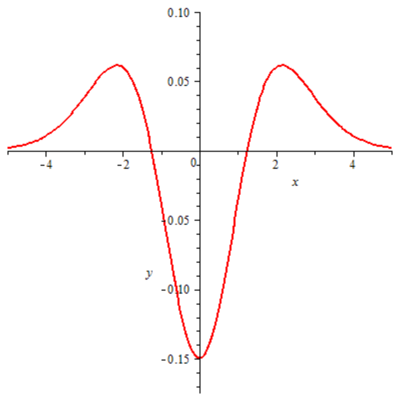
$$G_\sigma(x, y\ ) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

Difference of Gaussians (DoG)

Marr & Hildreth (1980)

A Laplacian of Gaussian can be approximated by a difference of Gaussians:





$$\mathrm{LoG}(x, y) = L \star G_\sigma$$

$$\mathrm{DoG}(x, y) = G_{\sigma_i}(x, y) - G_{\sigma_e}(x, y)$$

Good engineering solution:
$\sigma_i = 1.6 \cdot \sigma_e$

Fast to implement since Gaussian is separable

Difference of Gaussians (DoG)

Marr & Hildreth (1980)

Zero-crossing are found by thresholding:

Smooth DoG Edges

Winnemöller et al. (2006)

An approach to created smooth edges was proposed by Winnemöller et al.:

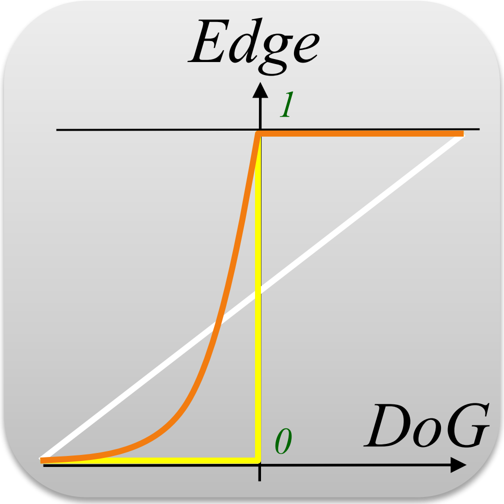
$$D(\sigma_e, \tau, \varphi_e) = \begin{cases} 1 & \text{if } \left(G_{\sigma_e} - \tau\, G_{1.6\cdot\sigma_e}\right) > 0 \\ 1 + \tanh(\varphi_e \cdot G_{\sigma_e} - \tau G_{1.6\cdot\sigma_e}) & \text{otherwise} \end{cases}$$

- The parameter τ controls the sensitivity to noise. A typical values are $\tau = 0.98$ or $\tau = 0.99$.
- The falloff parameter φ_e determines the sharpness of edge representations, typical values are $\varphi_e \in [0.75, 5.0]$.

Smooth DoG Edges

Winnemöller et al. (2006)

tanh
(half-truncated)



Credit for slide: H. Winnemöller

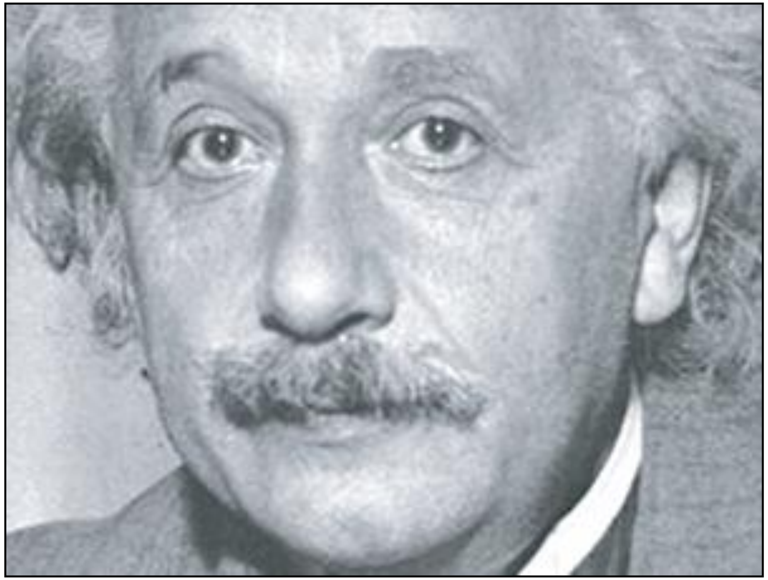
Edge Tangent Flow

Kang et al. (2007)

Edge Tangent Flow (ETF):

- Smoothly varying vector field
- Feature-preserving flow

Image credit: Kang et al. (2007)



Input image

Edge Tangent Flow

Edge Tangent Flow

Kang et al. (2007)

Weighted vector smoothing similar to bilateral filter:

Multiple iterations (≈ 3)

$$t^{n+1}(x) = \frac{1}{k} \sum_{y \in \Omega(x)} \phi(x,y) \cdot t^n(y) \cdot w_s(x,y) \cdot w_m(x,y) \cdot w_d(x,y)$$

t^0 is calculated using the Sobel filter.

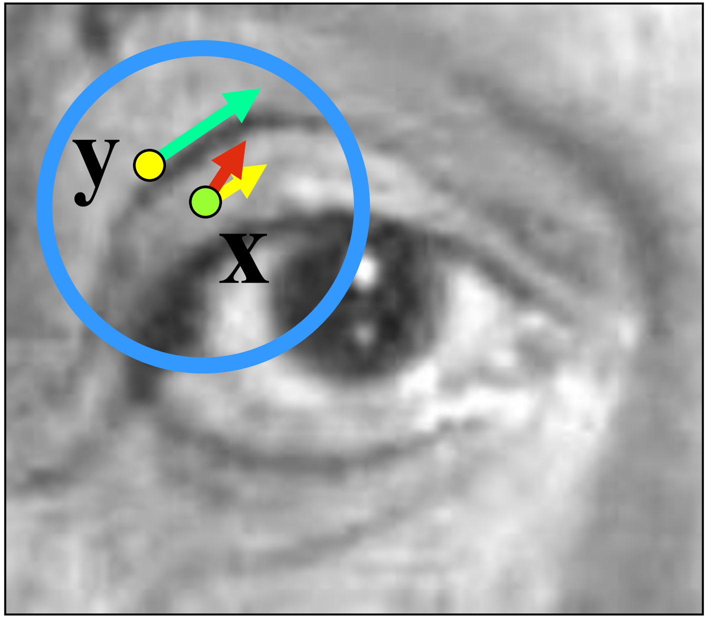


Image credit: Kang et al. (2007)

Edge Tangent Flow

Kang et al. (2007)

$$t^{n+1}(x) = \frac{1}{k} \sum_{y \in \Omega(x)} \phi(x,y) \cdot t^n(y) \cdot w_s(x,y) \cdot w_m(x,y) \cdot w_d(x,y)$$

Assure different vectors point in the same direction

$$\phi(x,y) = \mathrm{sign}(t^n(x) \cdot t^n(y))$$

$$w_s(x,y) = \begin{cases} 1 & |x-y| < r \\ 0 & \text{else} \end{cases}$$

Restrict filtering to a predefined radius

More weight to vectors with higher gradient magnitude

$$w_m(x,y) = \frac{1}{2}[1 + \tanh(|g(x)| - |g(y)|)]$$

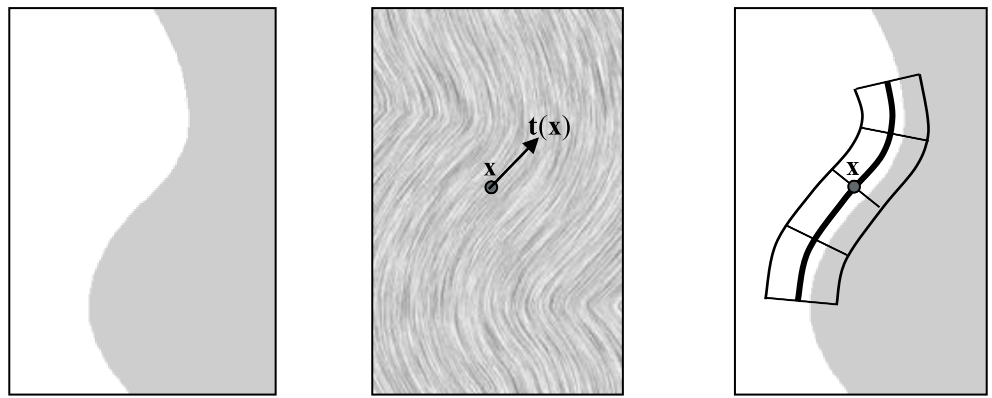
$$w_d(x,y) = |t^n(x) \cdot t^n(y)|$$

More weight for vectors with direction similar to current filter origin

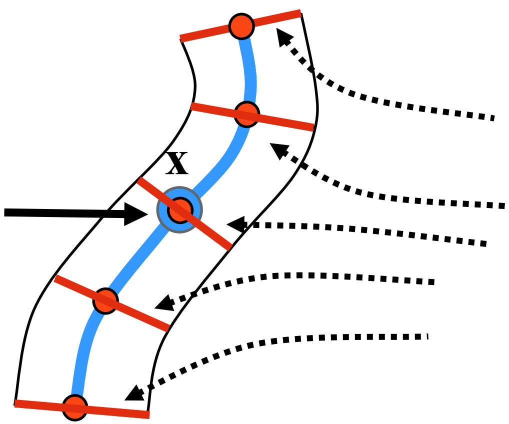
Flow-based Difference of Gaussians

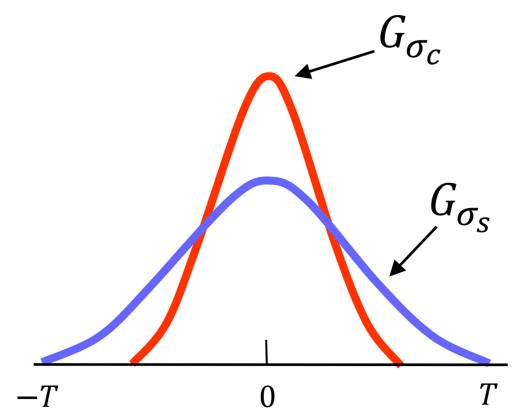
Kang et al. (2007)

Image credit: Kang et al. (2007)



FDoG response





DoG filter

Structure Tensor

Let $f: \mathbb{R}^2 \to \mathbb{R}^3$ denote the input image and let

$$\frac{\partial f}{\partial x} = \begin{pmatrix} \frac{\partial R}{\partial x} & \frac{\partial G}{\partial x} & \frac{\partial B}{\partial x} \end{pmatrix}^t \qquad \frac{\partial f}{\partial y} = \begin{pmatrix} \frac{\partial R}{\partial y} & \frac{\partial G}{\partial y} & \frac{\partial B}{\partial y} \end{pmatrix}^t$$

These can be implemented for example using Gaussian derivatives or the Sobel filter.

be the partial derivatives of f.

The structure tensor is then defined by:

$$(g_{ij}) = J^t J = \begin{pmatrix} \left\langle \frac{\partial f}{\partial x}, \frac{\partial f}{\partial x} \right\rangle & \left\langle \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right\rangle \\ \left\langle \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right\rangle & \left\langle \frac{\partial f}{\partial y}, \frac{\partial f}{\partial y} \right\rangle \end{pmatrix} =: \begin{pmatrix} E & F \\ F & G \end{pmatrix}$$

The structure tensor is a 2×2 symmetric positive semidefinte matrix

In differential geometry the structure tensor is also known as first fundamental form

Structure Tensor

The induced quadratic form of the structure tensor measures the squared rate of change of f in direction of a vector $n = (n_x, n_y)$:

$$S(n) = En_x^2 + 2Fn_xn_y + Gn_y^2$$

The extremal values of $S(n)$ on the unit circle correspond to the eigenvalues of (g_{ij}):

$$\lambda_{1,2} = \frac{E + G \pm \sqrt{(E-G)^2 + 4F^2}}{2}$$

The corresponding eigenvectors are:

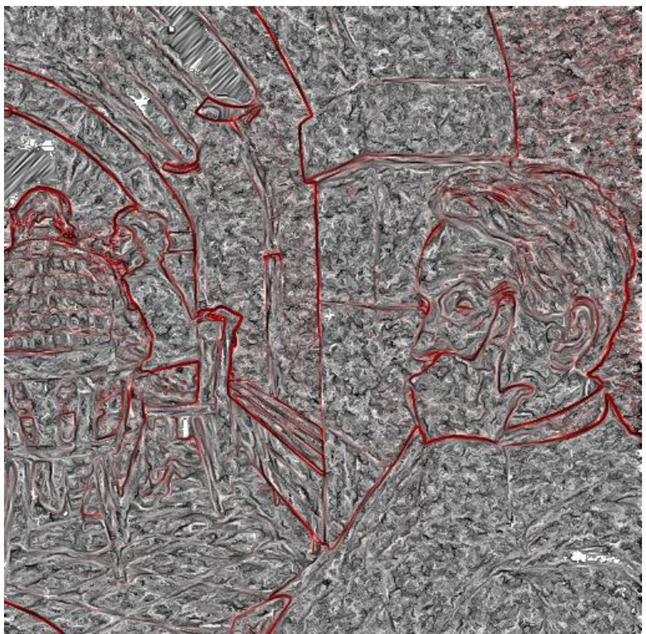
Eigenvector of major eigenvalue. Direction of maximum change: **gradient** direction.

