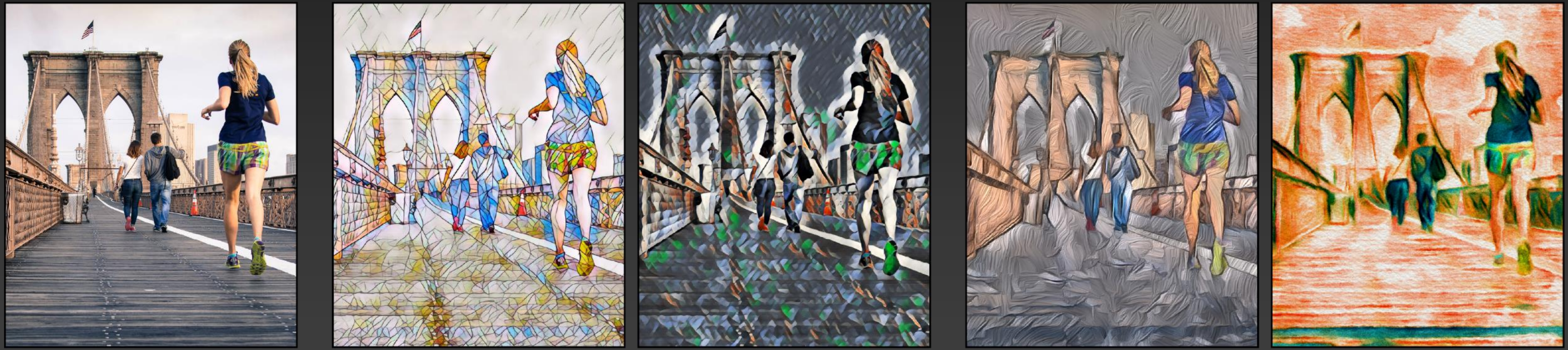
Neural Style Transfer:
A Paradigm Shift for Image-based Artistic Rendering?

AMIR SEMMO TOBIAS ISENBERG JÜRGEN DÖLLNER



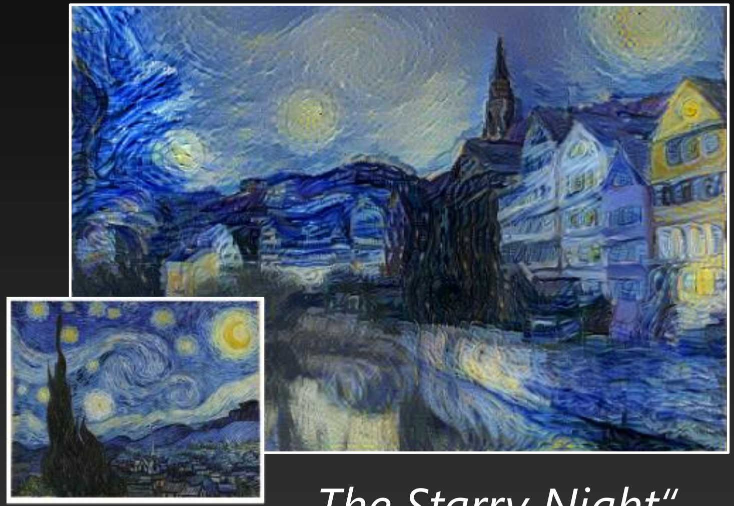
Hasso Plattner Institut
Universität Potsdam

EXPRESSIVE 2017 – 29TH JULY 2017

Inria
GEFÖRDERT VOM
Bundesministerium für Bildung und Forschung

Great popularity since [Gatys et al. 2015, arXiv]

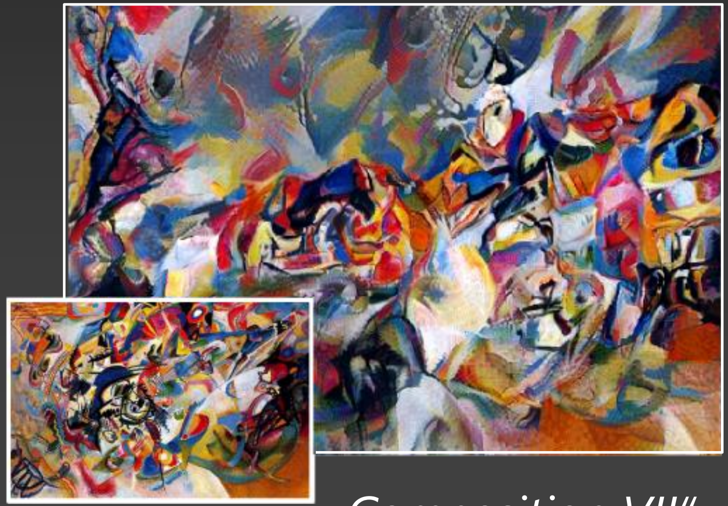
Input



„The Starry Night“

„The Scream“

„Femme nue assis“



„Composition VII“

„The Shipwreck of the Minotaur“

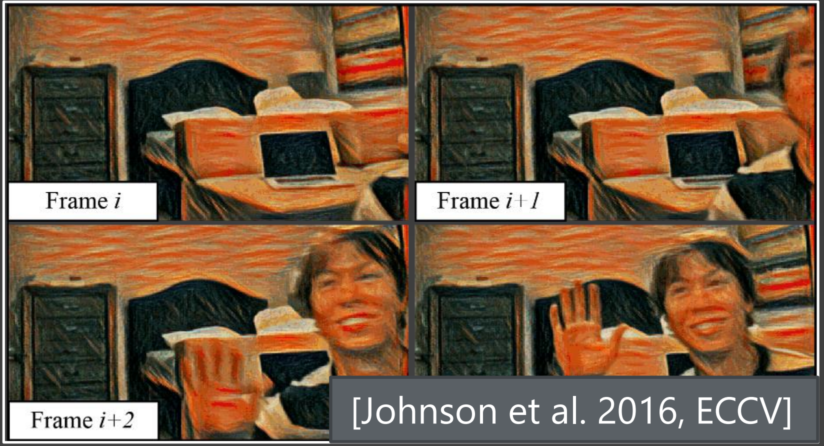
Great popularity since [Gatys et al. 2015, arXiv]

13 conference papers / 16 arXiv.org reports (and counting), mobile apps / services

[Risser et al. 2017, arXiv]

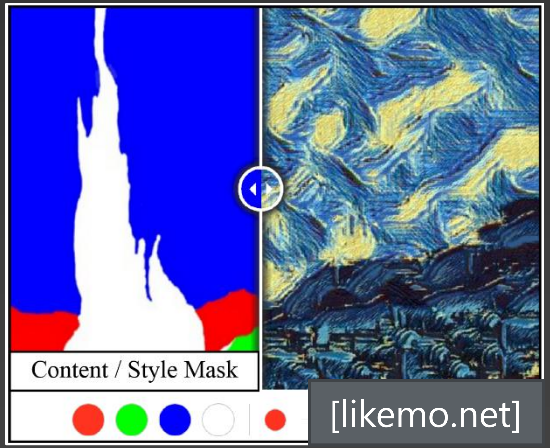
[Gatys et al. 2016, CVPR]

[Selim et al. 2016, SIGGRAPH]



[Johnson et al. 2016, ECCV]


[Prisma / iOS]

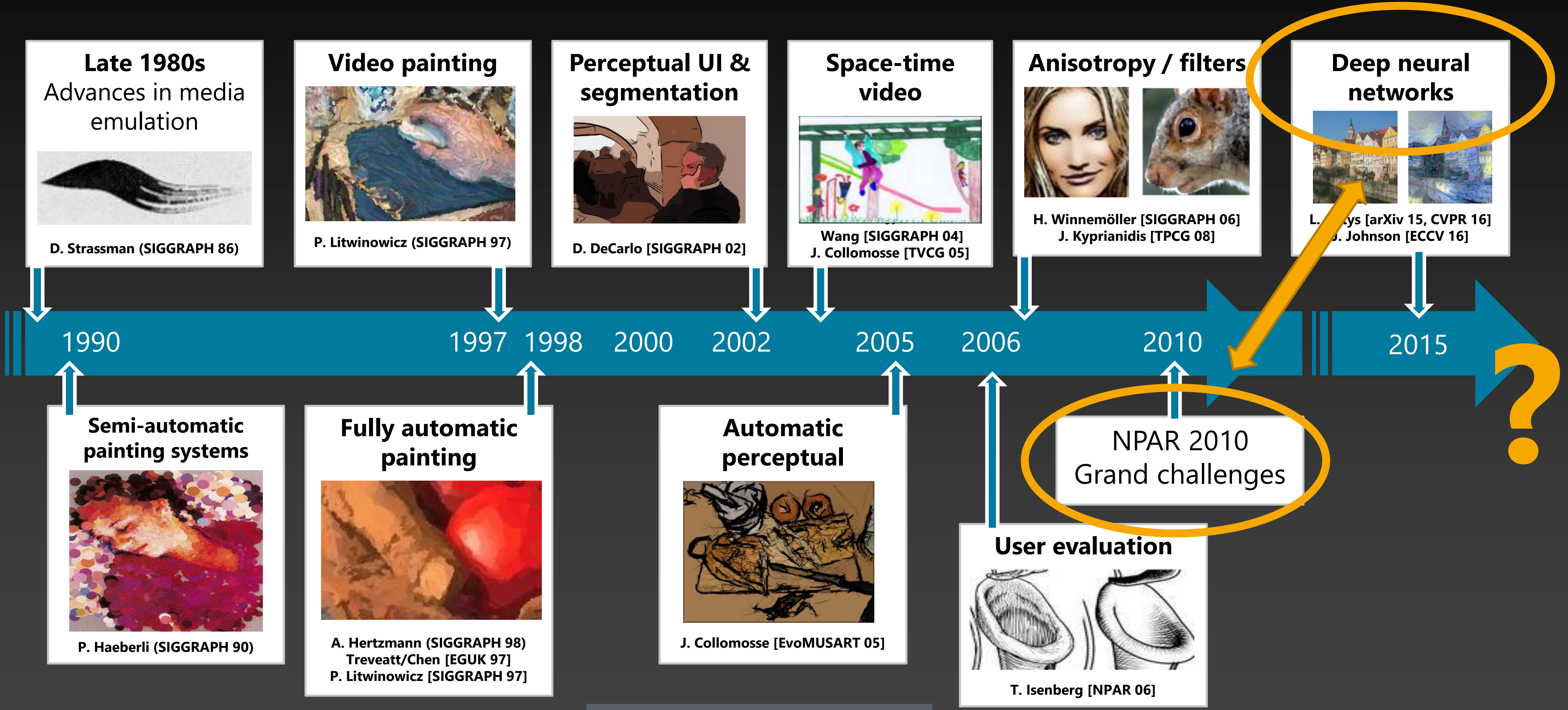


[likemo.net]

So far, primarily explored in a computer vision context …

What impact does *Neural Style Transfer* has on image-based artistic rendering and NPAR research?

In image-based artistic rendering, we‘ve come a long way …



[Kyprianidis et al. 2013, TVCG]

NPAR Grand Challenges

[Salesin 2002, NPAR]

Viewing Progress in Non-photorealistic Rendering through Heinlein's Lens

Amy A. Gooch, University of Victoria; Jeremy Long, University of Victoria; Li Ji, University of Victoria; Anthony Estey, University of Victoria; Bruce S. Gooch, University of Victoria

Abstract

1 Introduction

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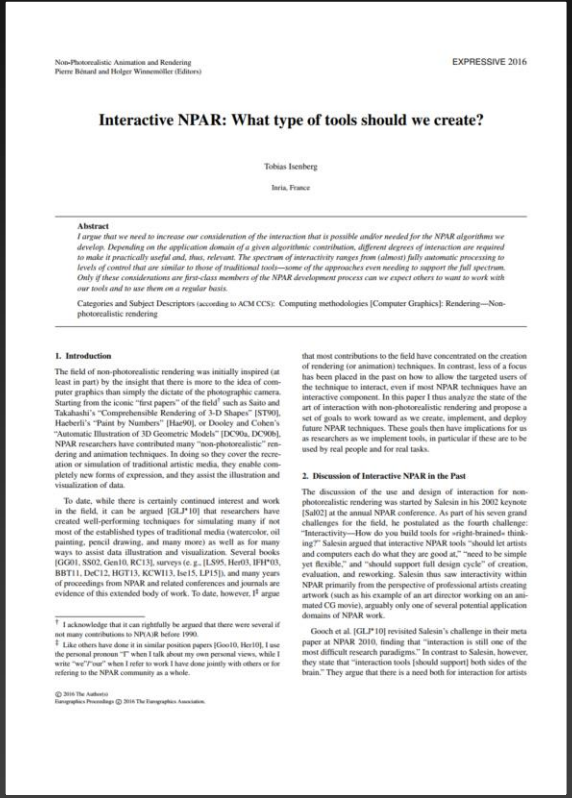
[Gooch et al. 2010, NPAR]



Non-Photorealistic Animation and Rendering
Pierre Bénard and Holger Winnemöller (Editors)

EXPRESSIVE 2016

Interactive NPAR: What type of tools should we create?