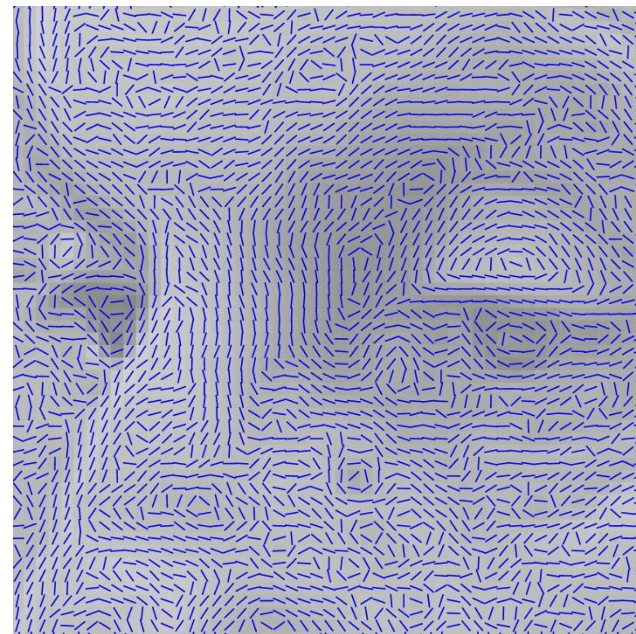
$$v_1 = \begin{pmatrix} F \\ \lambda_1 - E \end{pmatrix} \qquad v_2 = \begin{pmatrix} \lambda_1 - E \\ -F \end{pmatrix}$$

Eigenvector of minor eigenvalue. Direction of minimum change: **tangent** direction.

Structure Tensor

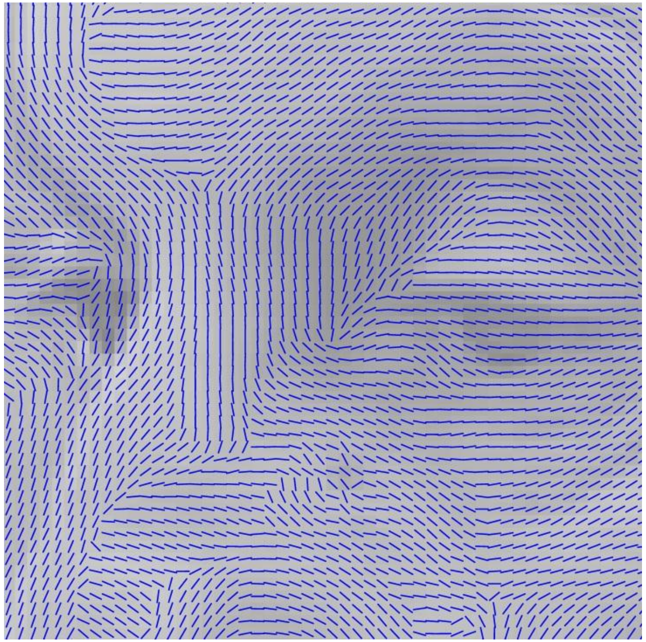
The eigenvectors corresponding to the minor eigenvalues of the structure define a vector field. Typically this field is not smooth:





Smoothed Structure Tensor

Smoothing the structure tensor prior to eigenanalysis with a Gaussian filter removes discontinuities in the vector field:



Smoothed Structure Tensor

Eigenvector field of the smoothed structure tensor is similar to the edge tangent flow, but allows a more efficient implementation:

3 iterations of edge tangent flow filter

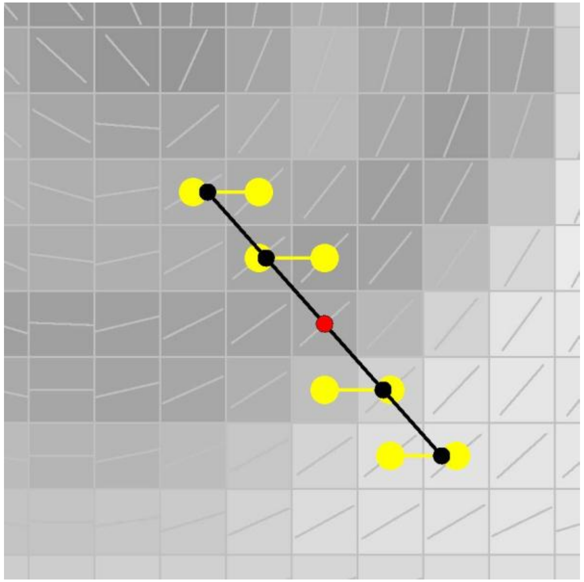
Eigenvector field of the smoothed structure tensor

Separable Flow-based Difference of Gaussians

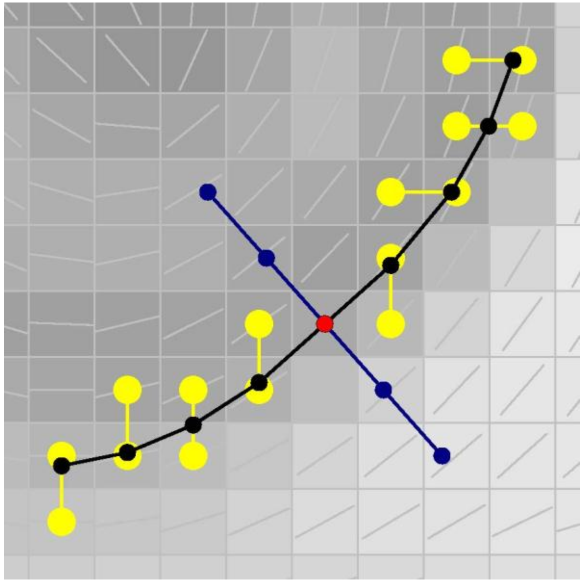
Kyprianidis & Döllner (2008)

Split flow-based difference of Gaussians into two passes:

- 1st Pass: one-dimensional DoG in direction of the major eigenvector
- 2nd Pass: smoothing along stream lines defined by minor eigenvector



1st Pass



2nd Pass

Bilateral Filter:

- Classical Bilateral Filter
- xy-Separable Bilateral Filter
- Orientation-aligned Bilateral Filter
- Flow-based Bilateral Filter

Bilateral Filter

Tomasi & Manduchi (1998)

The bilateral filter is a nonlinear operation that smoothes images while preserving edges:

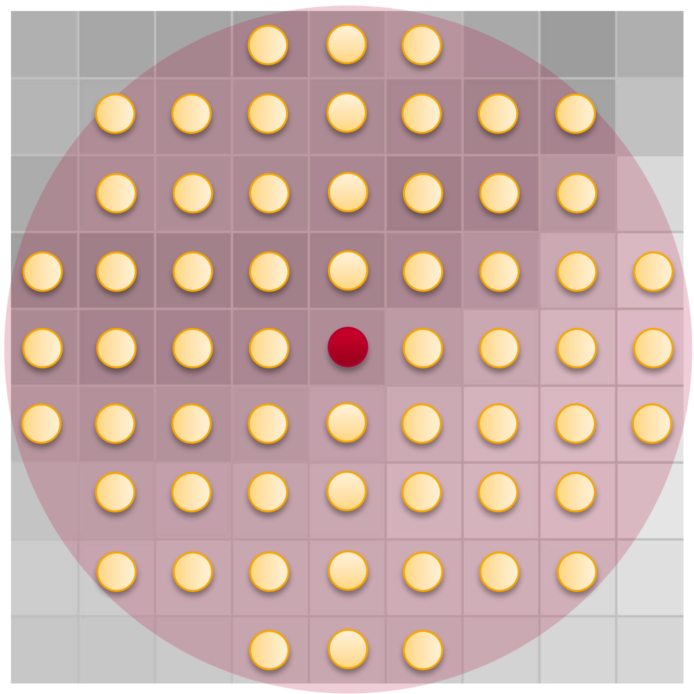
$$\frac{\sum_{x \in B_r(x_0)} f(x) \; \overbrace{G_{\sigma_d}(|x - x_0|)}^{\text{More weight to closer pixel}} \; \overbrace{G_{\sigma_r}(|f(x) - f(x_0)|)}^{\text{More weight to pixel with similar color}}}{\sum_{x \in B_r(x_0)} G_{\sigma_d}(|x - x_0|) \; G_{\sigma_r}(|f(x) - f(x_0)|)}$$

$$G_\sigma(t) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{t^2}{2\sigma^2}\right)$$

Bilateral Filter

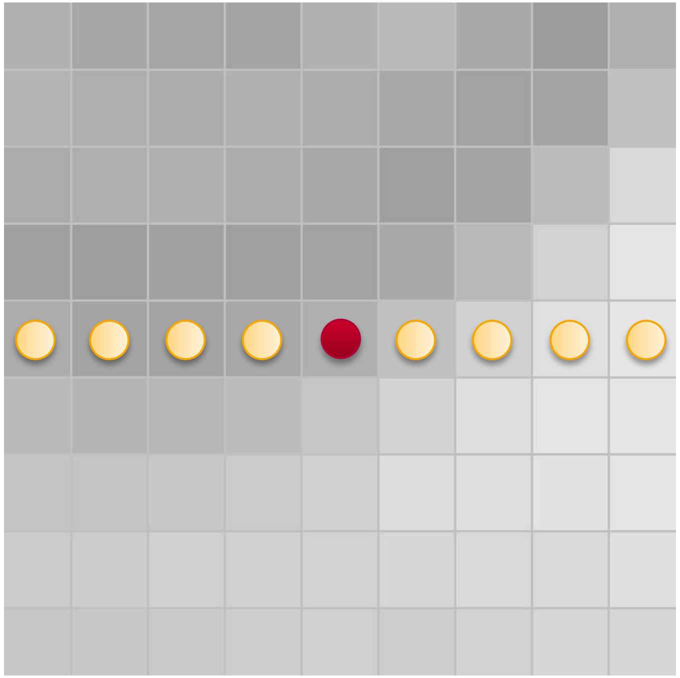
Tomasi & Manduchi (1998)

The bilateral filter is a powerful tool, but computationally very expensive ($O(r^2)$ per pixel).

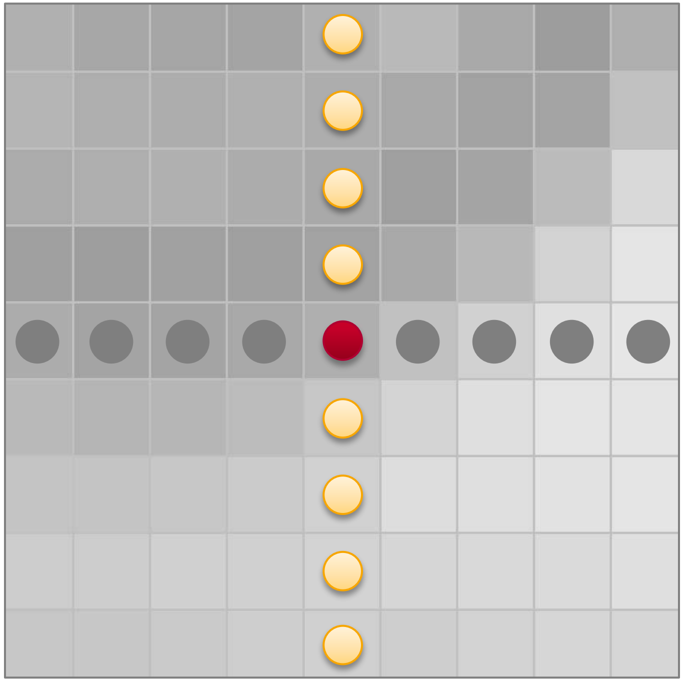


xy-Separable Bilateral Filter

Pham & van Vliet (2005)



1st Pass

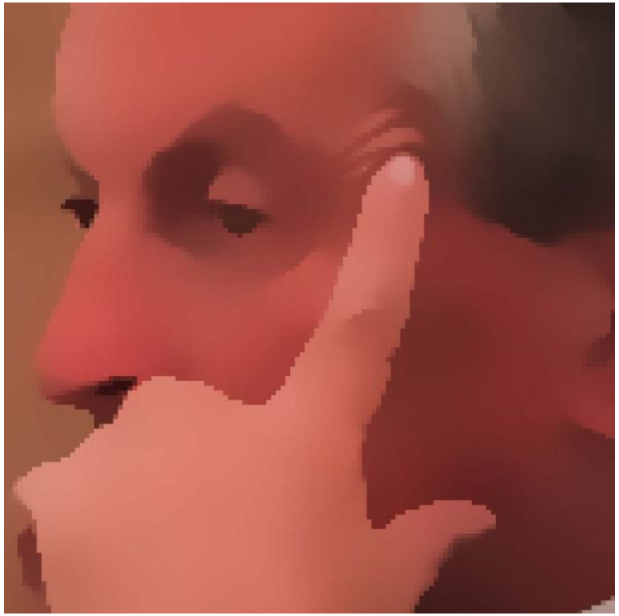


2nd Pass

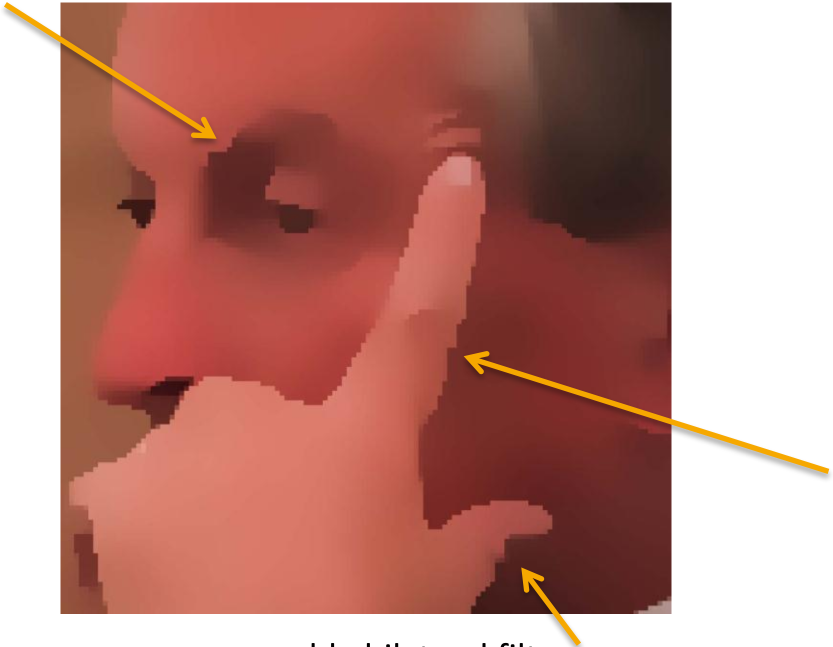
xy-Separable Bilateral Filter

Pham (2006)

- Much faster than classical bilateral filter
- But creates noticeable artifacts!



Full kernel bilateral filter

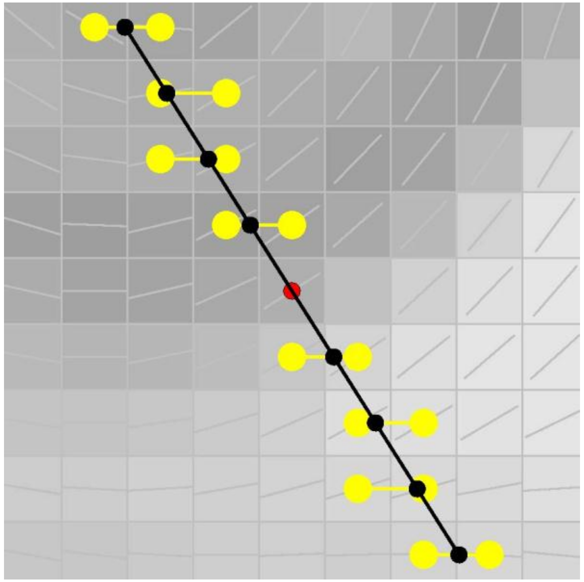


xy-separable bilateral filter

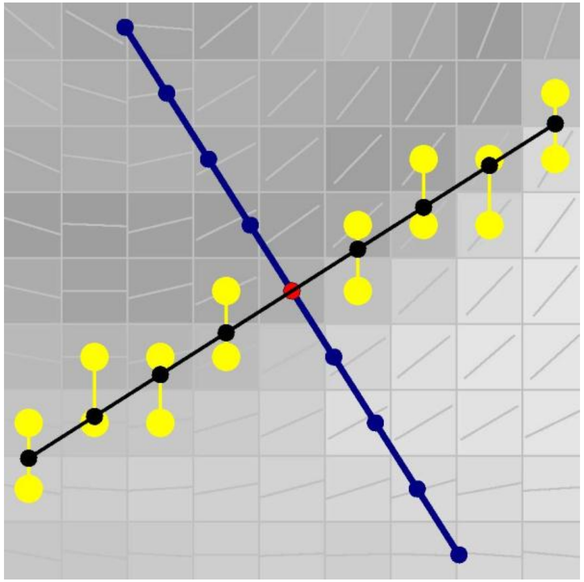
Orientation-aligned Bilateral Filter

Kyprianidis & Döllner (2008)

- Align separable bilateral filter to local orientation derived from the smoothed structure tensor



1st Pass

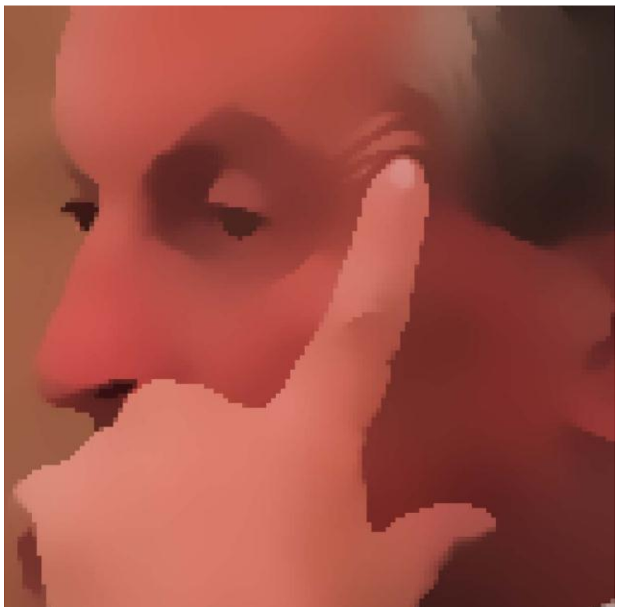


2nd Pass

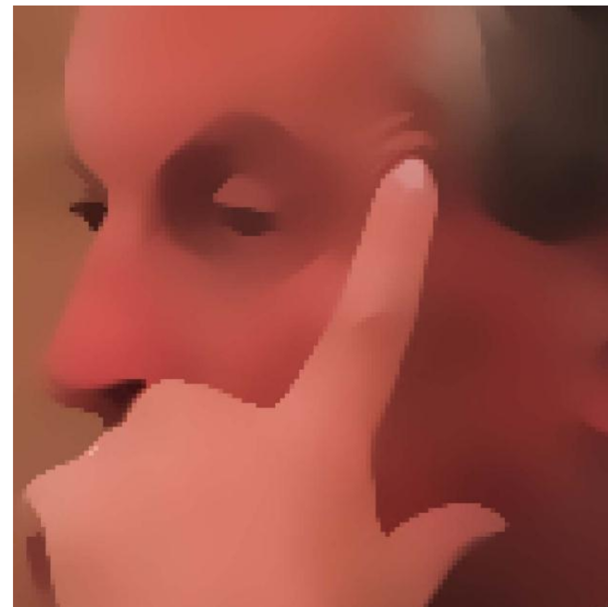
Orientation-aligned Bilateral Filter

Kyprianidis & Döllner (2008)

- Less artifacts. Very well suited for abstraction.



Full kernel bilateral filter



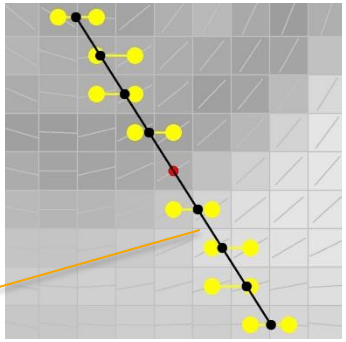
Orientation-aligned bilateral filter

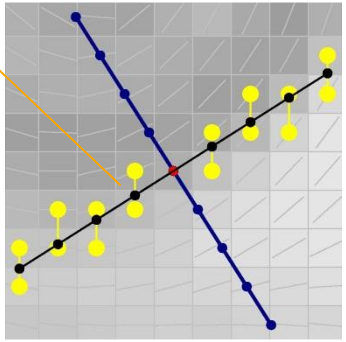
Orientation-aligned Bilateral Filter

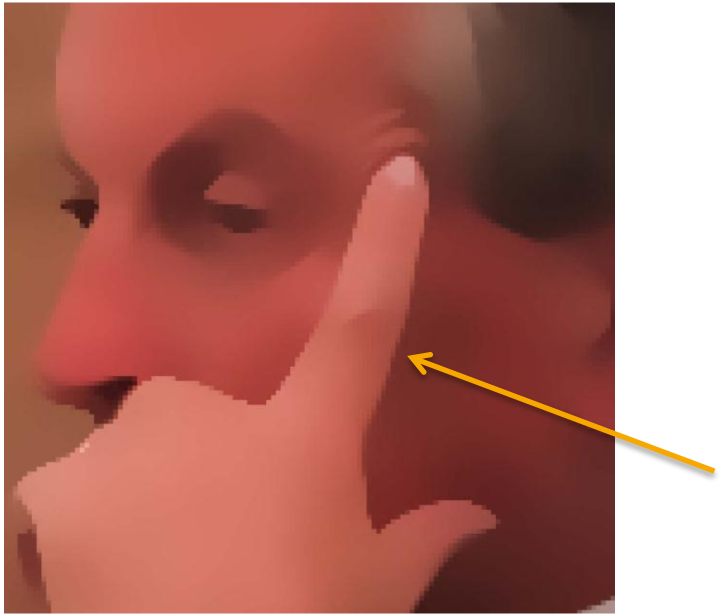
Kyprianidis & Döllner (2008)

- Linear smoothing of neighboring pixel values creates smooth color boundaries

Unit step size
either along
x- or y-axis



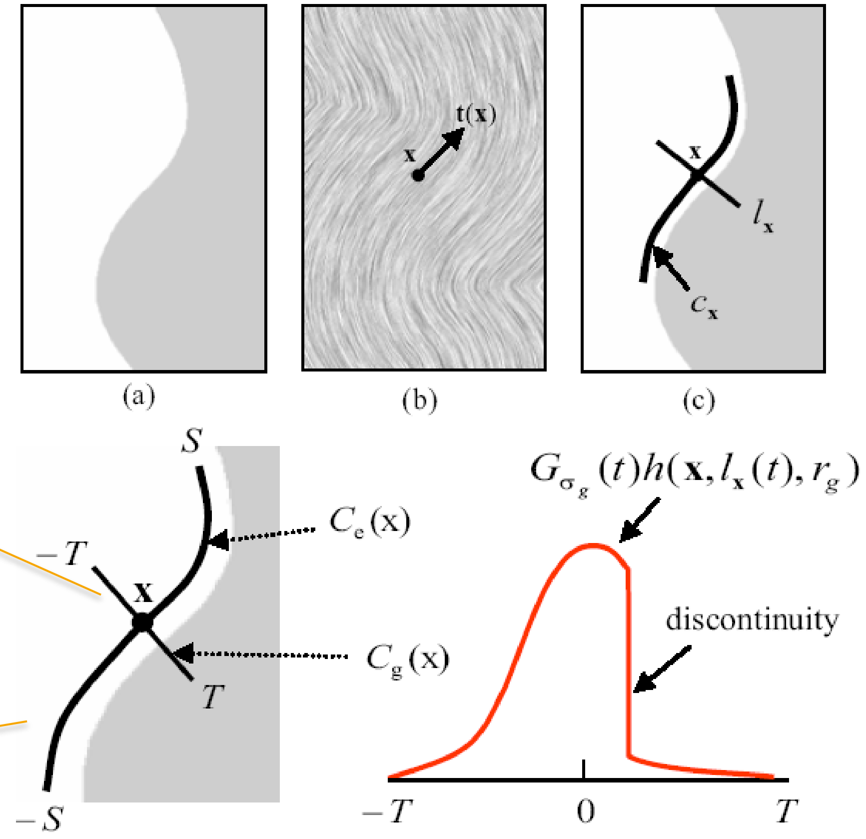




Flow-based Bilateral Filter
Kang et al. (2009)

- ETF-guided decomposition of bilateral filter

Image credit: Kang et al. (2009)



1st pass in direction of the tangent

2nd pass along stream line defined by the ETF

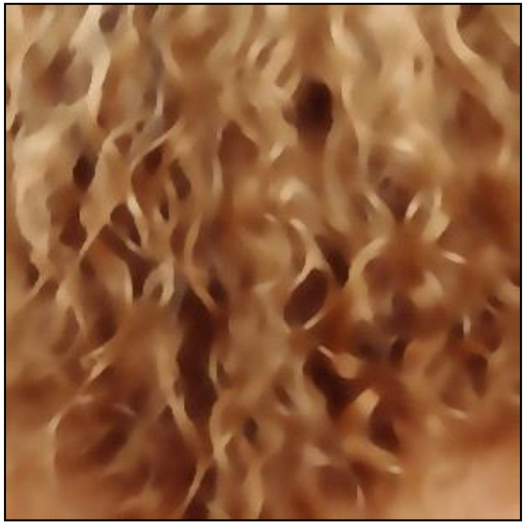
Flow-based Bilateral Filter

Kang et al. (2009)