Tobias Isenberg

Inria, France

Abstract

1. Introduction

2. Discussion of Interactive NPAR in the Past

[Isenberg 2016, NPAR]

Challenge 1: Algorithmic Aesthetics

How do you encode what makes something beautiful?

[Salesin 2002, NPAR] revisited by [Gooch et al. 2010, NPAR]

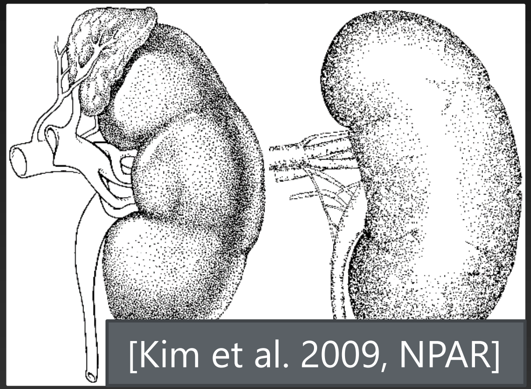
Two general categories of work [Gooch 2010, NPAR]:

- Simulate physical process of producing a piece of artwork
- **Derive algorithmic theory that approximates the artwork itself**

Artwork Approximation – Examples

[Bousseau et al. 2006, NPAR]

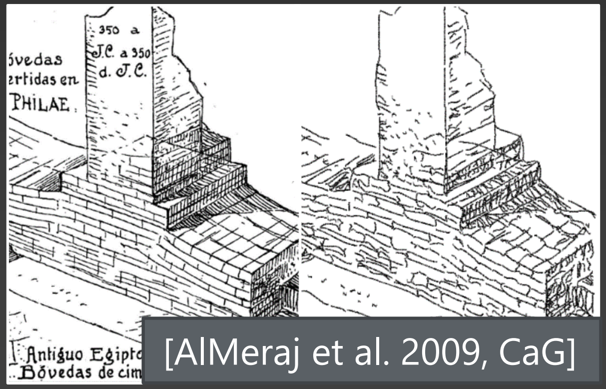
[DeCoro et al. 2007, NPAR]



[Kim et al. 2009, NPAR]

[Baxter et al. 2004, NPAR]

[Gooch et al. 2004, ToG]



[AlMeraj et al. 2009, CaG]

Kyprianidis et al.'s IB-AR Taxonomy [2013, TVCG]

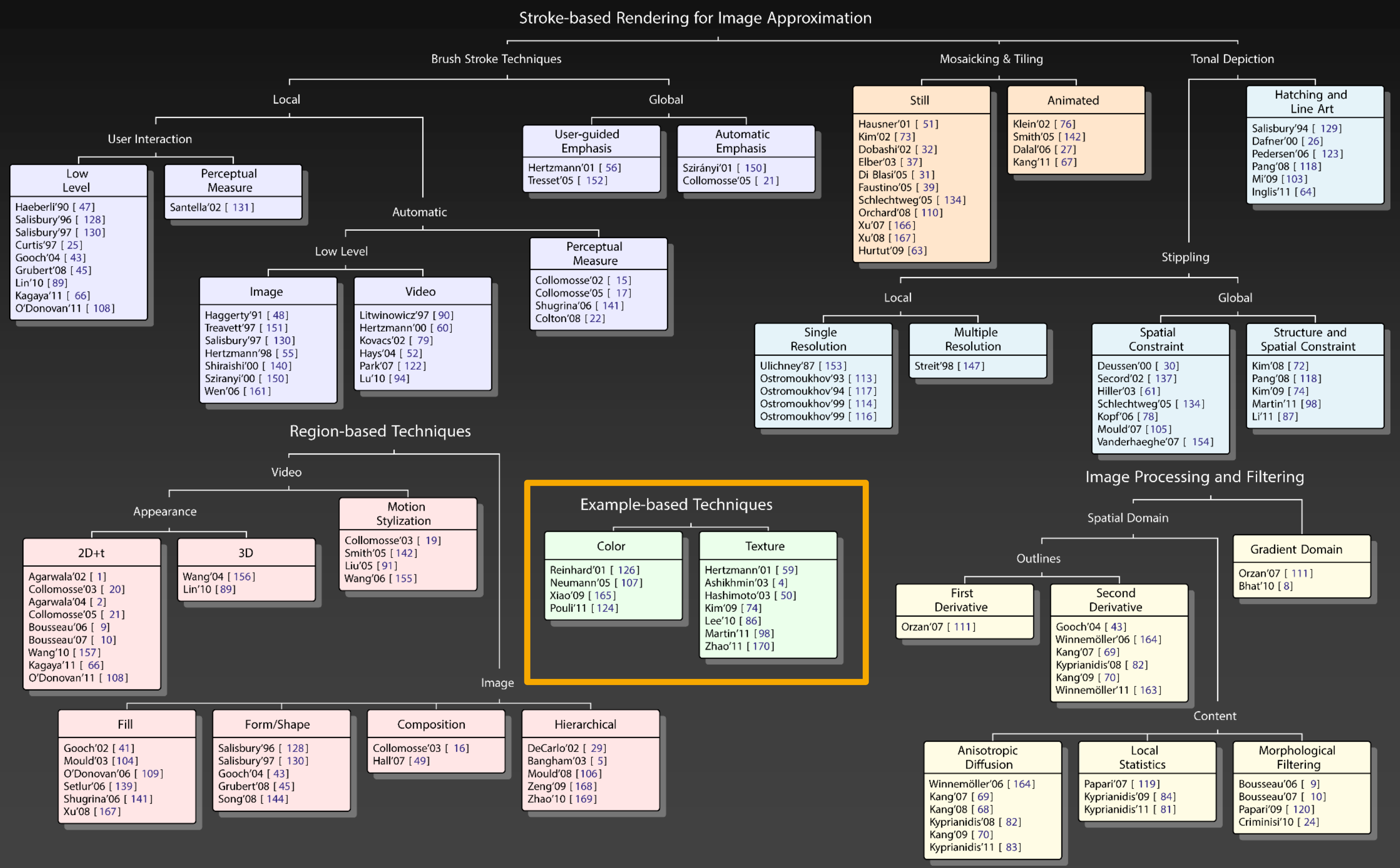


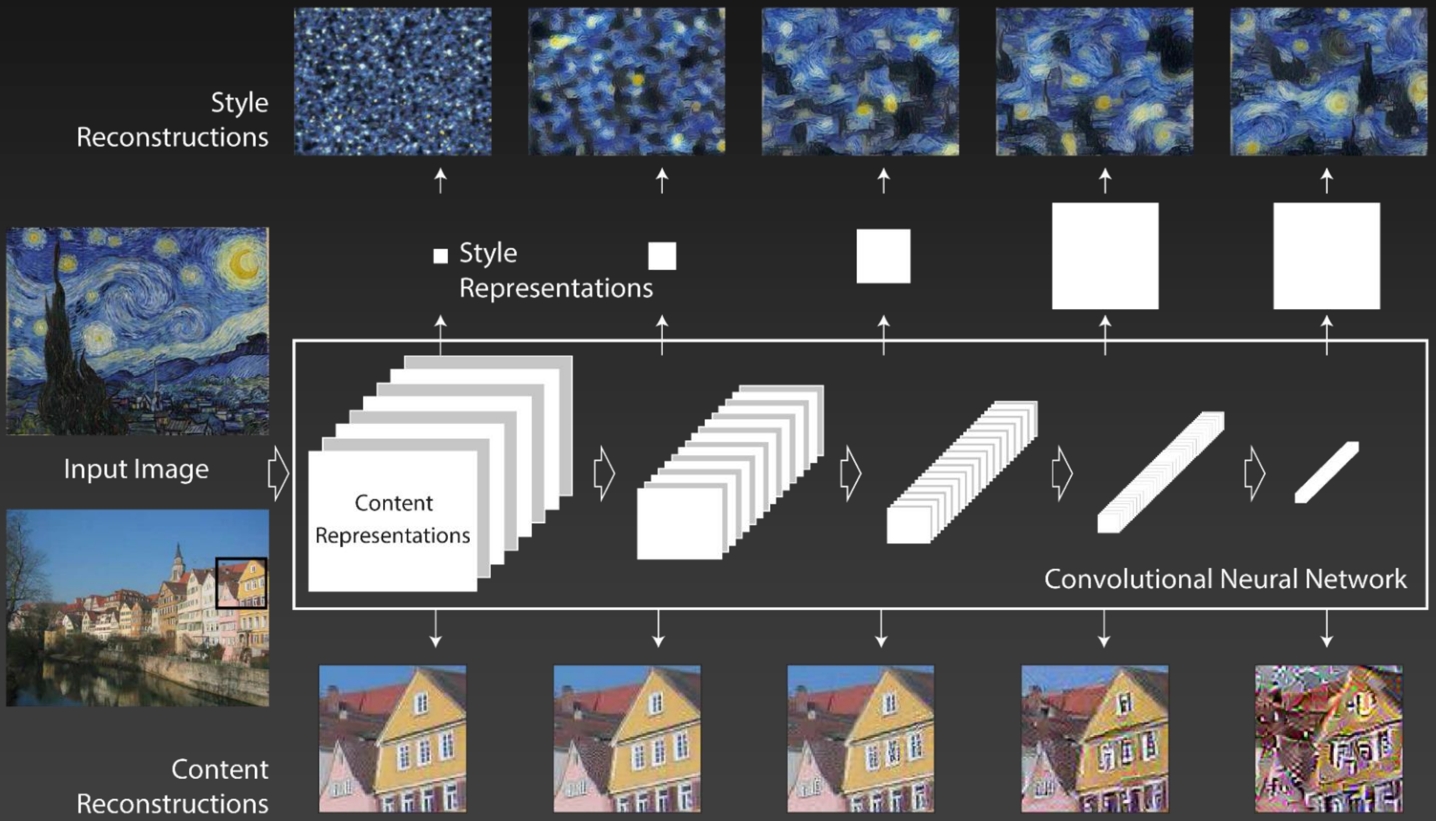
Image Analogies [Hertzmann et al. 2001, SIGGRAPH]

A : A′ :: B : B′

Limitations: Requires analogous style and content pairs for training, typically informs only low-level image features for texture transfer.

Neural Algorithm of Artistic Style

- Very deep convolutional neural networks (CNNs) can accurately classify high-level image contents [Simonyan & Zisserman 2015, arXiv]
- Layers of deep CNNs can be activated to match content and style statistics between arbitrary images [Gatys et al. 2016, CVPR]



[Gatys et al. 2016, CVPR]

Neural Style Transfer and Pictorial Language

How to define artistic style transfer in the context of „meaning making“ and determine if it is successful ?

– in professional (e.g., for artists) as well as casual creativity (i.e., for general public) applications –

Neural Style Transfer and Pictorial Language

Artists work in a pictorial language by following a set of standards, basics and rules of picture-making.

A Semiotic Structure for Artistic Style Transfer

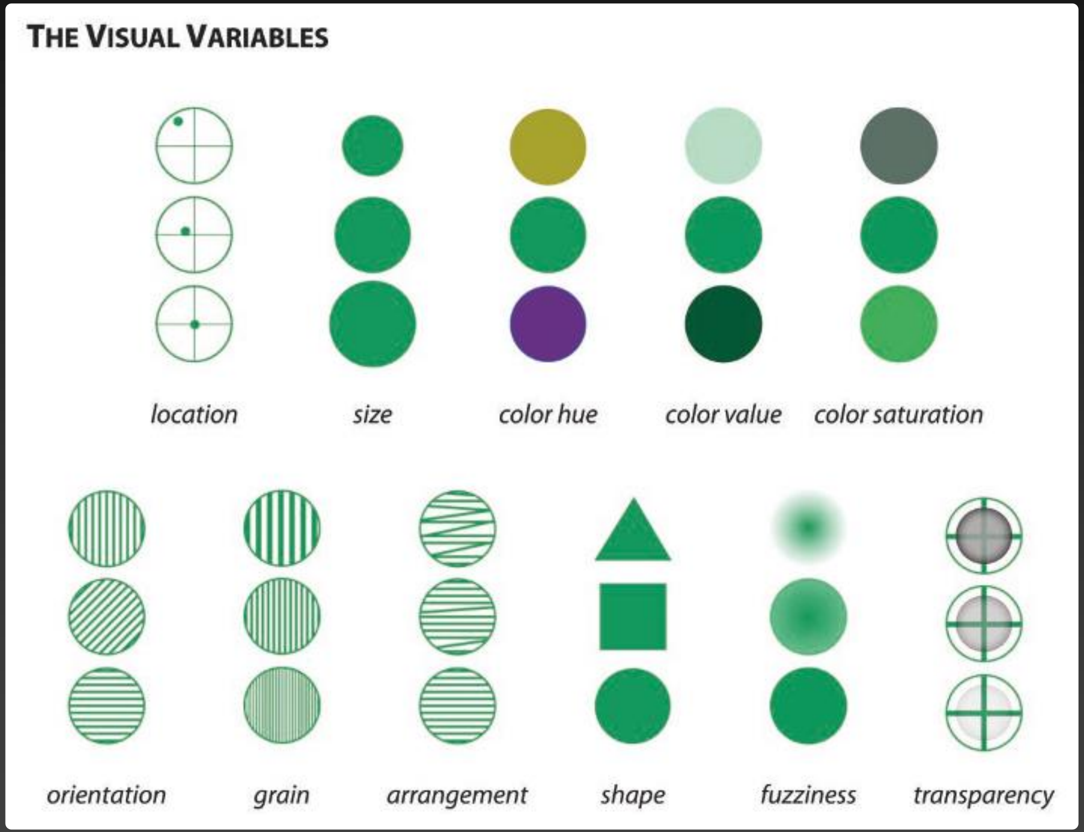
Style Image: Franz Marc – “The Tower of Blue Horses”