- Excellent preservation of highly anisotropic image features

Image credit: Kang et al. (2009)

Input image



Bilateral filter

Flow-based bilateral filter

Color Quantization

Winnemöller et al. (2006)

Credit for slide: H. Winnemöller

Input

Apply quantization to luminance channel

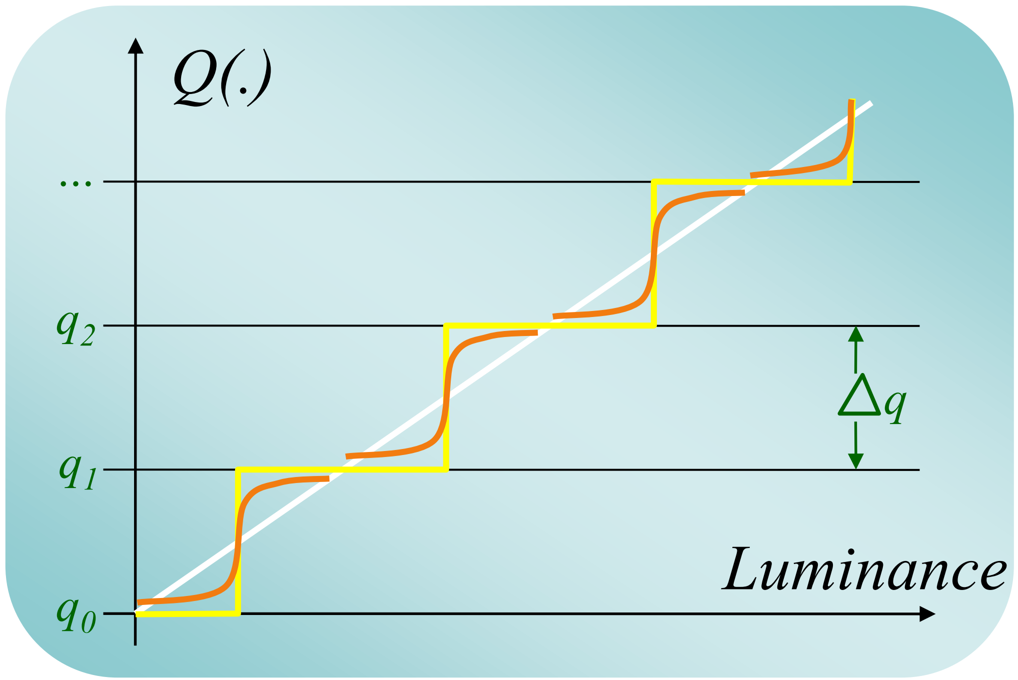
Result

Color Quantization

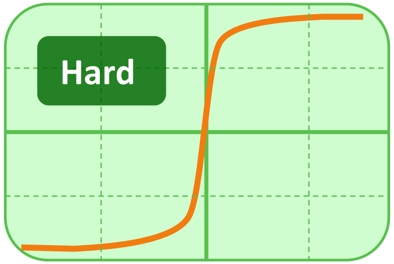
Winnemöller et al. (2006)

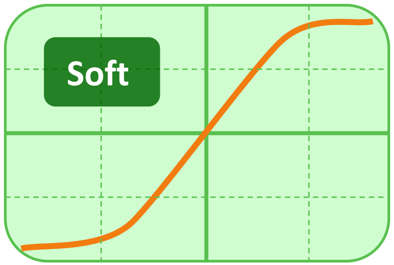
Luminance Mapping

q **bins**



tanh
per bin





Credit for slide: H. Winnemöller

Color Quantization

Winnemöller et al. (2006)

Image credit: Winnemöller et al. (2006)

Abstracted

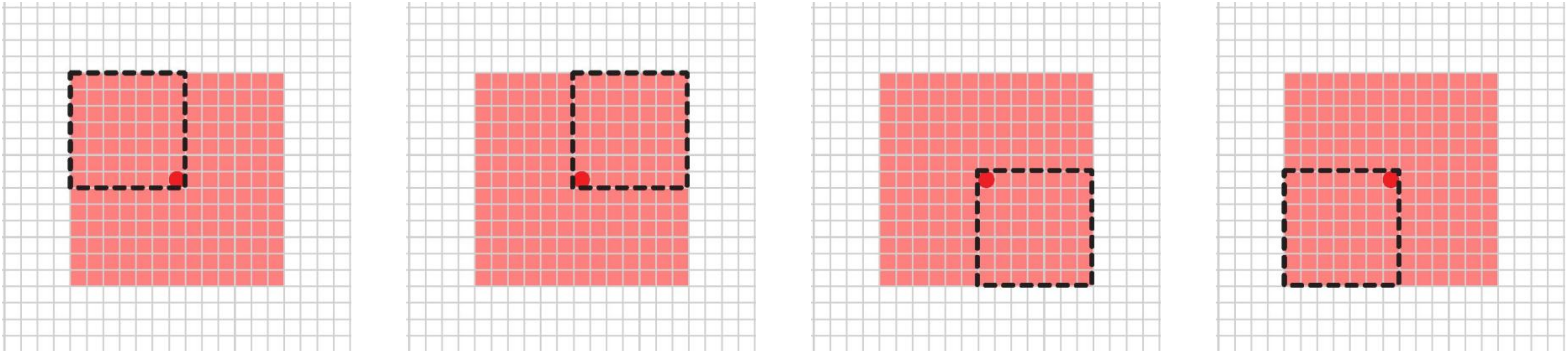
Sharp Quantization
(*Toon*-like)

Smooth Quantization
(*Paint*-like)

Kuwahara Filter:

- Classical Kuwahara Filter
- Kuwahara Filter with Weighting Functions
- Generalized Kuwahara Filter
- Anisotropic Kuwahara Filter
  - Convolution-based Weighting Functions
  - Polynomial Weighting Functions

Kuwahara Filter



$$W_0 = [x_0 - r, x_0] \times [y_0, y_0 + r]$$
$$W_1 = [x_0, x_0 + r] \times [y_0, y_0 + r]$$
$$W_2 = [x_0, x_0 + r] \times [y_0 - r, y_0]$$
$$W_3 = [x_0 - r, x_0] \times [y_0 - r, y_0]$$

Kuwahara Filter

For every subregion W_i calculate the mean

$$m_i = \frac{1}{|W_i|} \sum_{(x,y)\in W_i} I(x,y)$$

and the variance:

$$s_i^2 = \frac{1}{|W_i|} \sum_{(x,y)\in W_i} (I(x,y) - m_i)^2$$

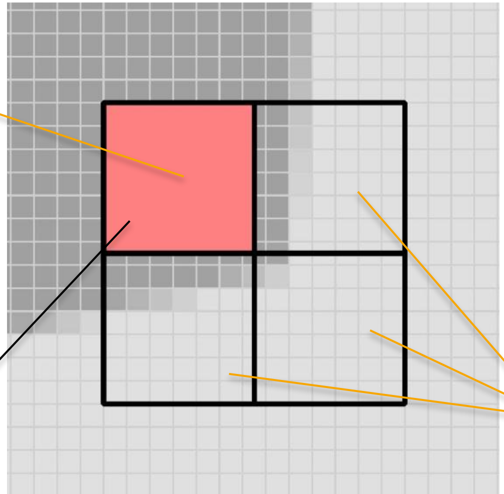
The output of the Kuwahara filter is then defined as the mean of a subregion with minimum variance:

$$F(x_0, y_0) \coloneqq m_k, \qquad k = \operatorname*{argmin}_{i=0,\ldots,3} s_i$$

Kuwahara Filter

Kuwahara filter for a corner

Region with **small variance**. All pixels of this region are similar.



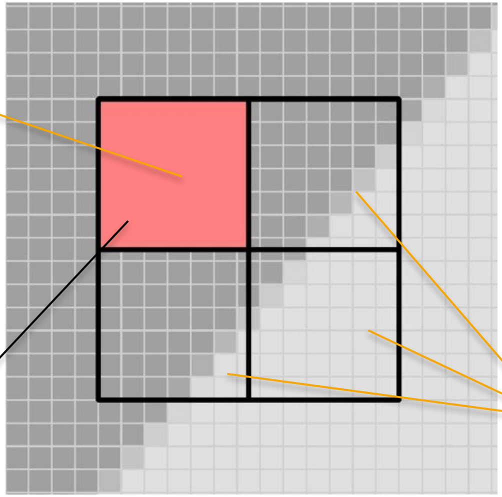
Result is the mean of the region with minimum variance

Regions with **high variance**. They all contain pixels from both color regions.

Kuwahara Filter

Kuwahara filter for an edge

Region with **small variance**. All pixels of the region lie on the same side of the edge.



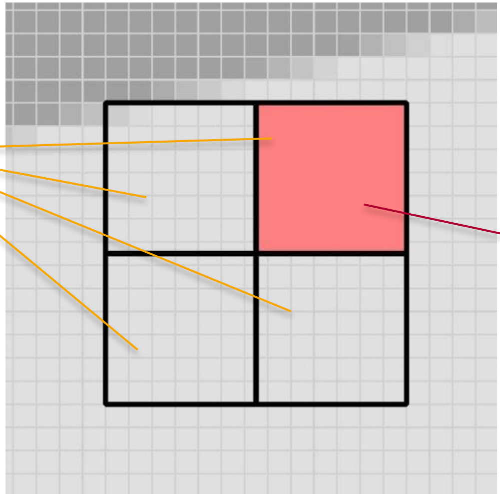
Result is the mean of the region with minimum variance

Regions with **high variance**. They all contain pixels from both sides of the edge.

Kuwahara Filter

Kuwahara filter for an homogenous neighborhood

All regions have **similar variance**!

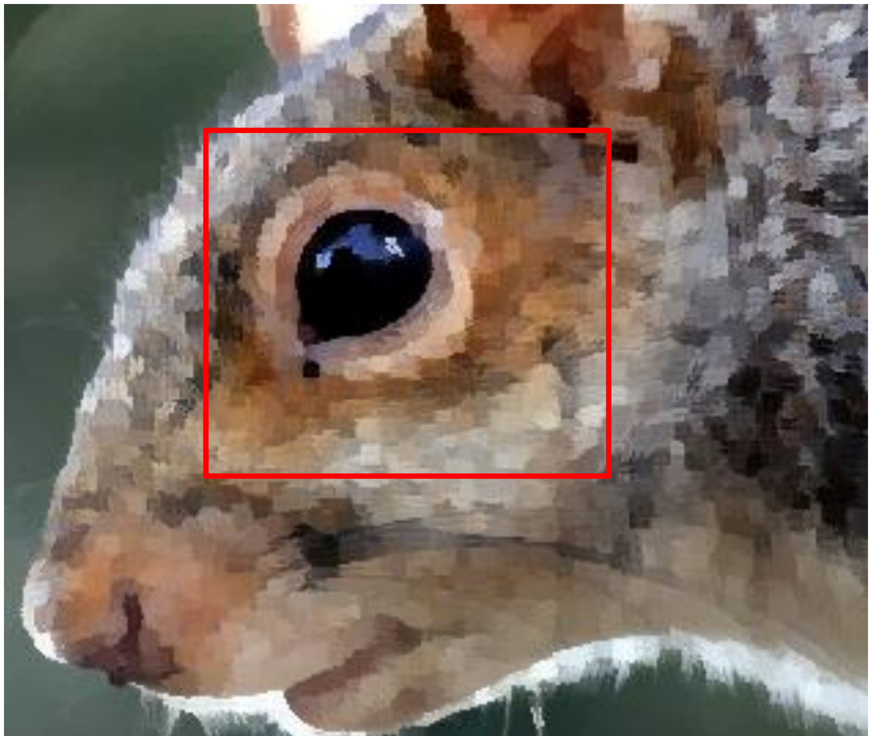


Selection of the region with minimum variance is highly unstable. For example if noise is present.