Visual Semiotics and Uncertainty Visualization

- Study of symbols and how they convey information in a meaningful way
- Not a new endeavor, e.g., connected to visualization, art theory and cartography

"The Semiology of Graphics" [Bertin, 1983]

- Attempt to classify all graphics marks as to how they could express data



[MacEachren et al., 2012, TVCG]

Pictorial Semiotics – Design Aspects

I. Modeling Aspects

- Color Maps
- Feature Maps
- Geometry Maps

Color *Depth*

[http://phandroid.com]

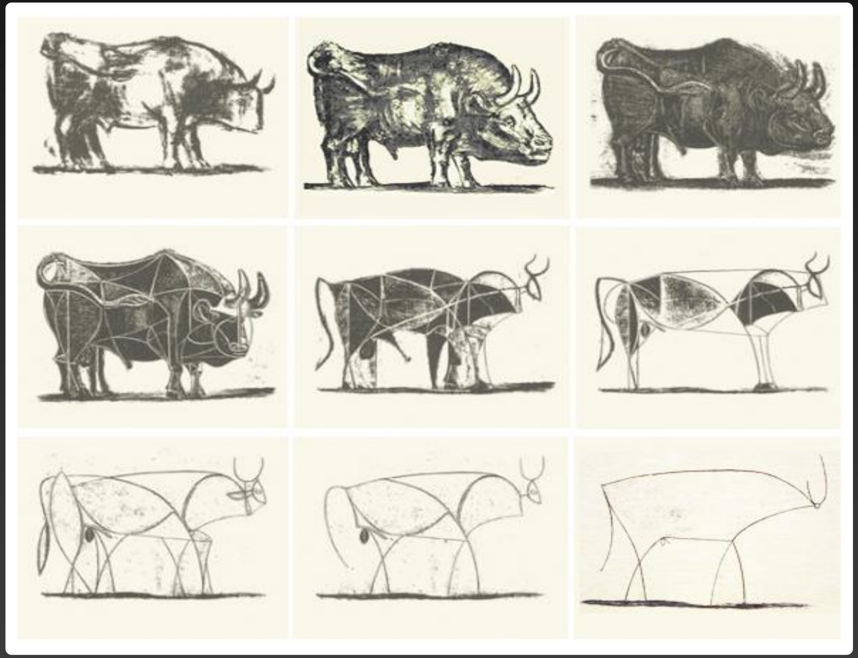
Pictorial Semiotics – Design Aspects

I. Modeling Aspects

- Color Maps
- Feature Maps
- Geometry Maps

II. Filtering Aspects

- Location-based
- Color-based
- Feature-based



Pablo Picasso [1945-46]

Pictorial Semiotics – Design Aspects

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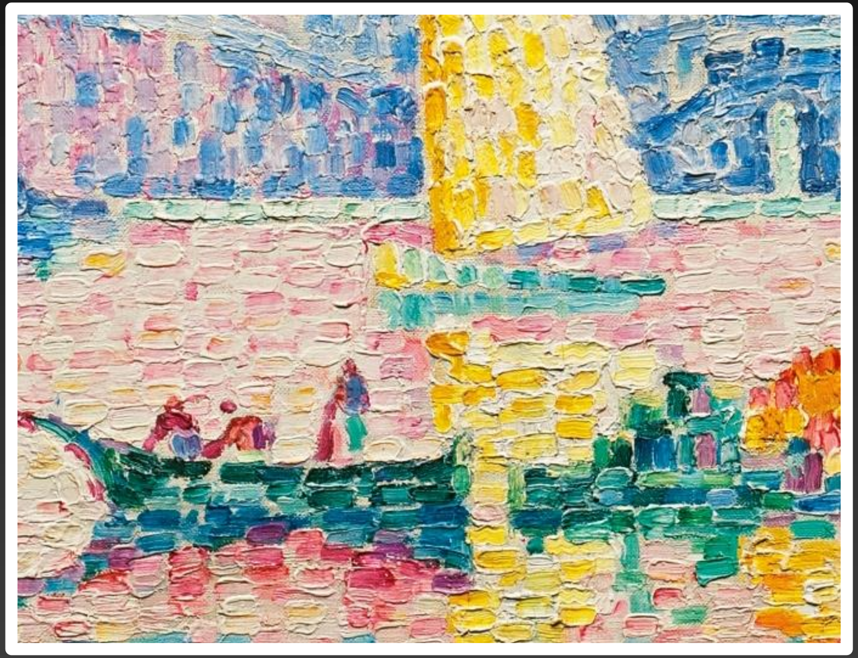
- Color-based
- Feature-based

III. Graphical Elements

- Point
- Line
- Area
- 2D Element



Paul Signac [1917]

Pictorial Semiotics – Design Aspects

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III. Graphical Elements
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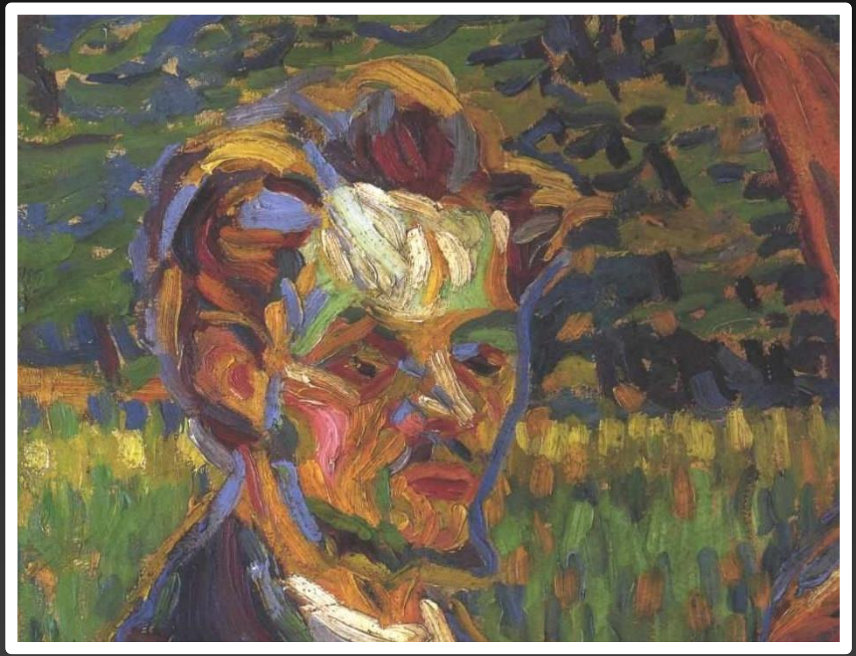
IV. Graphical Variables
- Form
- Shape
- Size
- Color



Ernst Ludwig Kirchner [1907]

Pictorial Semiotics – Design Aspects

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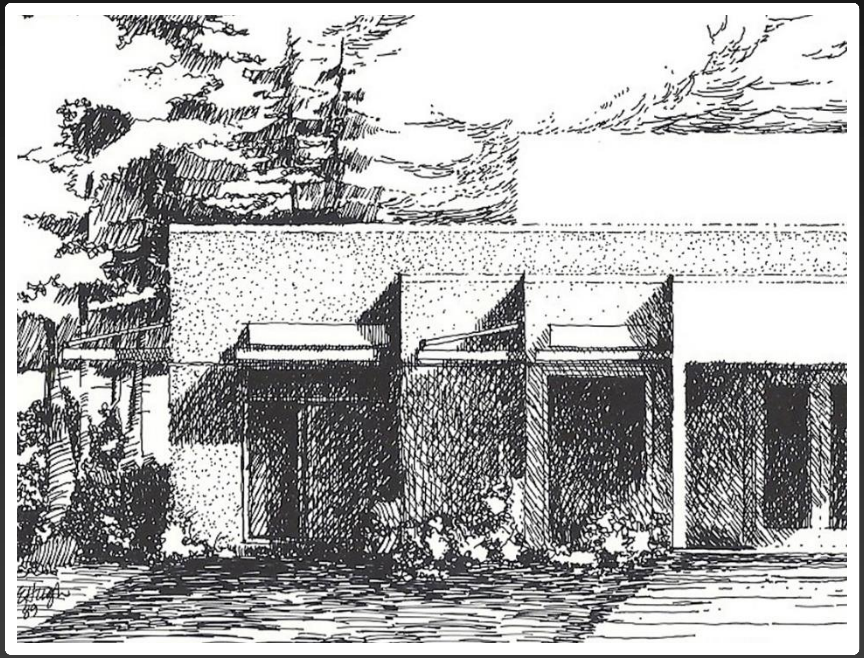
V. Design Mechanisms
- Space/Texture
- Transparency/Blending
- Shading
- Shadows
- Crispness
- Resolution



[http://sketchingjourney.com]

Pictorial Semiotics – Design Aspects

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VI. Perceptional Aspects
- Flatness
- Motion Coherence
- Temporal Continuity
- Pictorial Cues

Gustave Caillebotte [1877]

Pictorial Semiotics – Design Aspects

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Example-based Techniques

Color
- Reinhard'01 [126]
- Neumann'05 [107]
- Xiao'09 [165]
- Pouli'11 [124]

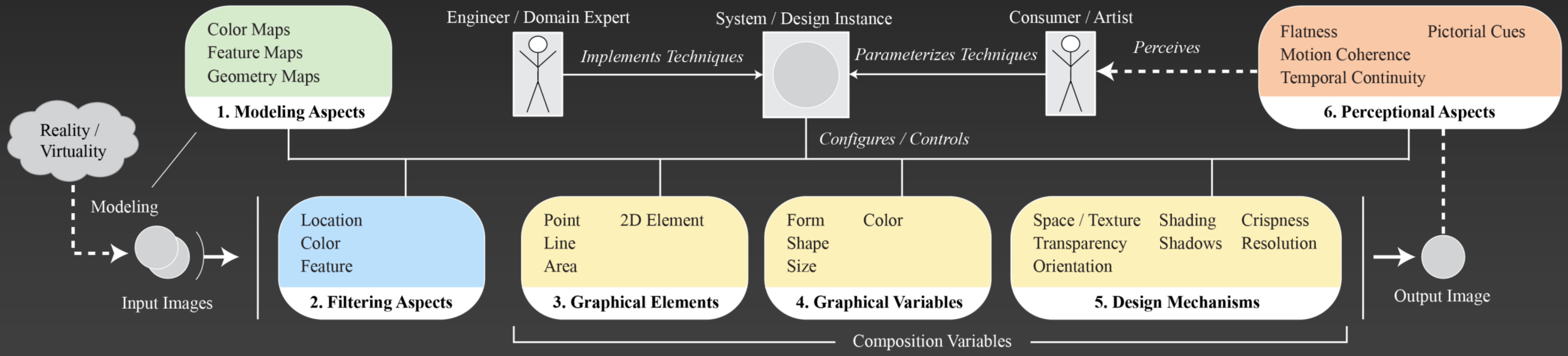
Texture
- Hertzmann'01 [59]
- Ashikhmin'03 [4]
- Hashimoto'03 [50]
- Kim'09 [74]
- Lee'10 [86]
- Martin'11 [98]
- Zhao'11 [170]

[Kyprianidis et al. 2013, TVCG]

Proposition: Neural style transfers need to mature from **color and texture transfers** to **interactive tools** that consider the **design aspects and mechanisms** involved in **artwork production**.

A Semiotic Structure for Artistic Style Transfer

- User involvement a key mechanism to maintain an iterative feedback loop between a system—as design instance—and user's requirements—as artist



A Semiotic Structure – Review of Style Transfer Techniques *

	Publication	Color Maps	Feature Maps	Geometry Maps	Location-based Filtering	Color-based Filtering	Feature-based Filtering	Point / Line / Area	Color / Brightness	Form / Shape / Size	Space / Texture	Transparency	Orientation	Shading / Shadows	Crispness / Resolution	Coherence / Continuity	Pictorial Cues	User Interaction
Image Statistics	Arbelot et al. [2016]	×	×				×		×		×					×		×
	Chang et al. [2015]	×	×				×		×									×
	Kim et al. [2009]	×				×		×	×	×	×			×	×			
	Maciejewski et al. [2008]	×				×		×	×	×	×			×	×			
	Martín et al. [2011]	×				×		×	×	×	×			×	×			×
	Neumann Broth. [2005]	×							×									
	Pouli & Reinhard [2011]	×							×									×
	Reinhard et al. [2001]	×							×									
	Wu et al. [2013]	×	×						×									
	Xiao & Ma [2009]	×	×						×									
	Yang et al. [2017]	×	×						×									
Image Analogies	Ashikhmin [2003]	×	×								×							×
	Bénard et al. [2013]	×	×	×			×			×	×	×		×		×	×	×
	Berger et al. [2013]	×			×		×	×										
	Efros & Freeman [2001]	×									×							
	Fiser et al. [2016]	×		×							×			×			×	×
	Hashimoto et al. [2003]	×	×								×					×		
	Hertzmann [2001]	×									×							
	Hertzmann et al. [2002]	×			×		×	×										
	Lee et al. [2011]	×	×	×							×							
	Wang et al. [2013]	×						×			×							
	Zhao & Zhu [2011]	×			×		×	×										

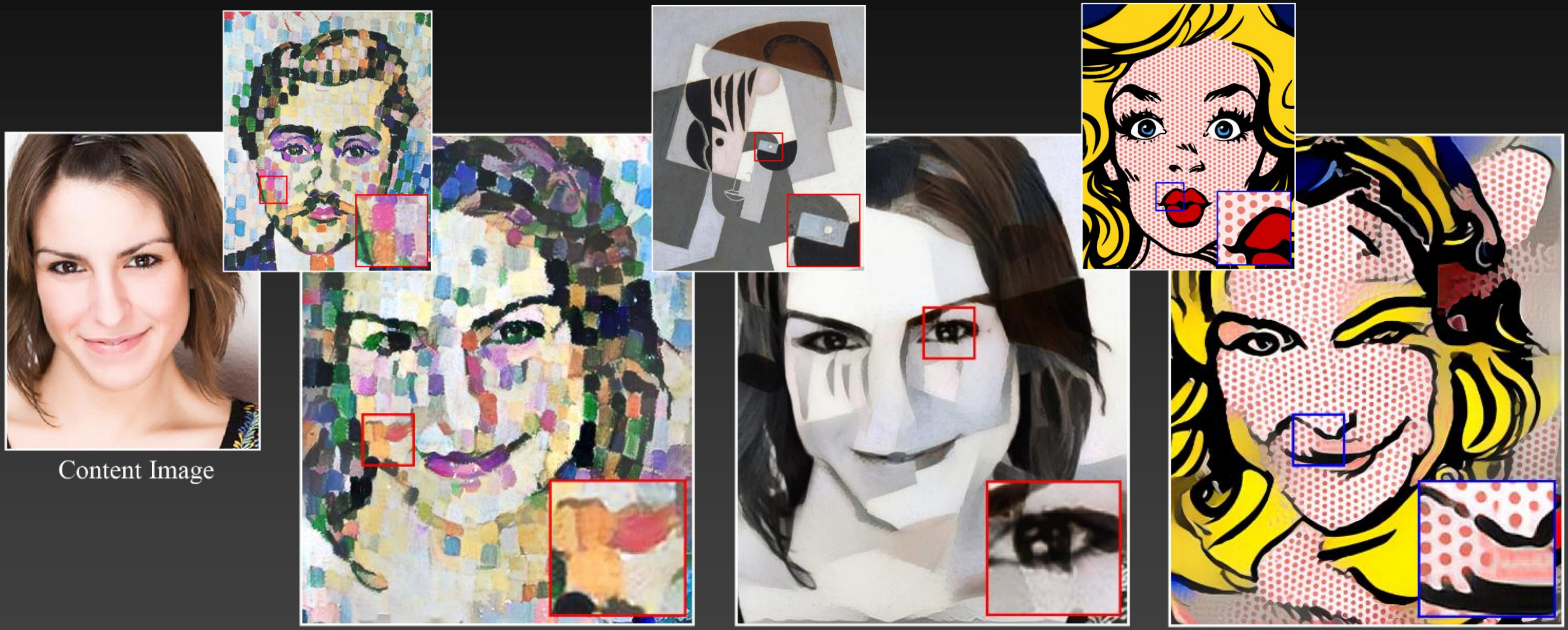
	Publication	Color Maps	Feature Maps	Geometry Maps	Location-based Filtering	Color-based Filtering	Feature-based Filtering	Point / Line / Area	Color / Brightness	Form / Shape / Size	Space / Texture	Transparency	Orientation	Shading / Shadows	Crispness / Resolution	Coherence / Continuity	Pictorial Cues	User Interaction
Neural Networks	Anderson et al. [2016]	×	×								×					×		
	Champandard [2016]	×	×		×		×				×							
	Chen & Schmidt [2016]	×									×							
	Dumoulin et al. [2017]	×									×							
	Gatys et al. [2016a]	×				×					×							
	Gatys et al. [2016b]	×				×					×							
	Gatys et al. [2016c; 2017]	×	×		×	×			×		×							
	Gupta et al. [2017]	×	×								×					×		
	Huang & Belongie [2017]	×									×				×			
	Iizuka et al. [2016]	×							×		×							
	Johnson et al. [2016a]	×									×				×			
	Li & Wand [2016]	×									×							
	Liu et al. [2017]	×		×	×						×						×	
	Risser et al. [2017]	×	×		×		×				×							
	Ruder et al. [2016]	×	×								×					×		
	Selim et al. [2016]	×	×				×			×	×					×		
	Taigman et al. [2016]	×									×							
	Ulyanov et al. [2016a]	×									×							
	Ulyanov et al. [2017a]	×	×				×				×							
	Ulyanov et al. [2016b]	×									×							

** non-exhaustive general picture as of 05/2017*

Proposal 1: Semiotics-based Optimization

Style Image: Vincent van Gogh – "Starry Night"

Current Limitations



Content Image

Neural Style Transfer

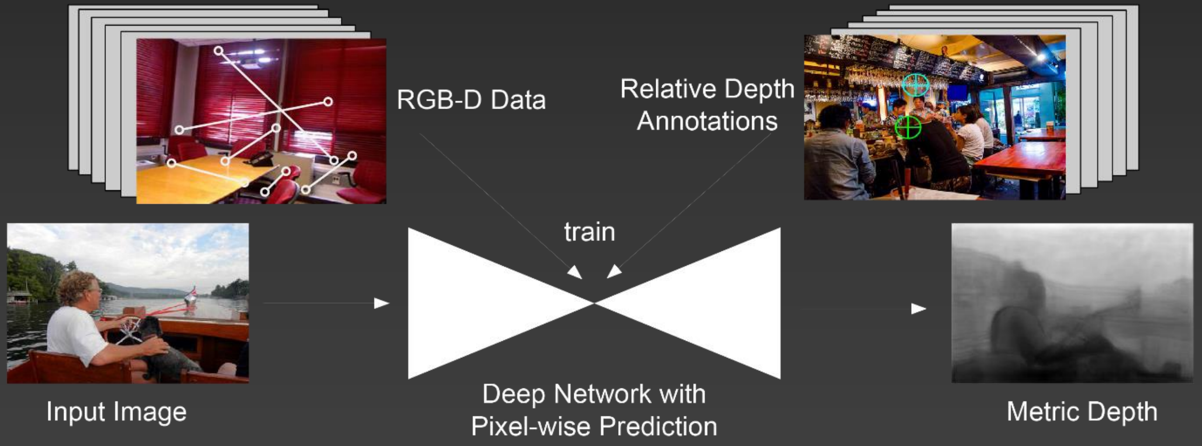
Neural Style Transfer

Neural Style Transfer

Proposal – Use / Model additional Image Information

Use additional information besides color to “separate style from content”:

- Modeling aspects: semantics, depth, shading/lighting, orientation, segmentation
- Use semiotics-based loss functions to weight aspects in optimization stage



“Single-Image Depth Perception in the Wild” [Chen et al. 2016, NIPS]

“Intrinsic Images in the Wild” [Bell et al. 2014, SIGGRAPH]

Example – Image Masking [Gatys et al. 2017, CVPR]

“Controlling Perceptual Factors in Neural Style Transfer”

- Use image masks to mix style representations, adjust color and spatial scale

Location-based Style Control

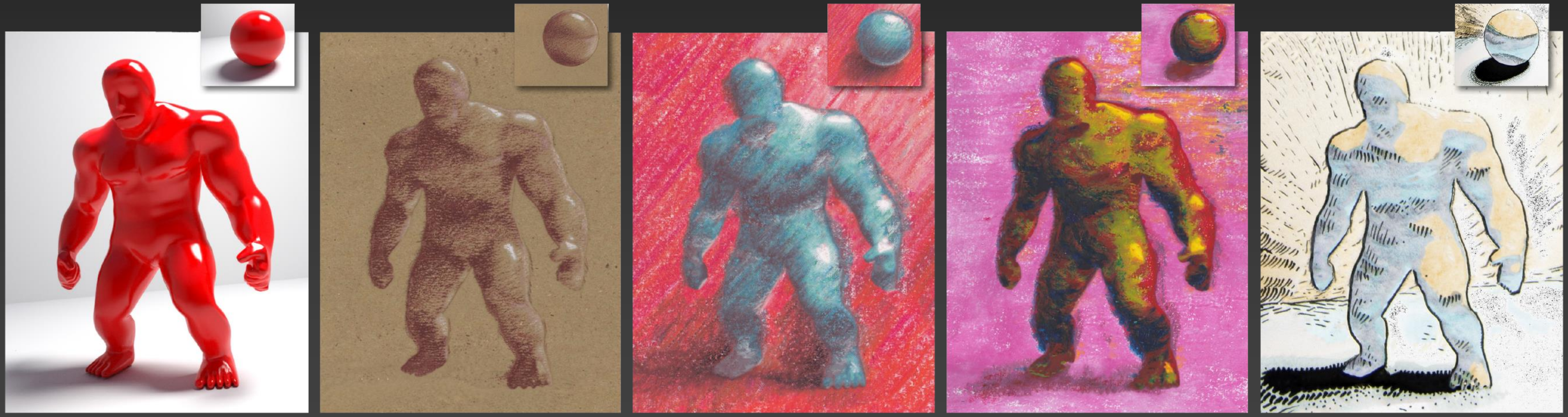
Color Control

Size Control

Example – StyLit [Fišer et al. 2016, SIGGRAPH]

“Illumination-Guided Example-Based Stylization of 3D Renderings”

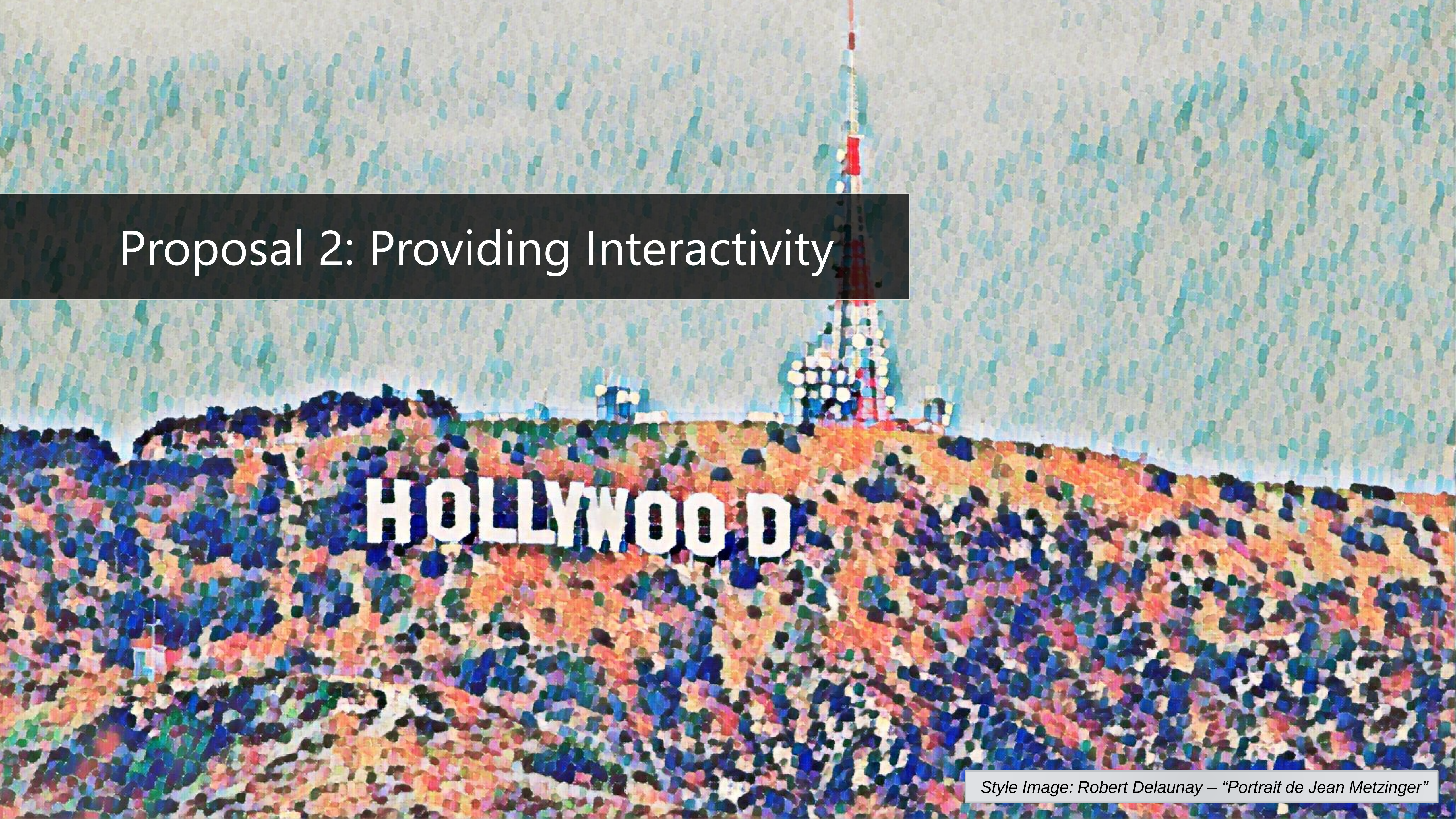
- Illuminations-specific guidance is necessary for faithful style transfer