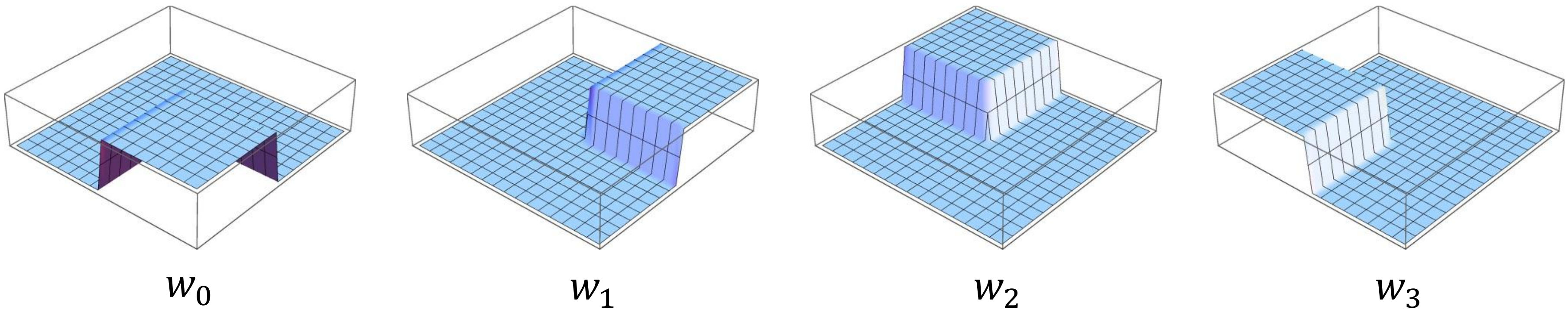
Kuwahara Filter

Original image by Keven Law@flickr.com

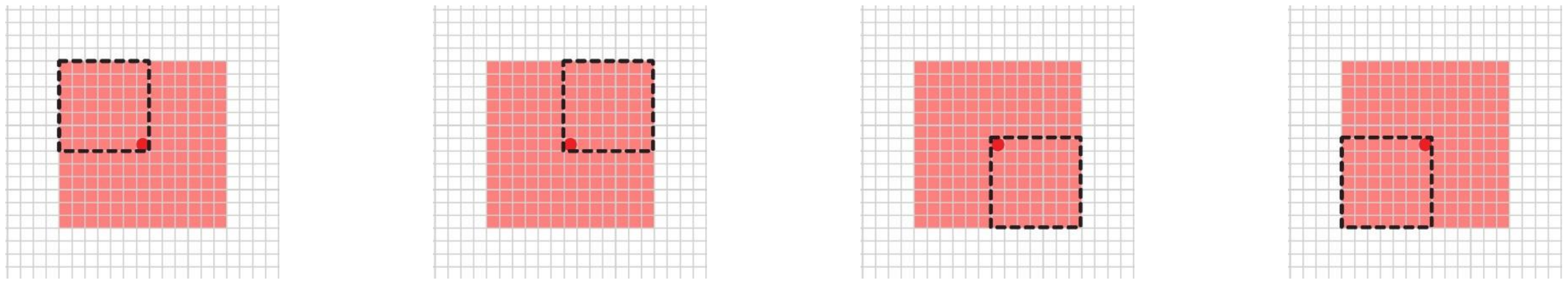
Kuwahara Filter



Kuwahara Filter with Weighting Functions



$$w_i(x,y) = \begin{cases} 1 & \text{if } (x,y) \in W_i \\ 0 & \text{otherwise} \end{cases}$$



Kuwahara Filter with Weighting Functions

Then the mean is given by:

$$m_i = \frac{1}{|W_i|} \sum_{(x,y) \in W_i} I(x,y)$$
$$= \frac{1}{|w_i|} \sum_{(x,y) \in \mathbb{Z}^2} I(x,y) \cdot w_i(x - x_0, y - y_0)$$

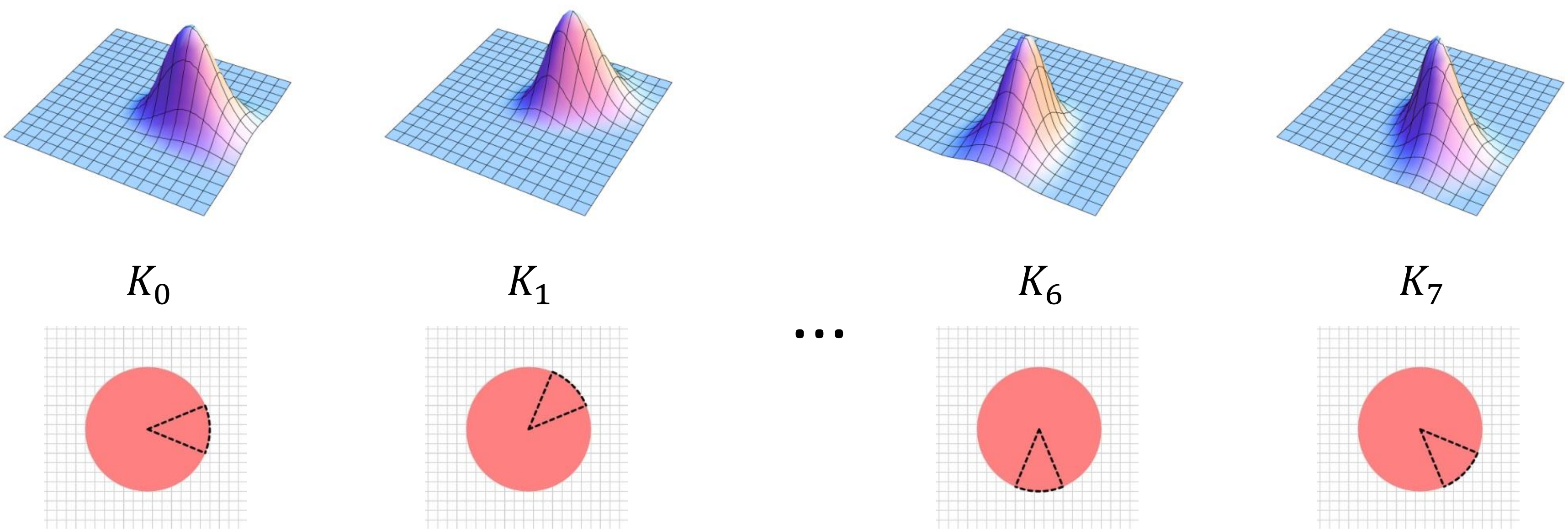
And the variance is given by:

$$s_i^2 = \frac{1}{|W_i|} \sum_{(x,y) \in W_i} (I(x,y) - m_i)^2$$
$$= \frac{1}{|w_i|} \sum_{(x,y) \in \mathbb{Z}^2} (I(x,y) - m_i)^2 \cdot w_i(x - x_0, y - y_0)$$

Generalized Kuwahara Filter

Papari et al. (2007)

Idea: Create smooth weighting functions over a disc those sum is a Gaussian

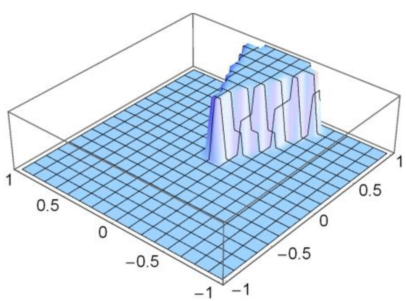


Generalized Kuwahara Filter

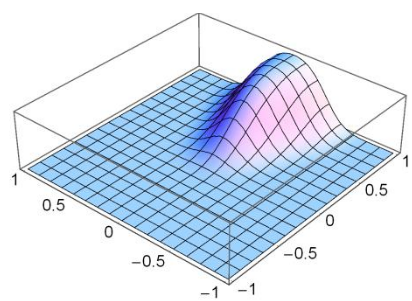
Weighting Function Construction

$$\chi_i(x,y) = \begin{cases} 1 & \dfrac{(2i-1)\pi}{N} < \arg(x,y) \le \dfrac{(2i+1)\pi}{N} \\ 0 & \text{otherweise} \end{cases} \qquad i = 1, \dots, N-1$$

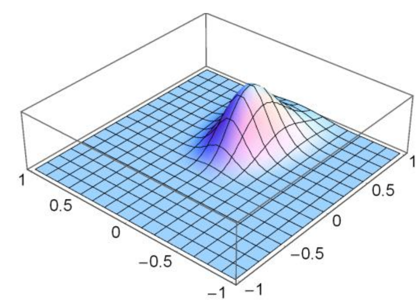
$$\begin{aligned} K_i &= (\chi_i \star G_{\sigma_s}) \cdot G_{\sigma_r} \\ &= K_0 \circ R_{-2\pi i/N} \end{aligned}$$



χ_0



$\chi_0 \star G_{\sigma_s}$



$(\chi_0 \star G_{\sigma_s}) \cdot G_{\sigma_r} =: K_0$

Generalized Kuwahara Filter

Then the mean is given by:

$$m_i = \frac{1}{|K_i|} \sum_{(x,y)\in\mathbb{Z}^2} I(x,y) \cdot K_i(x - x_0, y - y_0)$$

And the variance is given by:

$$s_i^2 = \frac{1}{|K_i|} \sum_{(x,y)\in\mathbb{Z}^2} (I(x,y) - m_i)^2 \cdot K_i(x - x_0, y - y_0)$$

The output of the generalized Kuwahara Filter is now defined by:

$$F(x_0, y_0) = \sum_{i=0}^{N-1} s_i^{-q} m_i \Big/ \sum_{i=0}^{N-1} s_i^{-q}$$

Generalized Kuwahara Filter

The parameter q is a tuning parameter that controls the sharpness of color boundaries. A typical value is $q = 8$.

$$F(x_0, y_0) = \sum_{i=0}^{N-1} s_i^{-q} m_i \Bigg/ \sum_{i=0}^{N-1} s_i^{-q}$$

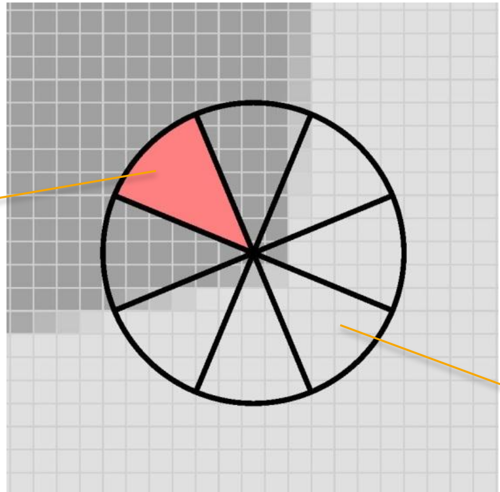
Sectors low high variance:
$s_i \to 0 \Rightarrow s_i^{-q} \to \infty$
(i.e. most influence to sum)

Sectors with high variance:
$s_i \gg 0 \Rightarrow s_i^{-q} \approx 0$
(i.e. almost no influence to sum)

Generalized Kuwahara Filter

Generalized Kuwahara filter for a corner

Sector with **small variance**. All pixels of this sector are similar. This sector contributes most to the final result

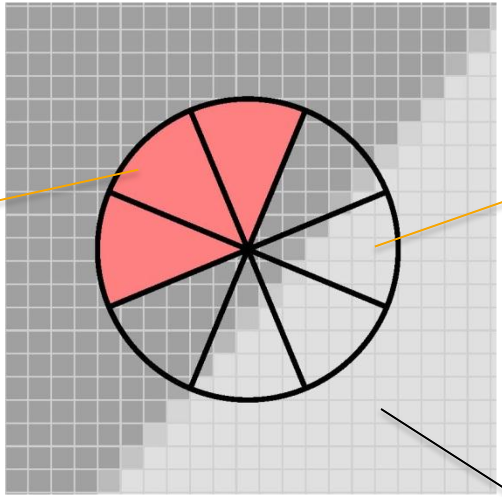


Sectors with **high variance**. They all contain pixels from both color regions. These sectors have almost no influence.

Generalized Kuwahara Filter

Generalized Kuwahara filter for an edge

Multiple sectors with **small variance**. All pixels of the sectors lie on the same side of the edge. Result is a weighted sum of the (weighted) mean values of the sectors.



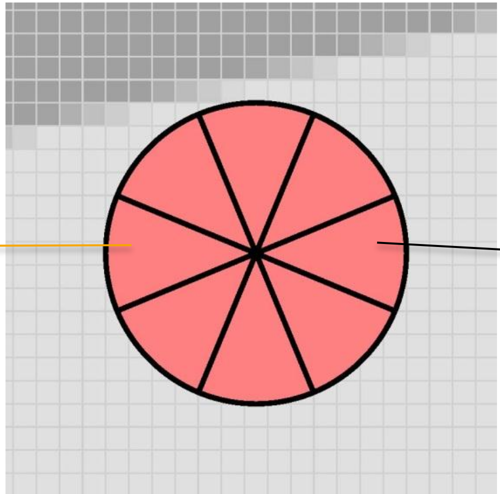
Regions with **high variance**. They all contain pixels from both sides of the edge. These sector have almost no influence.

Filter shape is similar to a truncated Gaussian

Generalized Kuwahara Filter

Generalized Kuwahara filter for an homogenous neighborhood

All regions have **similar variance**!