Challenges

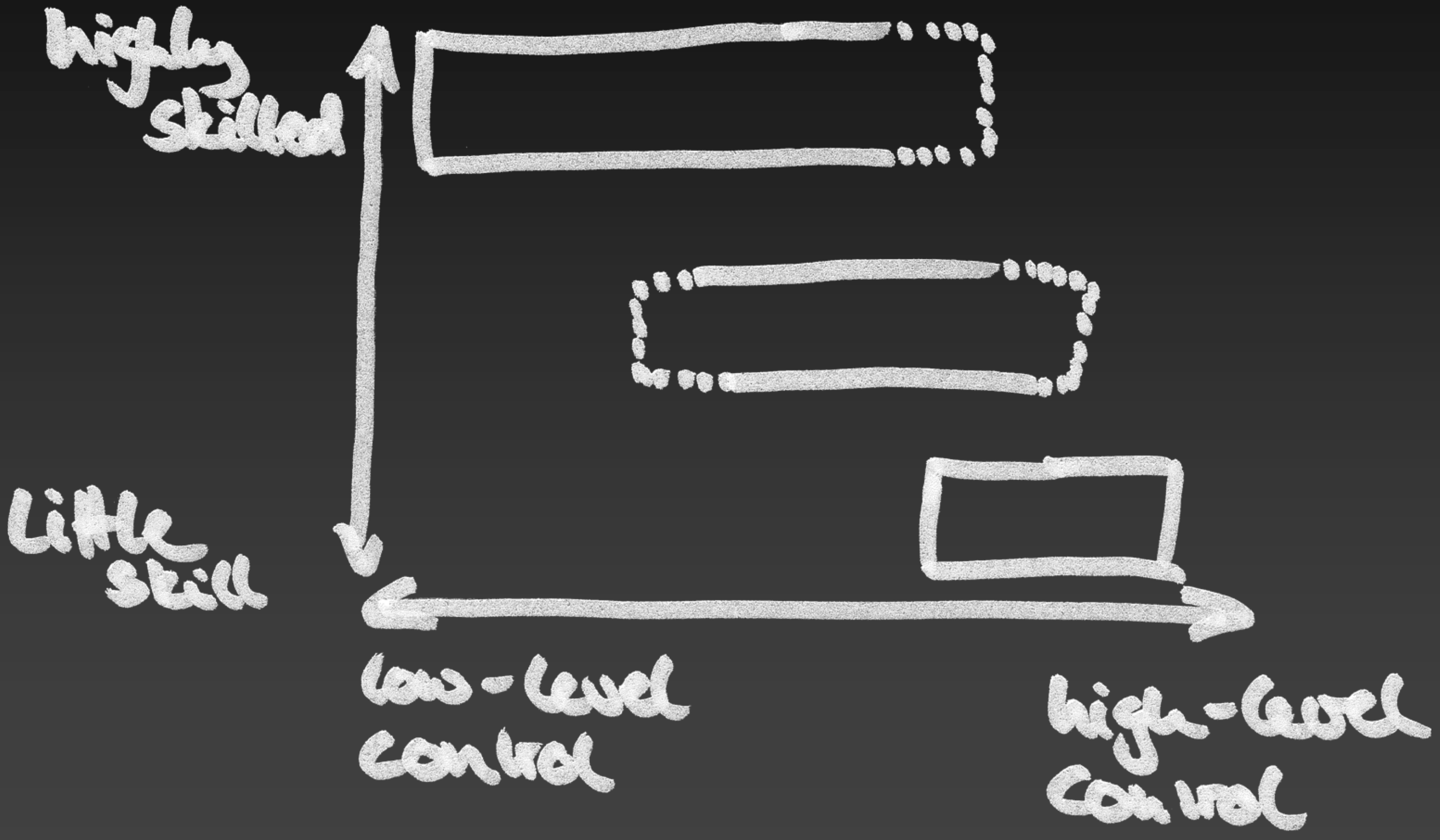
1. How to generally provide required modeling and filtering information for style and content images?
2. How to optimally weight semiotic aspects, e.g., by loss functions?
3. To what degree does or should a semiotics-oriented style transfer require supervision?
4. How to elementary control design aspects on low-level and high-level?

Proposal 2: Providing Interactivity



Style Image: Robert Delaunay – “Portrait de Jean Metzinger”

Mapping the Interaction Spectrum [Isenberg 2016, NPAR]



Build tools for “right-brained” thinking [Salesin 2002, NPAR]

NPAR for artists: Control needed at multiple levels

[„IMPaSTo“, Baxter et al. 2004, NPAR]

[„IntuPaint“, Vandoren et al. 2008, TABLETOP]

Build tools for “right-brained” thinking [Salesin 2002, NPAR]

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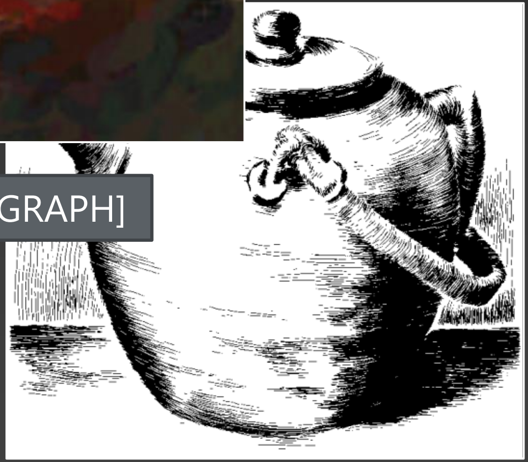
NPAR for non-artists: Simple UI with user-assisted control

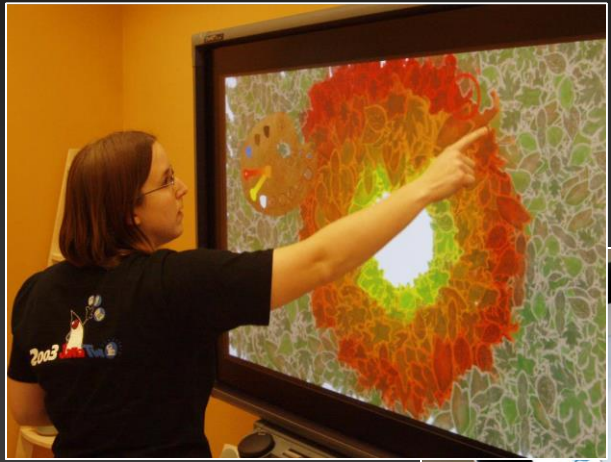
Techniques

[Hertzmann 1998, SIGGRAPH]

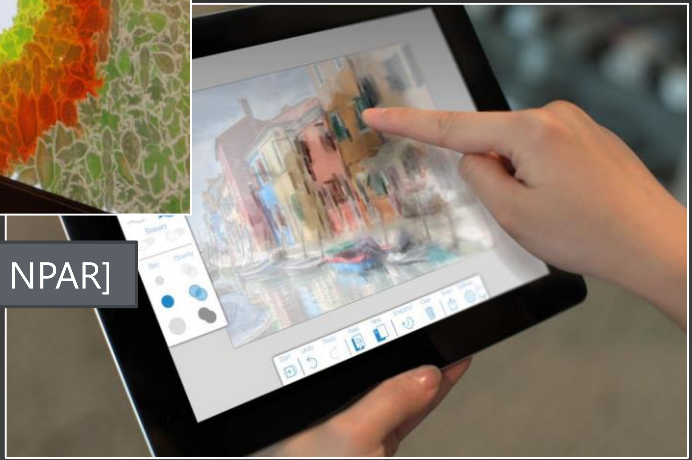


[Salisbury et al. 1997, SIGGRAPH]

Interactive tools / devices

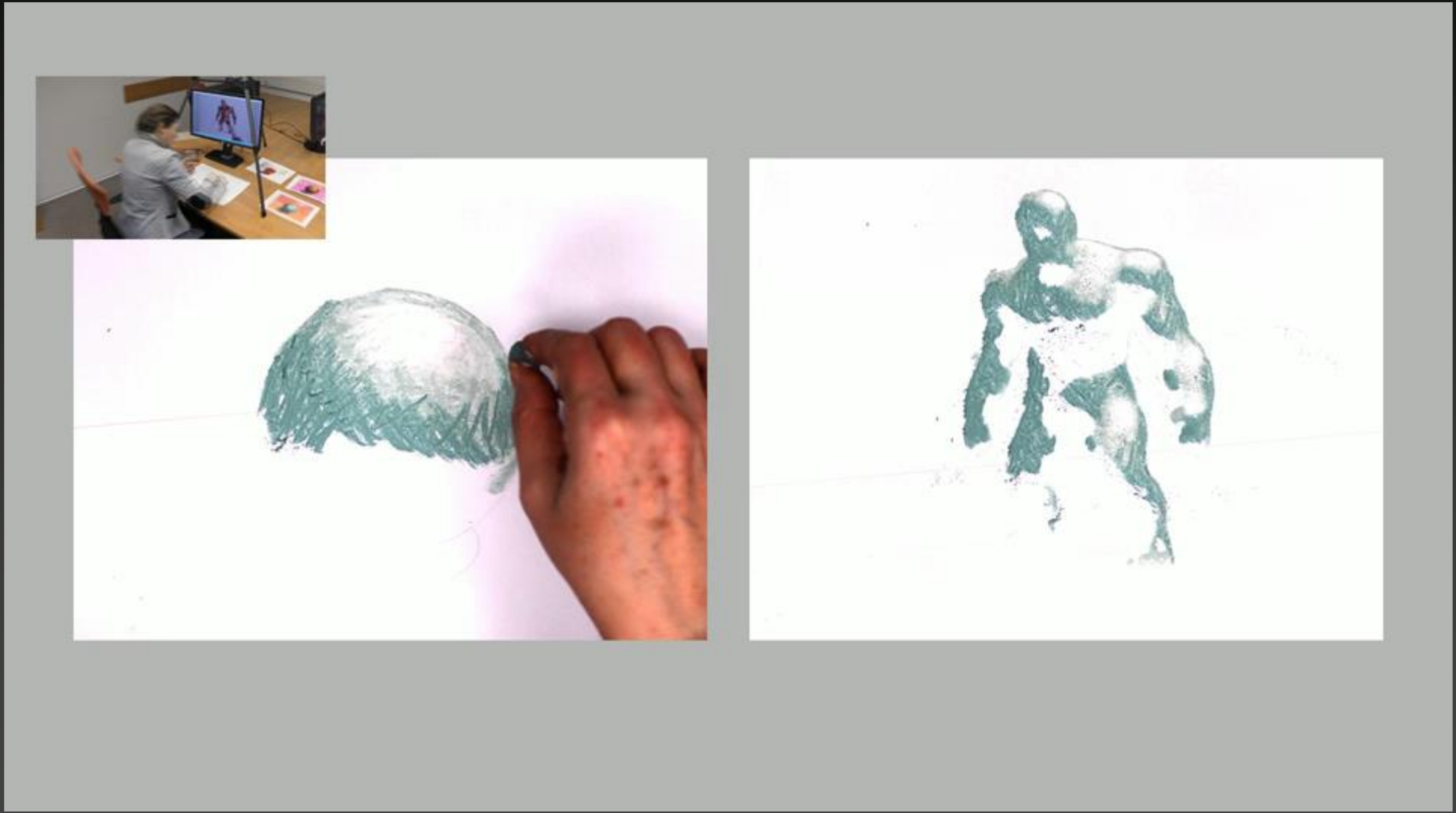


[Schwarz et al. 2007, NPAR]



[Adobe PaintCan]

Example – StyLit [Fišer et al. 2016, SIGGRAPH]



Interactive Tools For Low- and High-level Adjustment Required

How to locally adjust design aspects such as color, orientation, scale per „rendering primitive“ to adjust the final output ?

Proposal – Modifying a Latent Encoding of Style

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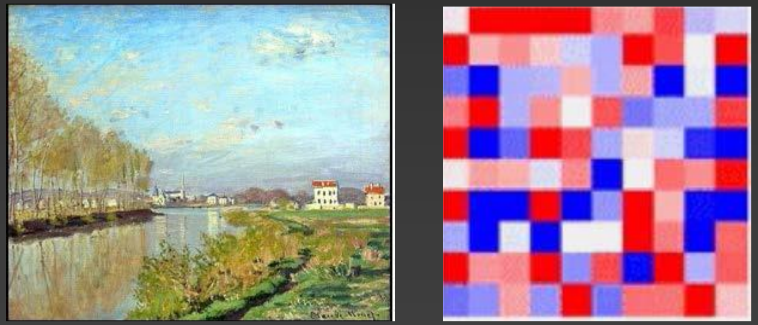
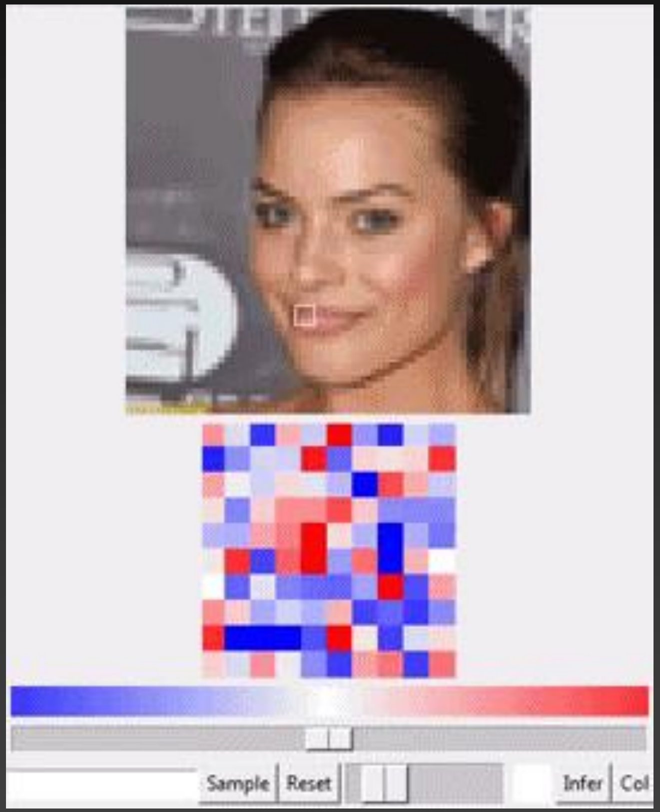
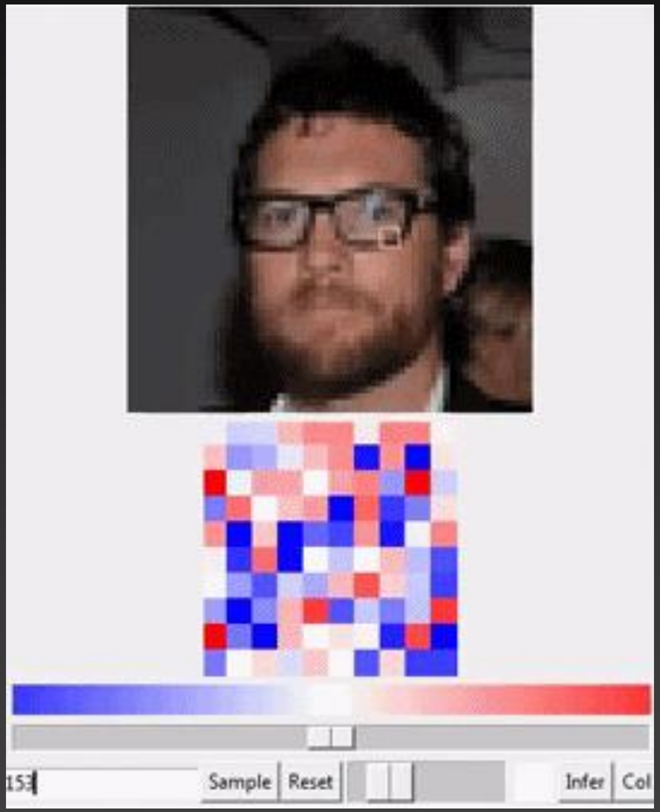
- Try to build on Introspective generative adversarial networks (GANs)
- <u>Challenge:</u> Learning a latent encoding is unsupervised



Latent encoding for a Monet painting

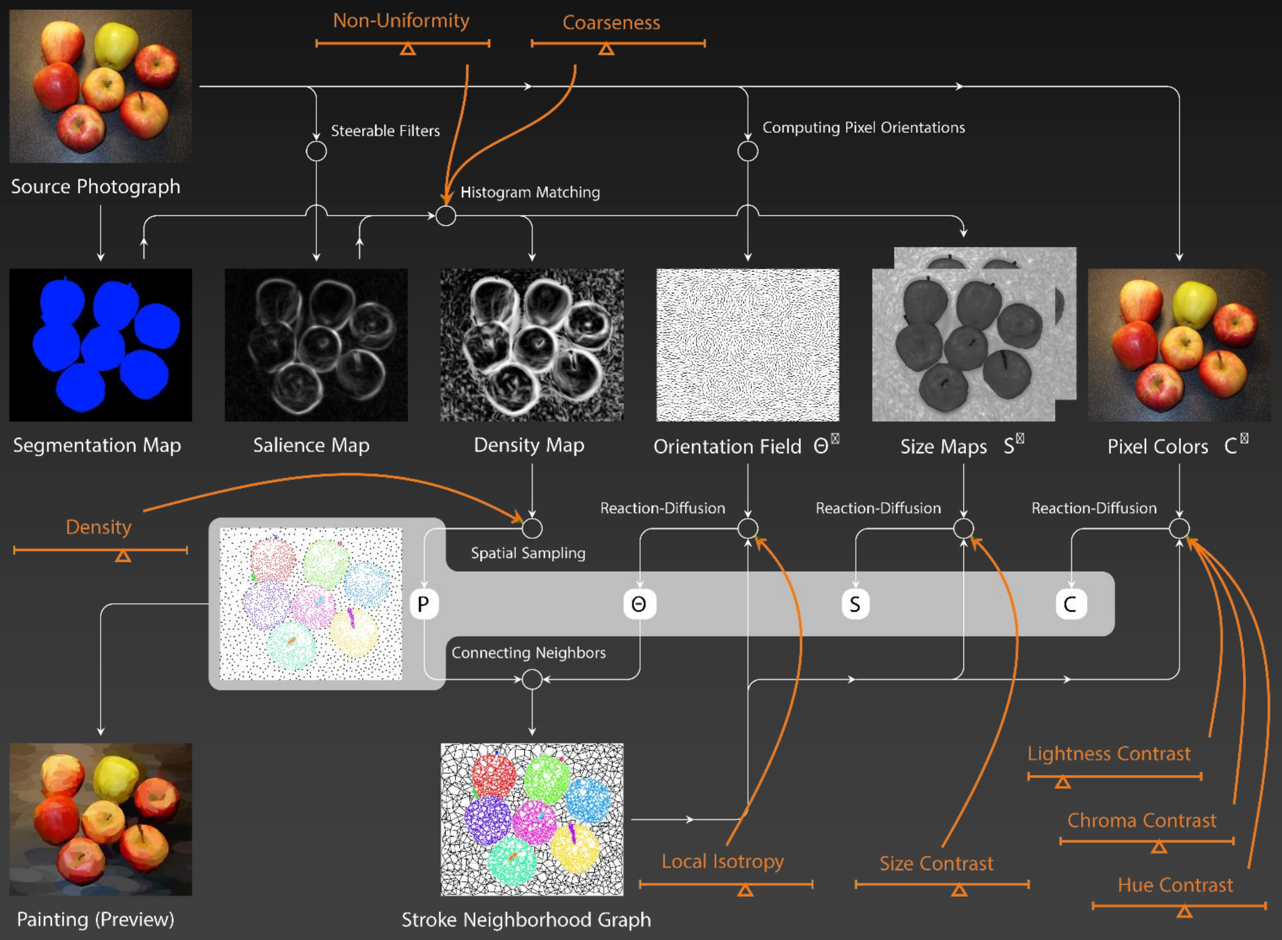




[„*Neural Photo Editing with Introspective Adversarial Networks*“, Brock et al. 2016, arXiv.org report]

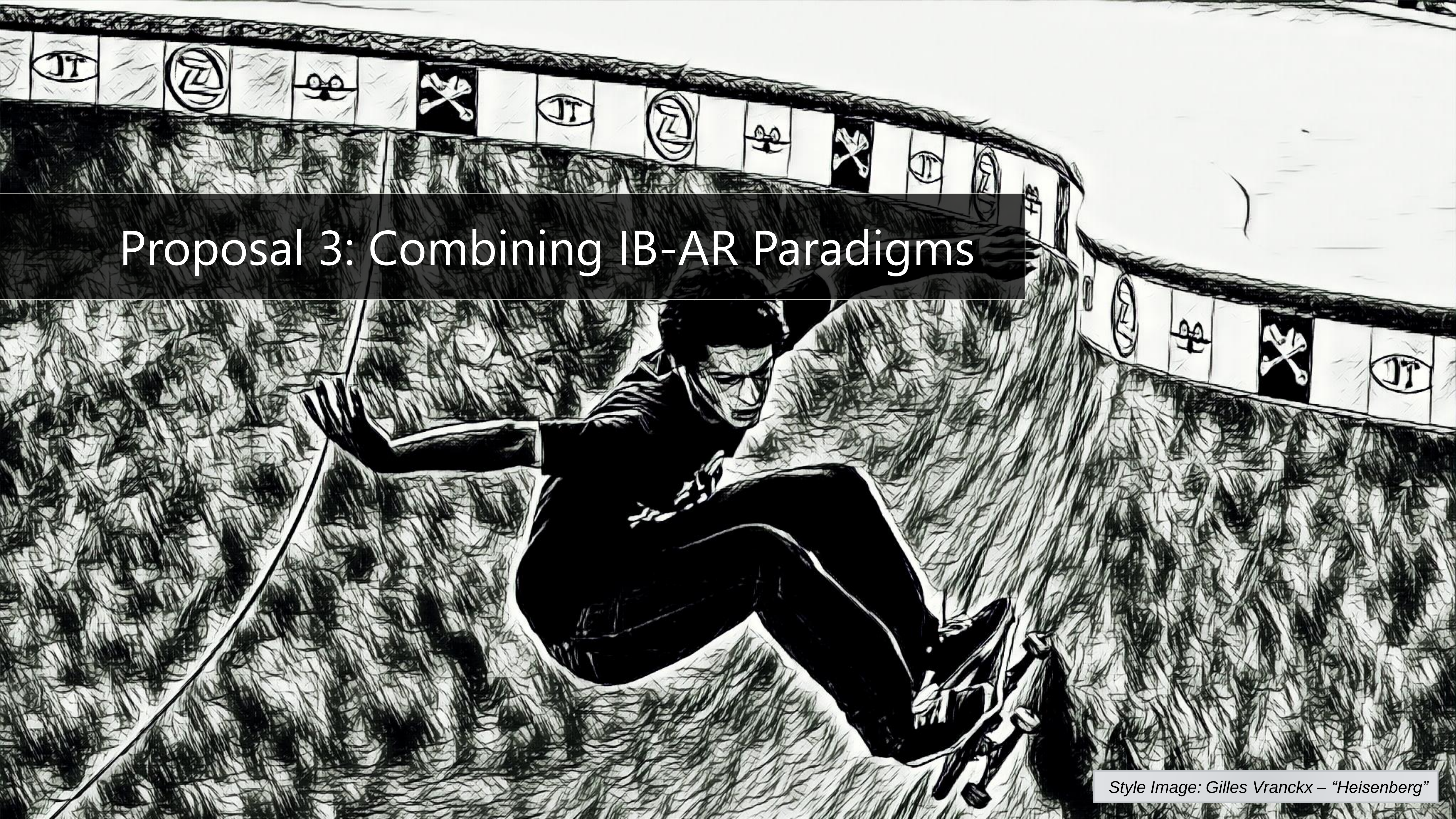
Proposal – Parameter Maps

- Feed parameter maps into optimization stage as additional constraints
- <u>Example:</u> Painterly rendering styles using stroke processes [Zhao and Zhu 2011, NPAR]
- Use intermediate results for re-initialization and fine-tuning [Gatys et al. 2017, CVPR]



[Zhao and Zhu 2011, NPAR]