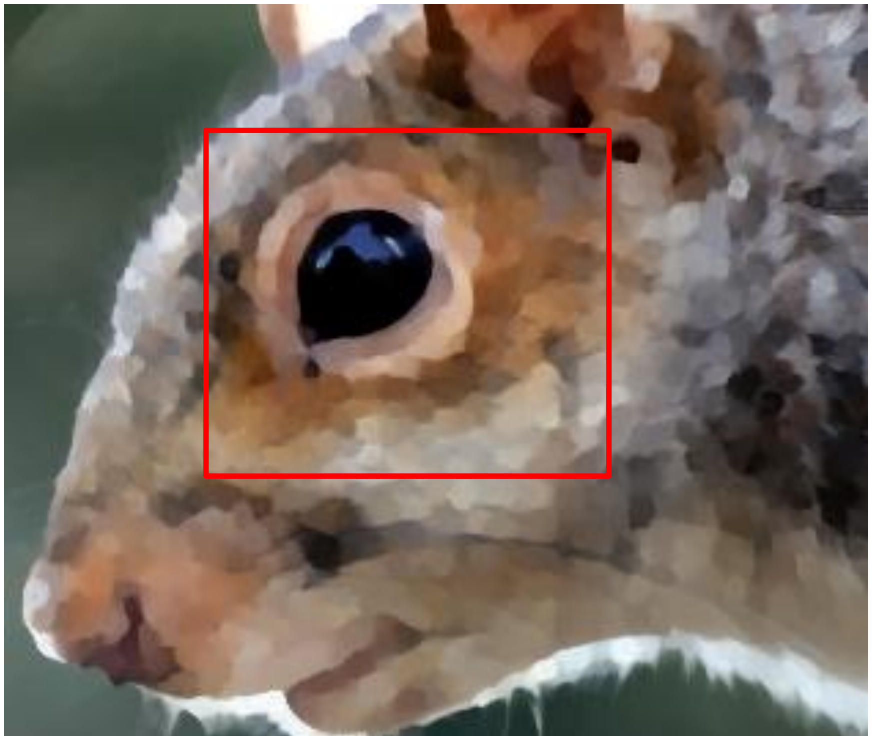


Filter shape is similar to a Gaussian filter

Generalized Kuwahara Filter

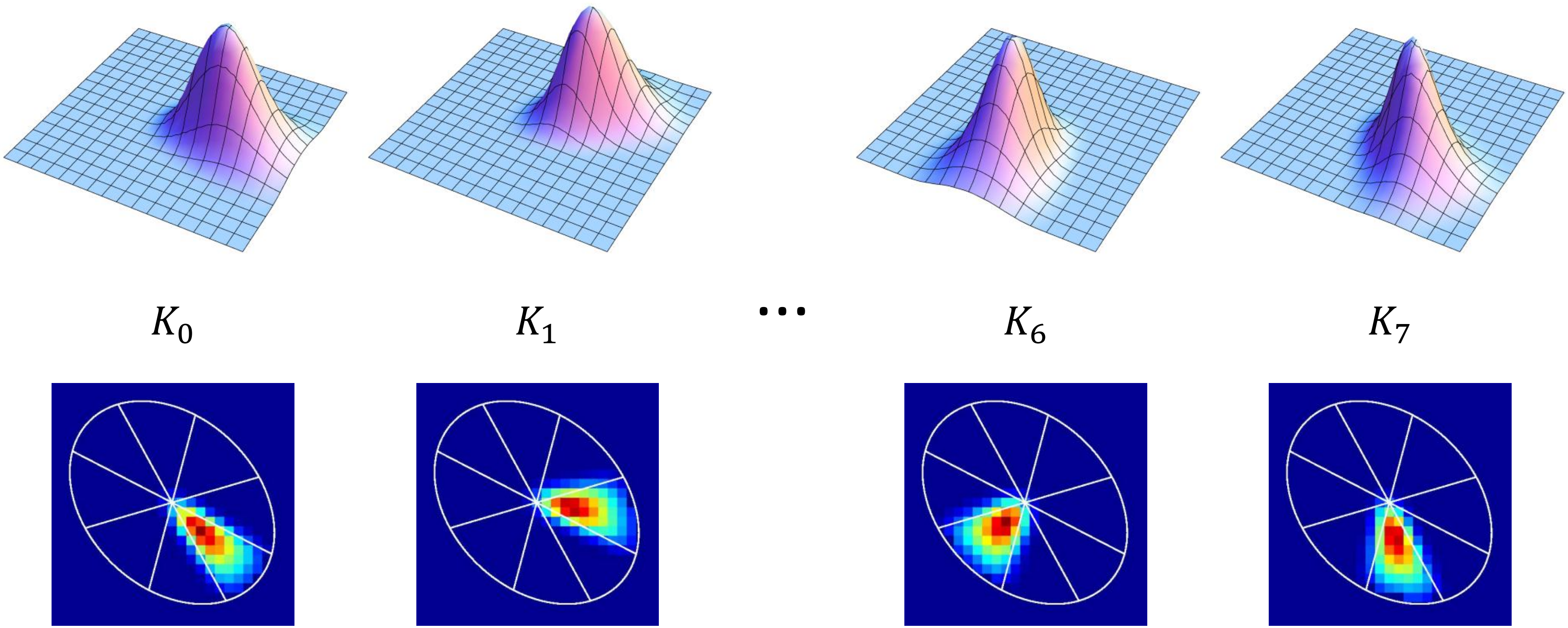
Original image by Keven Law@flickr.com

Generalized Kuwahara Filter



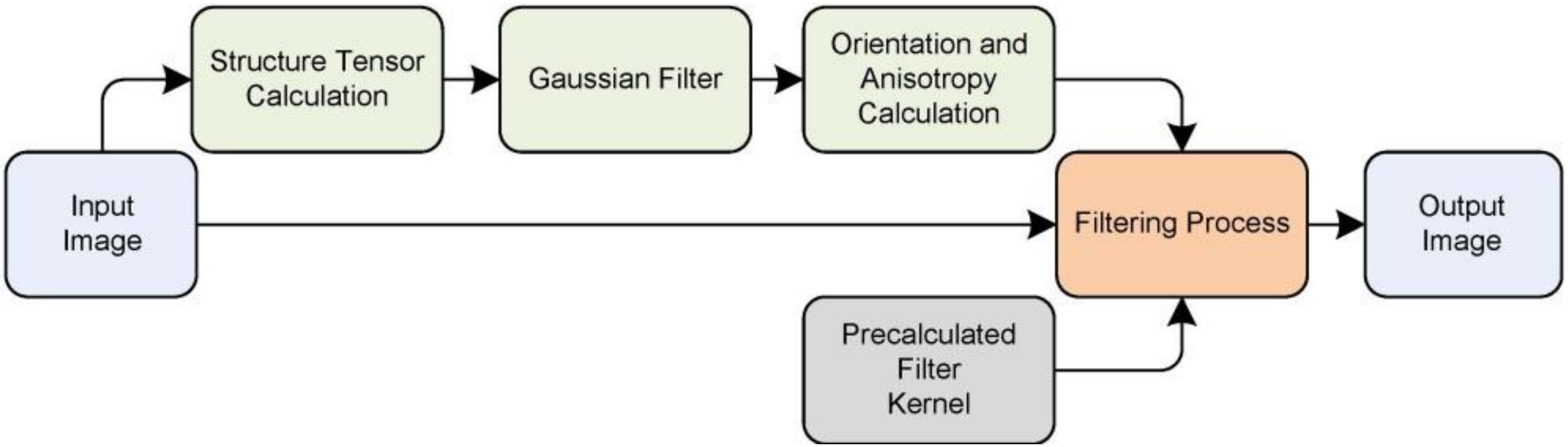
Anisotropic Kuwahara Filter

Kyprianidis et al. (2009)



Anisotropic Kuwahara Filter

Algorithm Overview

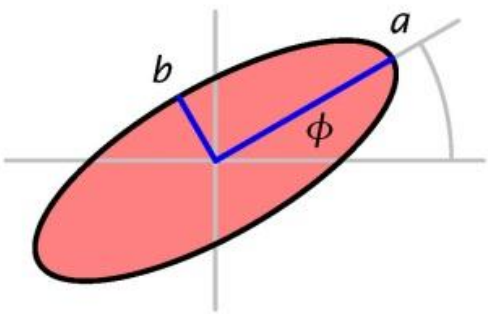


Anisotropic Kuwahara Filter

Filter Shape Definition

Elliptic filter shape (Pham, 2006)

$$a = \frac{\upsilon + A}{\upsilon} \qquad b = \frac{\upsilon}{\upsilon + A}$$



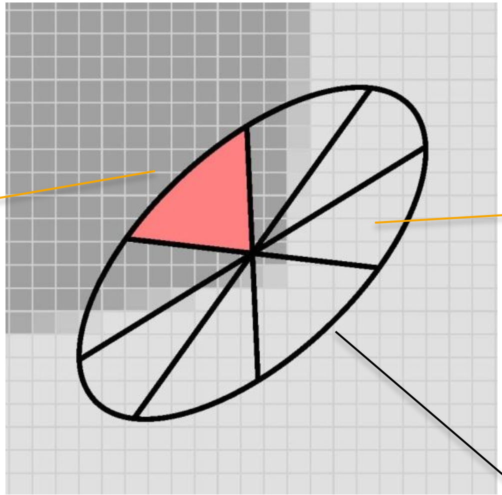
Here, $A \in [0,1]$ denotes the anisotropy measure derived from the structure tensor.

$\upsilon \in (0, \infty)$ is a user parameter that controls the eccentricity of the ellipse. A typical choice is $\upsilon = 1$.

Anisotropic Kuwahara Filter

Anisotropic Kuwahara filter for a corner

Sector with **small variance**. All pixels of this sector are similar. This sector contributes most to the final result



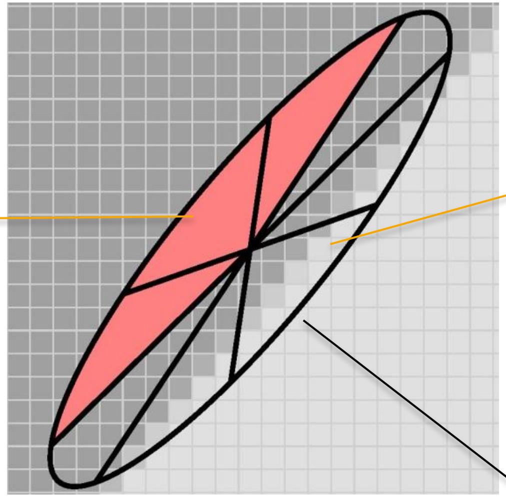
Sectors with **high variance**. They all contain pixels from both color regions. These sectors have almost no influence.

Filter shape is adapted per-pixel

Anisotropic Kuwahara Filter

Anisotropic Kuwahara filter for an edge

Multiple sectors with **small variance**. All pixels of the sectors lie on the same side of the edge. Result is a weighted sum of the (weighted) mean values of the sectors.



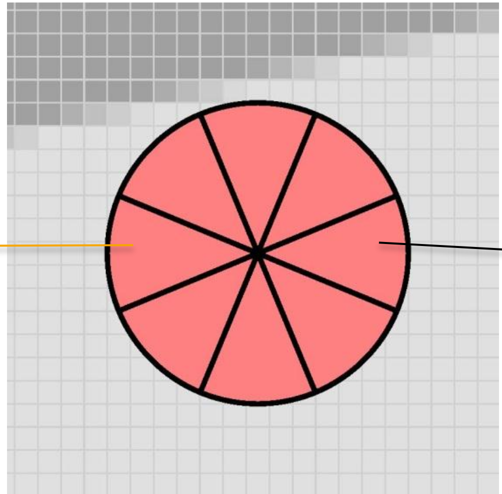
Regions with **high variance**. They all contain pixels from both sides of the edge. These sector have almost no influence.

Filter shape is adapted to anisotropic image structure

Anisotropic Kuwahara Filter

Anisotropic Kuwahara filter for an homogenous neighborhood

All regions have **similar variance**!

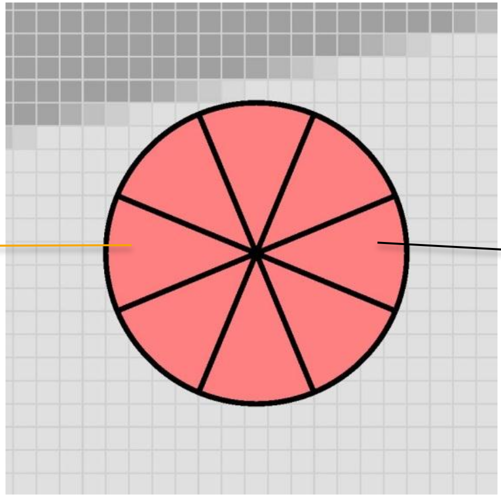


Filter shape is circular and similar to a Gaussian filter

Generalized Kuwahara Filter

Anisotropic Kuwahara filter for a homogenous neighborhood

All regions have **similar variance**!

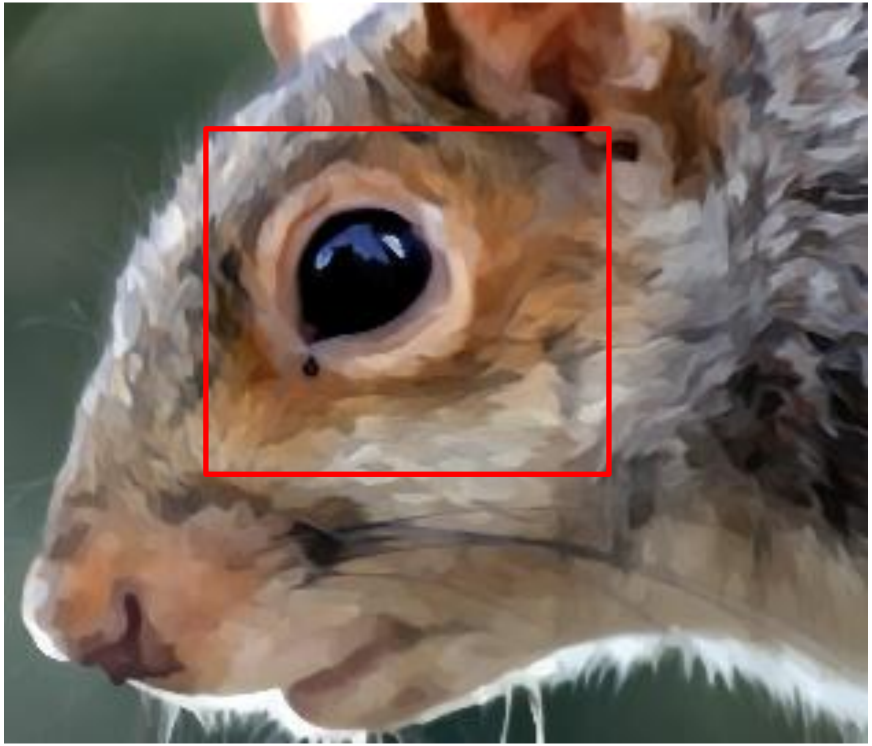


Filter shape is similar to a Gaussian filter

Generalized Kuwahara Filter

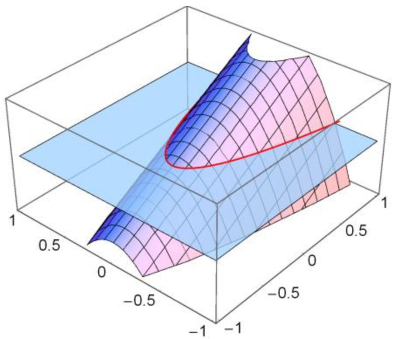
Original image by Keven Law@flickr.com

Generalized Kuwahara Filter

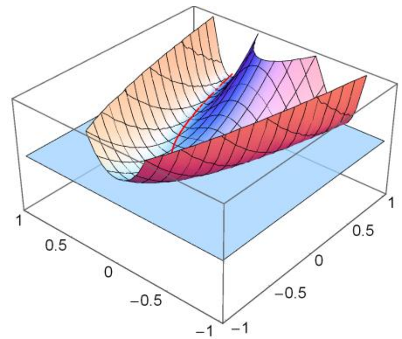


Anisotropic Kuwahara Filter

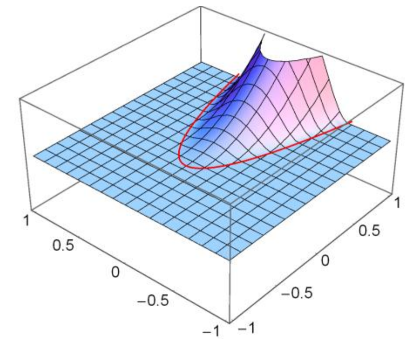
Polynomial Weighting Functions



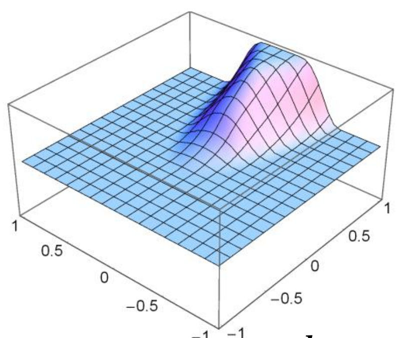
$$(x+\zeta)-\eta y^2$$



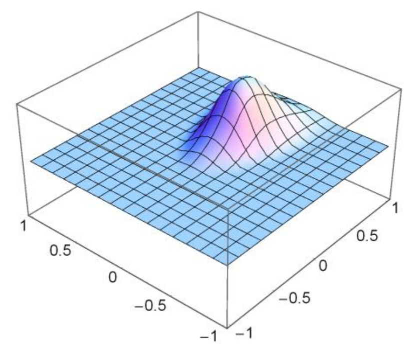
$$\left((x+\zeta)-\eta y^2\right)^2$$



$$\max\left\{0,\left((x+\zeta)-\eta y^2\right)^2\right\} \coloneqq k_0$$



$$\tilde{k}_0(x,y)=\frac{k_0}{\sum_i k_i(x,y)}$$



$$\tilde{K}_0=\tilde{k}_0\cdot G_{\sigma_s}$$

Shape-simplifying Image Abstraction

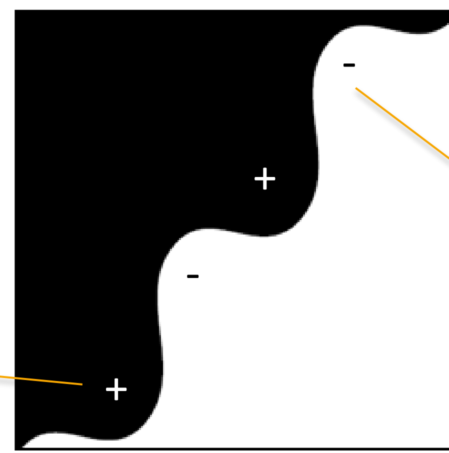
Kang & Lee (2008)

Mean curvature flow (Alvarez et al., 1992):

$$I_t = \kappa \, |\nabla I|$$

Curvature

Image gradient



Increasing the intensity here moves the level curve

Decreasing the intensity here moves the level curve

Shape-simplifying Image Abstraction

Kang & Lee (2008)

Mean curvature flow

Image credit: Kang & Lee (2008)

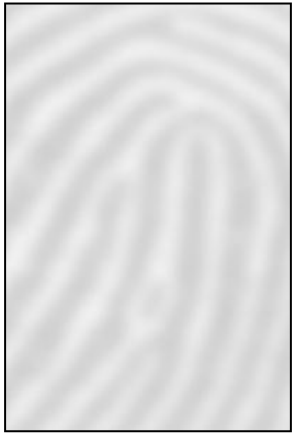
Input | 20 iterations | 60 iterations

Shock filter (Osher and Rudin, 1990; Alvarez and Mazorra 1994):

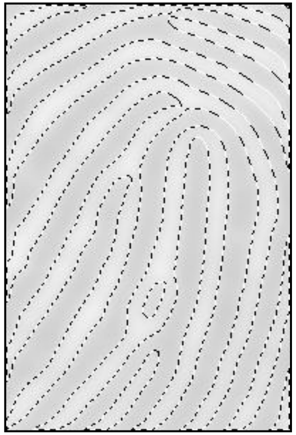
$$I_t = -\mathrm{sign}(\Delta G_\sigma \star I)\ |\nabla I|$$

In the influence zone of a maximum, the Laplacian ΔI is negative and, therefore, a dilation is performed.

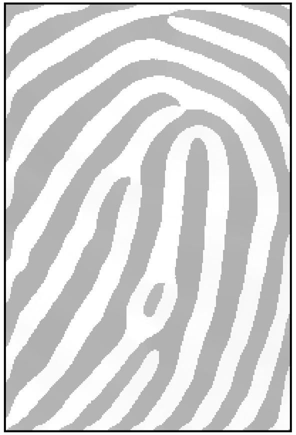
In the influence zone of a minimum, the Laplacian ΔI is positive, which results in an erosion.



Input



Influence zones



Output

Image credit: Kang & Lee (2008)

Shape-simplifying Image Abstraction

Kang & Lee (2008)

Algorithm 1 Image Abstraction by MCF

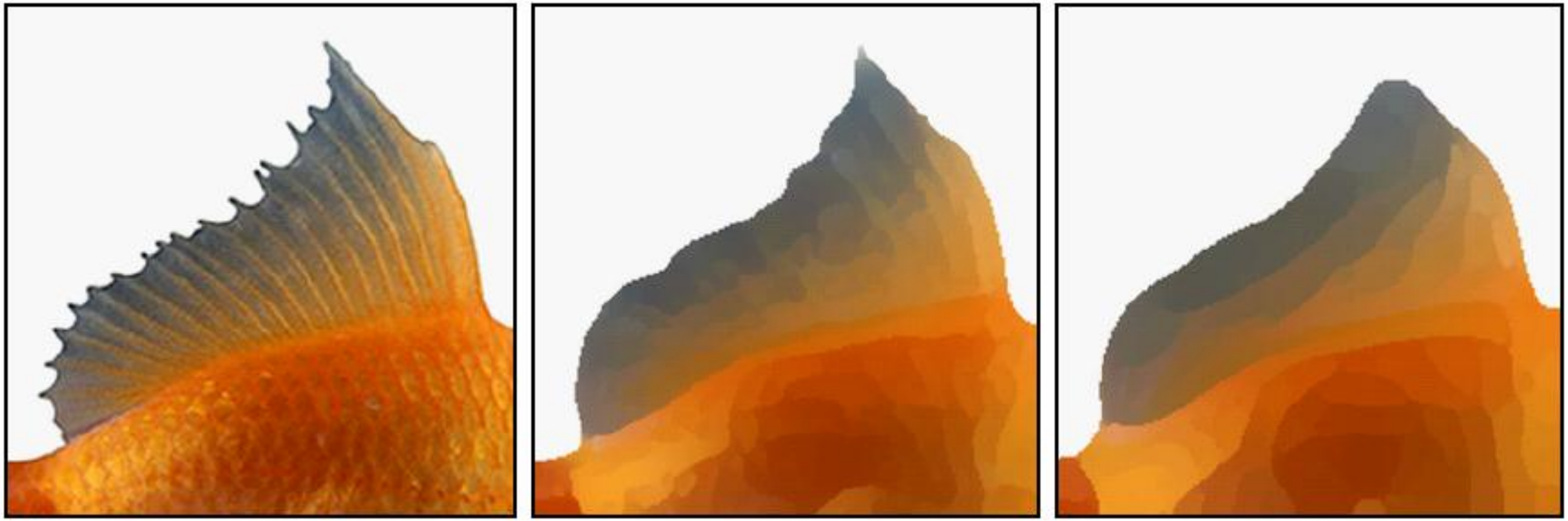
loop
    for 1 to k **do**
        $I \leftarrow MeanCurvatureFlow(I)$
    end for
    $I \leftarrow ShockFiltering(I)$
end loop

Shape-simplifying Image Abstraction

Kang & Lee (2008)

Image abstraction by mean curvature flow

Image credit: Kang & Lee (2008)



Input | 20 iterations | 60 iterations

Shape-simplifying Image Abstraction

Kang & Lee (2008)

Constrained mean curvature flow:

$$I_t = s \cdot \kappa \, |\nabla I|$$

Stop diffusion if grafient is not aligned to edge tangent flow (ETF)

with

$$s(x) = |t(x) \cdot \nabla I(x)|$$

Edge tangent flow (ETF)

Image gradient

Shape-simplifying Image Abstraction

Kang & Lee (2008)

Algorithm 2 Image Abstraction by CMCF

loop
  for 1 to k **do**
    $\mathbf{t} \leftarrow TVF(I)$
    $I \leftarrow ConstrainedMeanCurvatureFlow(I, \mathbf{t})$
  end for
  $I \leftarrow ShockFiltering(I)$
end loop

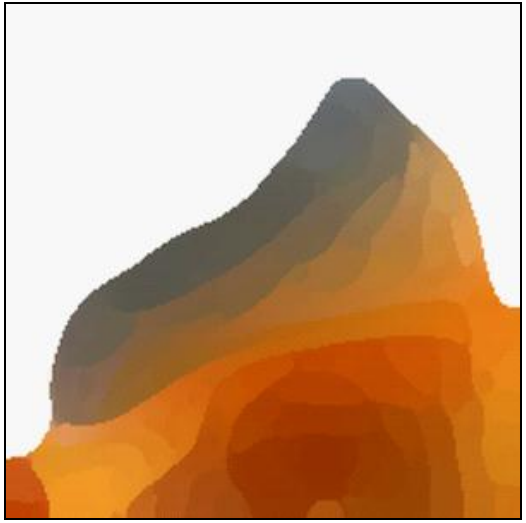
Shape-simplifying Image Abstraction

Kang & Lee (2008)

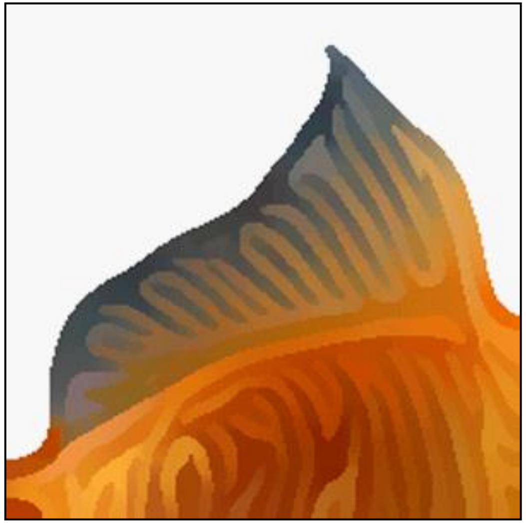
Image abstraction by constrained mean curvature flow

Image credit: Kang & Lee (2008)

Input



60 iterations image abstraction by MCF



60 iterations image abstraction by CMCF

Artistic Stylization of Images and Video

Part IV – Future Challenges

Eurographics 2011

John Collomosse

Centre for Vision Speech and Signal Processing (CVSSP),
University of Surrey, United Kingdom

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- **"Aaron's Code: Meta-art, Artificial Inteligence and the Work of Harold Cohen"**
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  B. Gooch, E. Reinhard, A. Gooch. ACM ToG 2004.
- **Influencing User Perception Using Real-time Adaptive Abstraction**
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- **Human Facial Illustrations: Creation and psychophysical evaluation**
  B. Gooch, E. Reinhard, A. Gooch. ACM ToG 2004.
- **Where do people draw lines?**
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- **Waking Life (Movie)**
  Directed by R. Linklater. Fox Searchlight 2001.
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  www.paintingfool.com (S. Colton, Imperial College)
- **Genetic Paint: A search for salient paintings**
  J. Collomosse, P. Hall. EvoMUSART 2005.