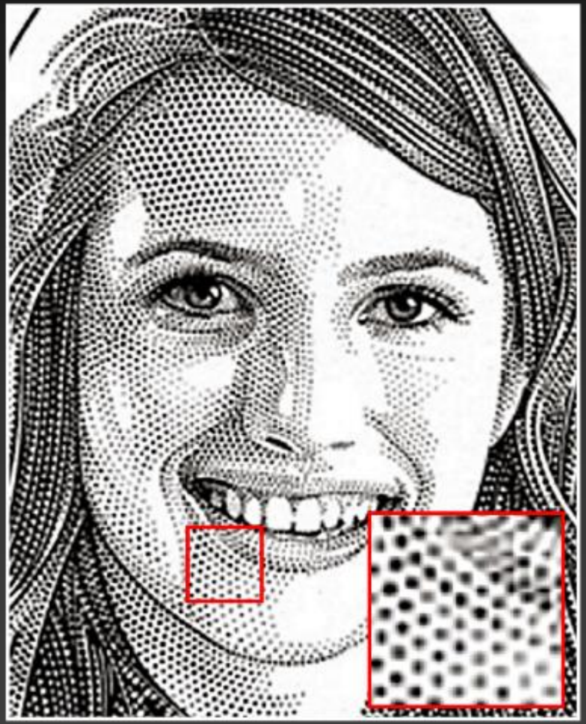
Proposal 3: Combining IB-AR Paradigms



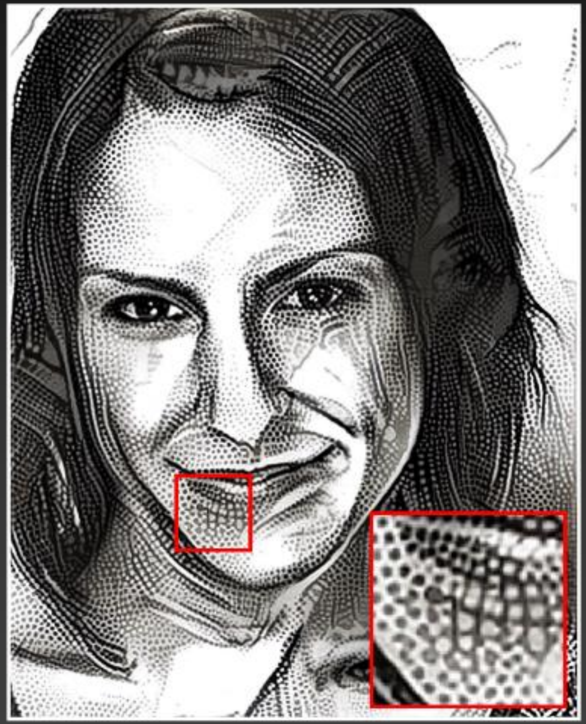
Style Image: Gilles Vranckx – "Heisenberg"

Limitations – Example: Image Stippling

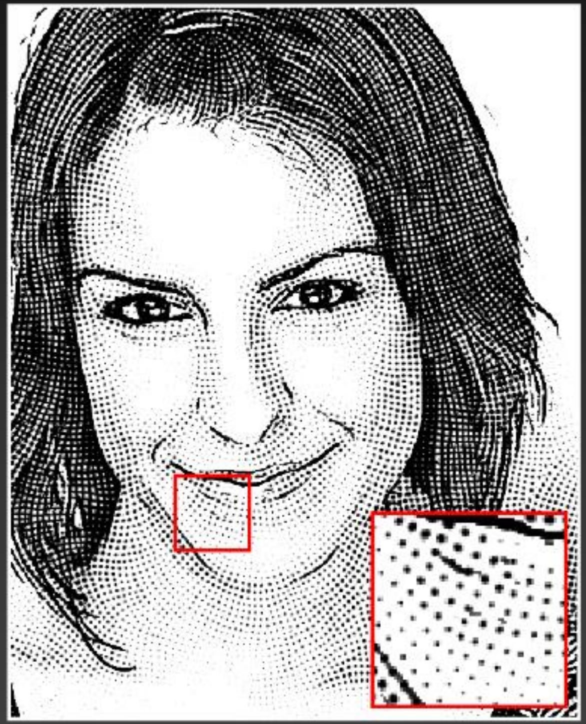
[Content Image]



[Style Image by Randy Glass]



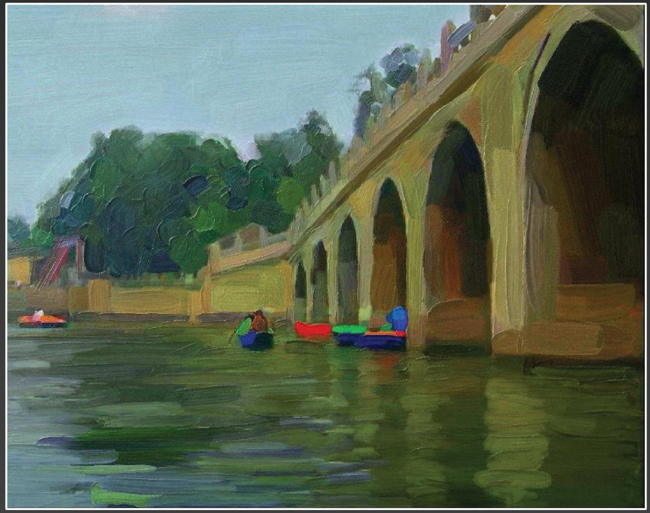
[Neural Style Transfer, Pikazo]



[Son et al. 2011, Graphical Models]

Proposal: Use IB-AR Paradigms for Tasks They Are Good At

SBR: Blending, layering

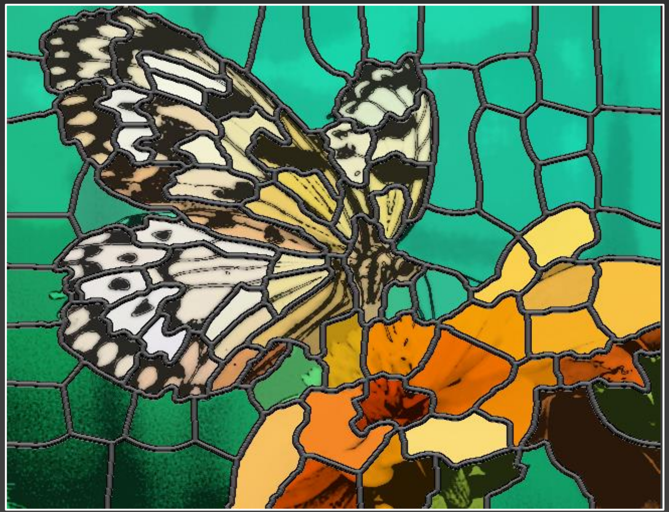


[Zeng et al. 2009, ToG]

IPF: Noise reduction

[Kyprianidis & Kang 2011, Eurographics]

RBT: Segmentation



[Doyle & Mould 2016, CAe]

Case Study: Combining Neural Style Transfer and Image Filtering

Content Image | NST (FJBU as closeup) | NST with Post-process Oil Paint Filtering | NST with Post-process Watercolor Rendering

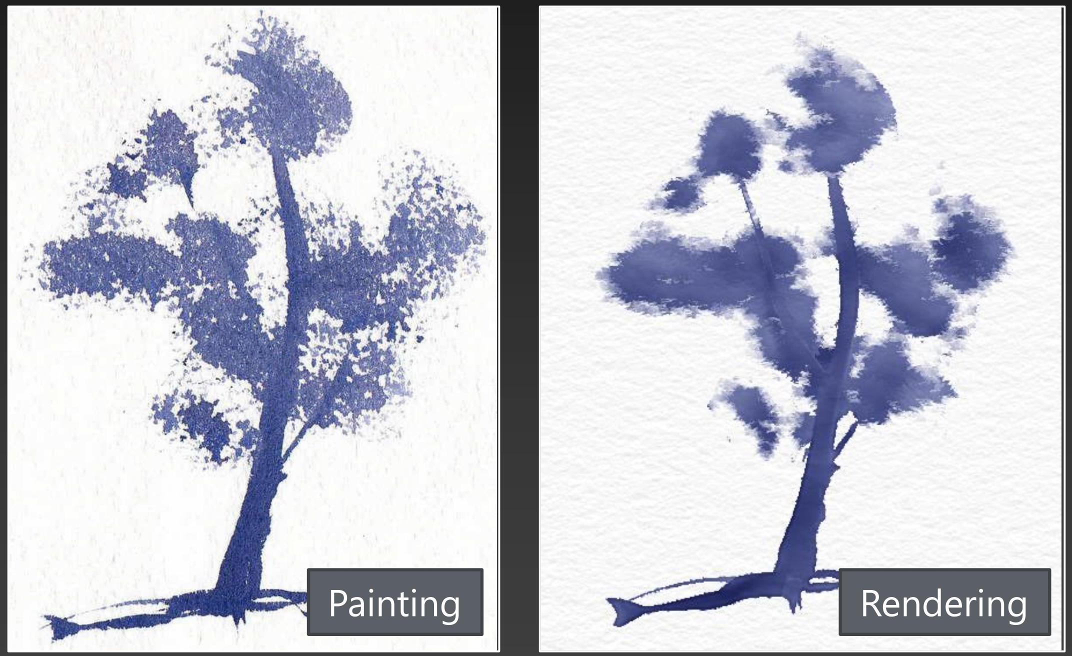
[Semmo et al. 2017, SIGGRAPH Appy Hour]

Case Study: Combining Neural Style Transfer and Image Filtering

Further Additions: Physically-based and Distortion Effects

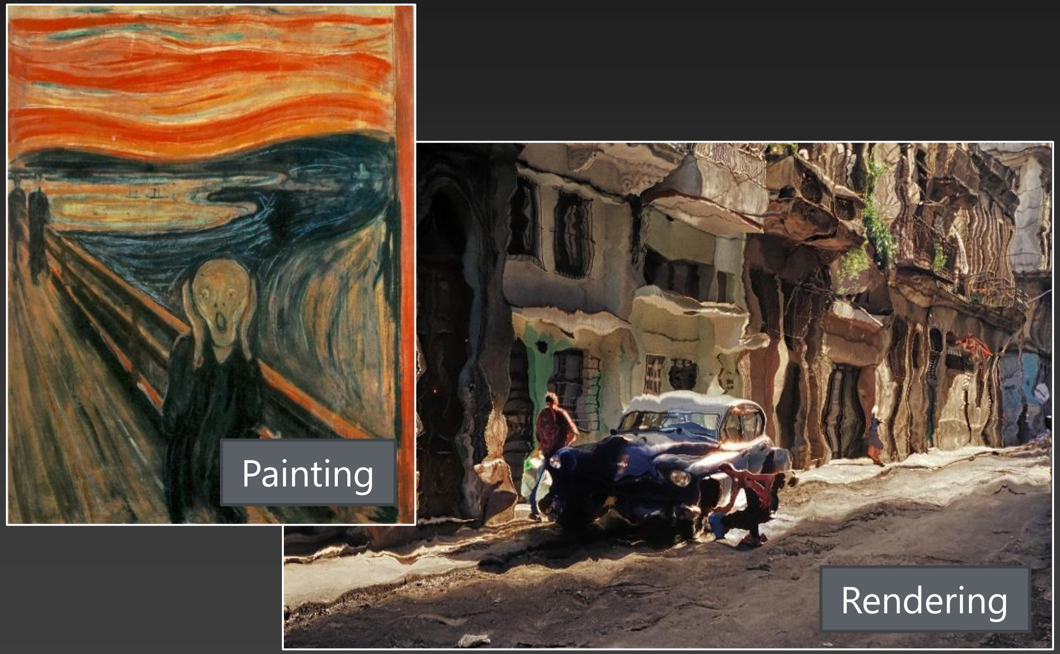
Hasso Plattner Institut

Substrate-based Effects



[Montesdeoca et al. 2017, NPAR]

Image Warping



[Li & Mould et al. 2015, CAe]

Proposal 4: New Forms of Art

Style Image: Francis Picabia – “Udnie”

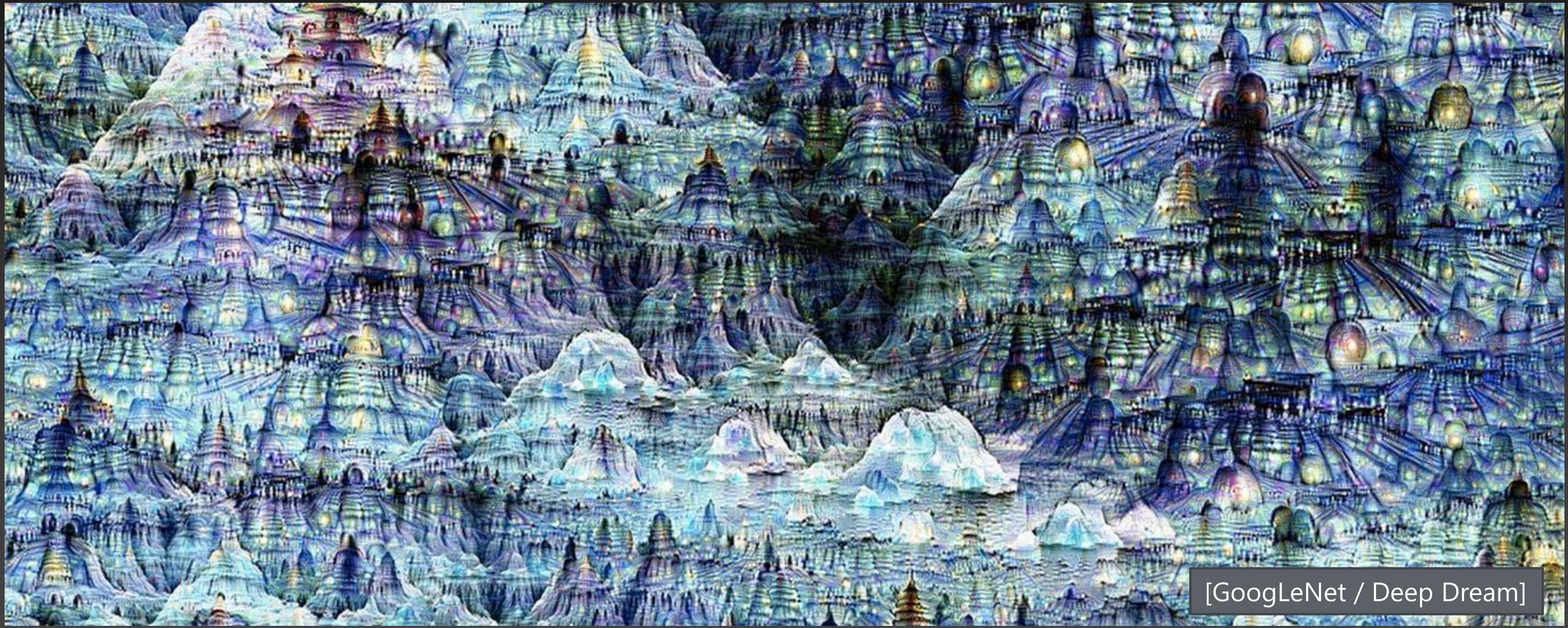
Challenge:

Can computing be used to create some entirely new and original forms of art?