Recap – Common NPR Motivations

Artistic Stylization

- **Why?**

Comprehension

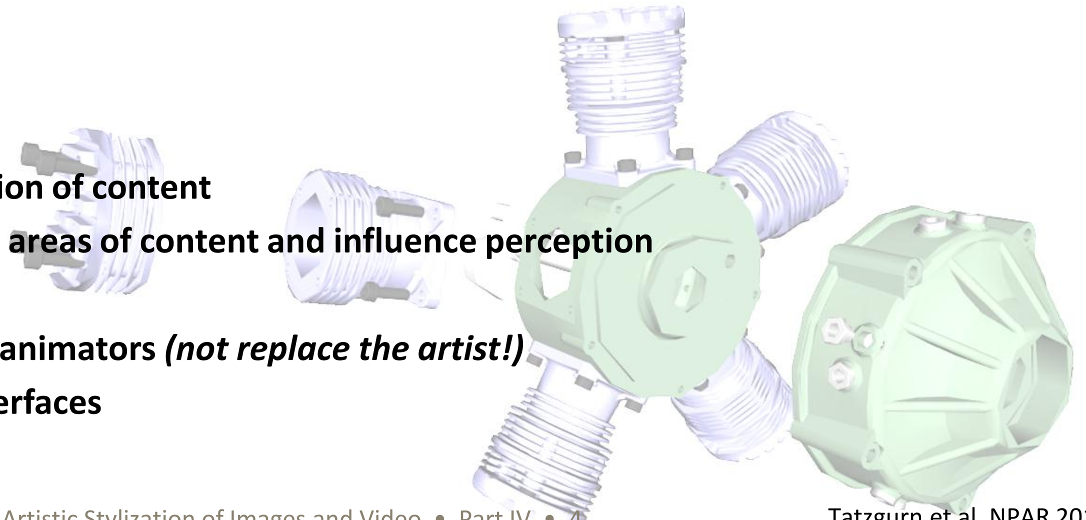
Communication

Visualization

Aesthetics

Animation

- **Artistic Stylization can**
  - **Simplify and structure the presentation of content**
  - **Selectively guide attention to salient areas of content and influence perception**
  - **Learn and emulate artistic styles**
  - **Provide assistive tools to artists and animators *(not replace the artist!)***
  - **Help us to design effective visual interfaces**



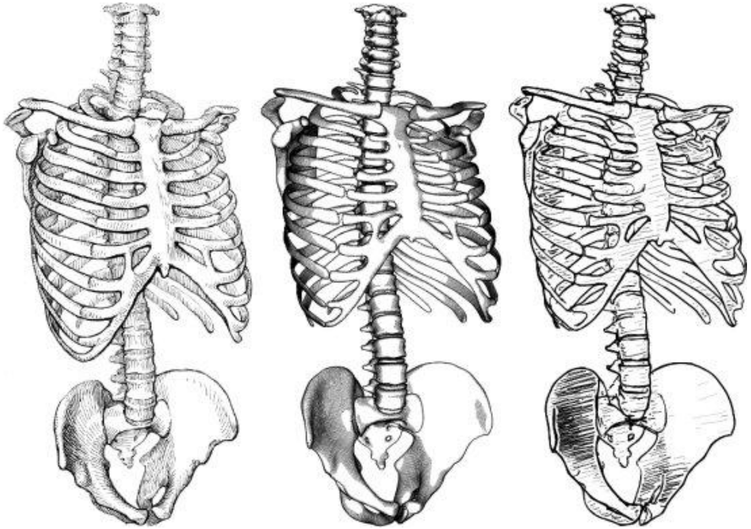
Tatzgurn et al. NPAR 2010

Challenge - Evaluation

- Challenges in Aesthetics
  - Easy to show novelty in style
  - … but today there are few styles remaining to pioneer
  - Difficult to show superiority of one style vs. another
  - Usually papers include visual comparisons side-by-side

Collomosse et al. EvoMUSART 2005

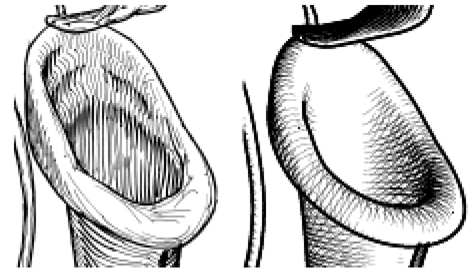
- Evaluation
  - First qualitative study by Isenberg et al. ’06
  - Compares hand-drawn and NPR images
  - Unconstrained pile-sort
    - No prescribed criteria
    - Users manually group images
  - Semi-structured Interview



Isenberg et al. NPAR 2006

Challenge - Evaluation

- **Observations (on 3D pen-and-ink renderings)**
  - **Visual "Turing test" not yet passed**
    - **Pure line art mots obviously CG**
    - **Regularities should be avoided**
      - **c.f. more recent work by Cole et al. (SIGGRAPH '08 '09, NPAR '10)**
  - **Styles less obviously CG**
    - **Stippling**
    - **Sketchy (Renderbots)**
    - **Simplified forms**
- **Know the goal / audience**
- **Portray materials (c.f. Zhu et al. ACM ToG 09)**



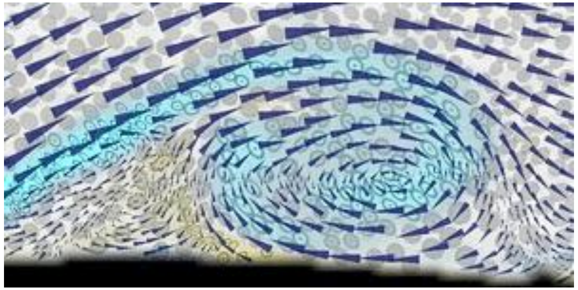
Isenberg et al. NPAR 2006

Challenge - Evaluation

- **Challenges of Communication/Comprehension**
- NPR often claims to be aiming for, or to have achieved:
  - creation of a useful artist / animator's tool
  - simplification of content
  - improvements in of visual communication
- But these are rarely backed up by any form of user study

- No standard methodology has yet been agreed
  - Few have been proposed
  - Task specific:
    - Portrait recognition (Gooch, Winnemoeller)
    - Scientific visualisation (Healey)

Winnemoeller et al. 2006



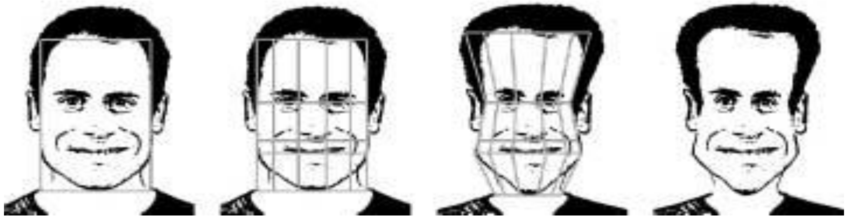
C. Healey. 2002

Real-time Video Abstraction

Winemoeller et al. (2006)

- **Early studies measuring the effect of NPR on visual communication**
  - **Recognition speed from caricature (Gooch et al. 2004)**
  - **Recognition speed and image recall speed / accuracy (Winnemoeller et al. 2006)**

- **Results:**
  - **Participants recognise stylized celebrities more quickly.**
    - **Abstraction reduces recognition latency (13% reduction)**
  - **Participants can recall stylized images more quickly / accurately.**
    - **Memory “pairs” game faster with stylized images (28% faster)**



Gooch et al. 2004

Influencing User Perception Using Real-time Adaptive Abstraction

Redmond (2011)

- NPR influences perception in real-time interactive environments
    - Timed recognition tasks
    - Attention measurement (Gaze tracking)
- Tasks evaluated
    - Person / face recognition
    - Shape / object recognition
    - Crowds
    - Urban Navigation
    - Volume Visualisation
- Multi-way ANOVA to measure real effect
- Newman-Keuls post-hoc analysis

Redmond 2011

Challenge - Temporal Coherence

- **Challenge of Temporal Coherence**
  - Reducing flicker in stylized video remains unsolved in the general case
    - Segmentation is stable but content limited
    - Filtering is more general btu unstable where texture is absent or poorly expressed
  - Flicker most distracting from **6-10Hz** *(typical NPR fps!)*

- **Twin Challenges**
  - Defining temporal coherence beyond *“shower door effect”*
    - Objective measures of coherence
    - Community agreement on a preferred definition
  - Solving temporal coherence
    - Flicker reduction may take priority over accuracy

Defacto test clips

Hayes & Essa (NPAR 04)
J. Wang [SIGGRAPH 04]

Challenge – Interaction

- Interaction with Creatives
  - Most NPR is pitched as a creative tool
  - Few are built with users in the loop
  - …Even fewer study use of tool in a creative context

- Mainstream NPR could collaborate with creative communities
- Examples of Computer Science/Artist interaction
  - Evolutionary Art Community (EvoMUSART)
  - Computational Aesthetics (CAe)

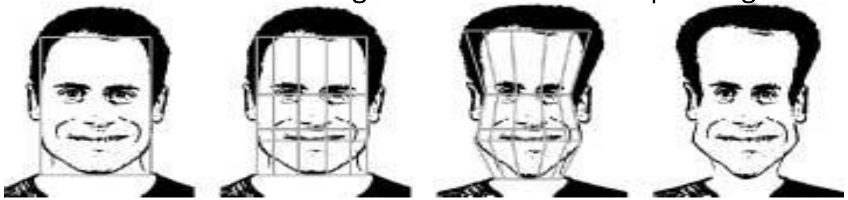
- This year NPAR, SBIM and CAe combined workshop (at SIGGRAPH'11)
  - Paper submission 25 April
  - http://www.cl.cam.ac.uk/conference/cae-sbim-npar-2011

Challenge - People

- **Portraits and Caricature**
  - **Common NPR applications are in consumer media**
    - **Mainly people and faces**
    - **Strong perceptual prior and high expectation**
- **Current NPR for portraits**
  - **Caricatures by global non-linear warping (e.g. Gooch '04)**
  - **Generally poor at emphasising salient facial detail**
  - **Higher level models needed**


Waking Life. Linklater. (c) Fox Searchlight. 2001


"Painting Fool". Colton. 2007. paintingfool.com


Gooch et al. 2004

Challenge - Depiction

- **Composition and Depiction**
  - **Most NPR still focuses on low-level representation, preserving scene structure**
  - **Artistic projections are common in artwork**
    - **Depiction of form not sufficiently addressed (Durand, NPAR 2002)**
    - **Related to "Computational Photography"**

RTCams – Artistic views from stereo

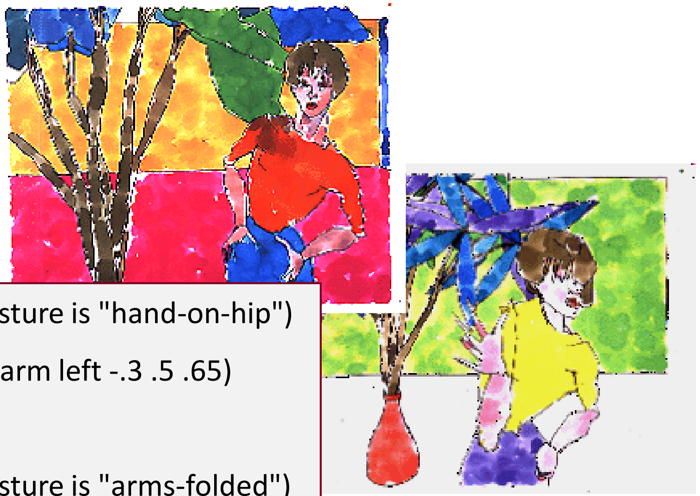
Hall et al. 2007

Cubist-like Composition

Collomosse et al. 2003

Challenge - Depiction

- **Full circle**
  - **Artistic composition was arguably the first NPR problem tackled (~30 years)**
    - **Harold Cohen's AARON – heuristic / expert system generative art**
  - **And it is still unsolved…**



```
if (left-arm-posture is "hand-on-hip")
   (add-upper-arm left -.3 .5 .65)
else
if (left-arm-posture is "arms-folded")
   ...
```

"Aaron's Code". W.H. Freeman & Co. 1990

Tutorial End

Open Q & A Session