[Salesin 2002, NPAR]

Large-scale Visual Recognition by Deep Neural Networks

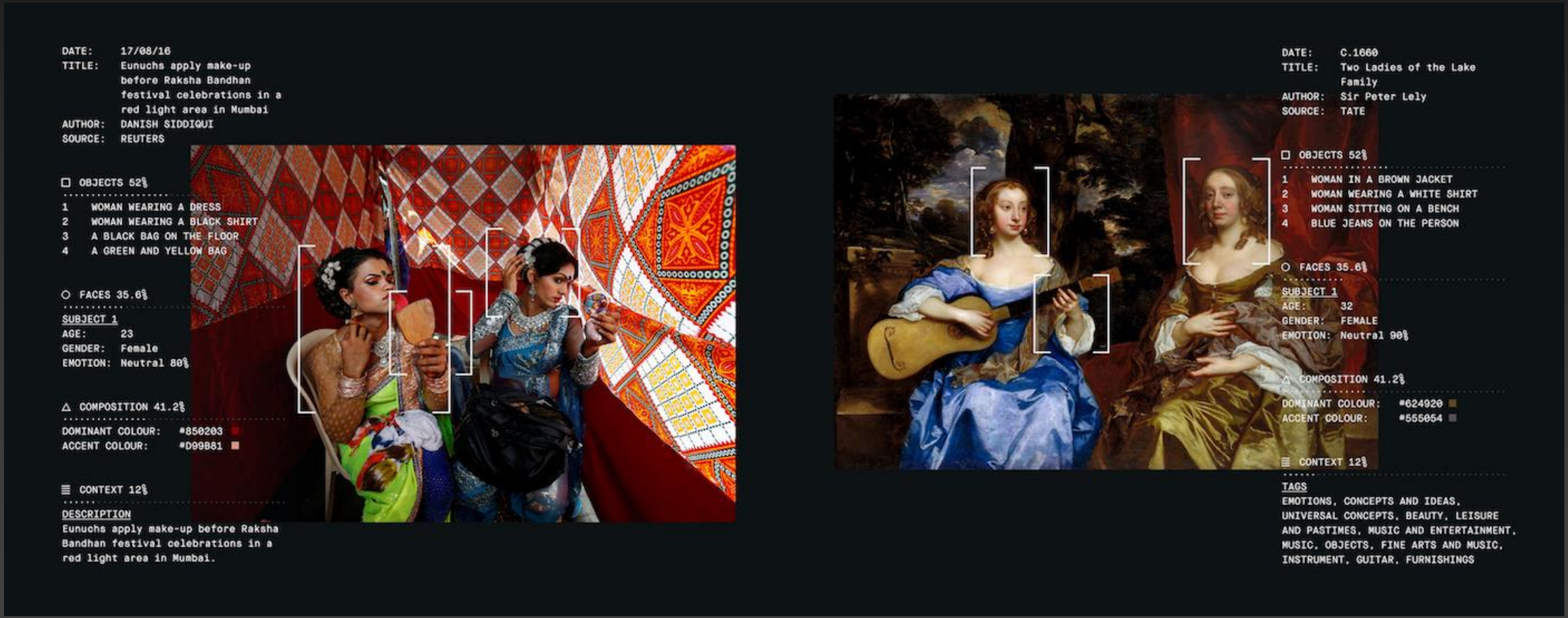
- First used in an artistic context by Google's Deep Dream engine



[GoogLeNet / Deep Dream]

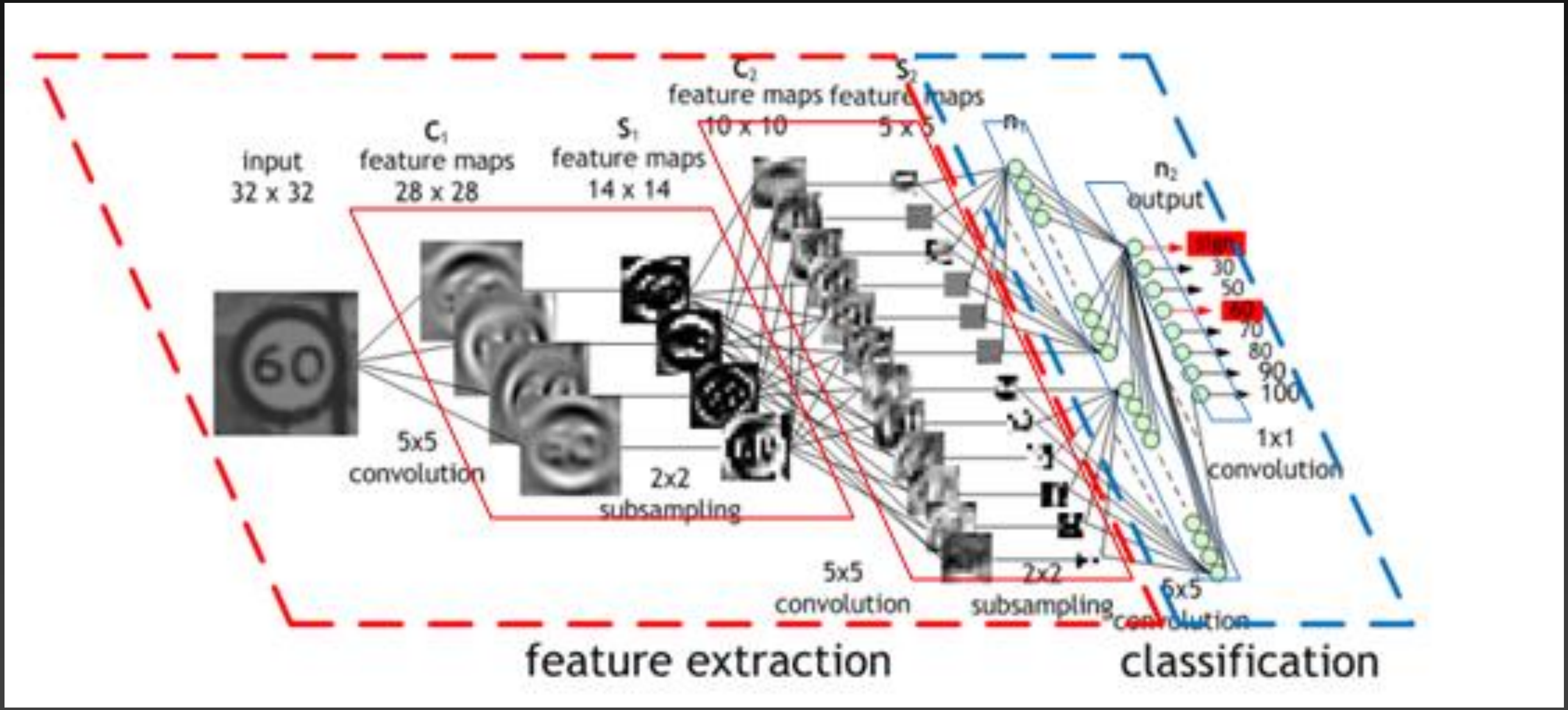
Large-scale Visual Recognition by Deep Neural Networks

"Recognition AI" (Tate IK 2016): Matches old British art to new photojournalism



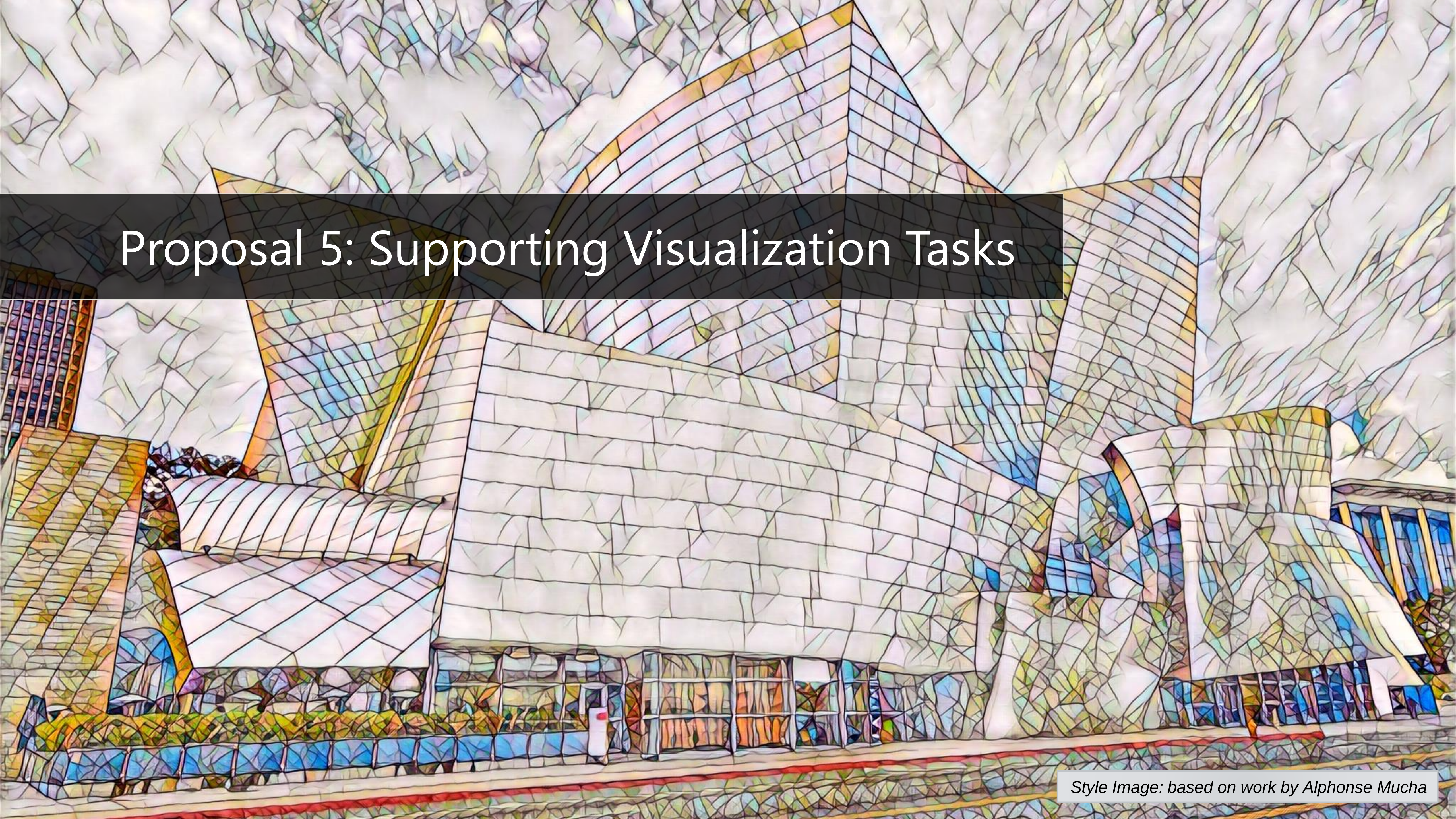
Use style descriptions to transfer style characteristics from rule-based sets and assets rather than style images to create new forms of art?

Proposal: Use Classification to Inject Custom Style Representations



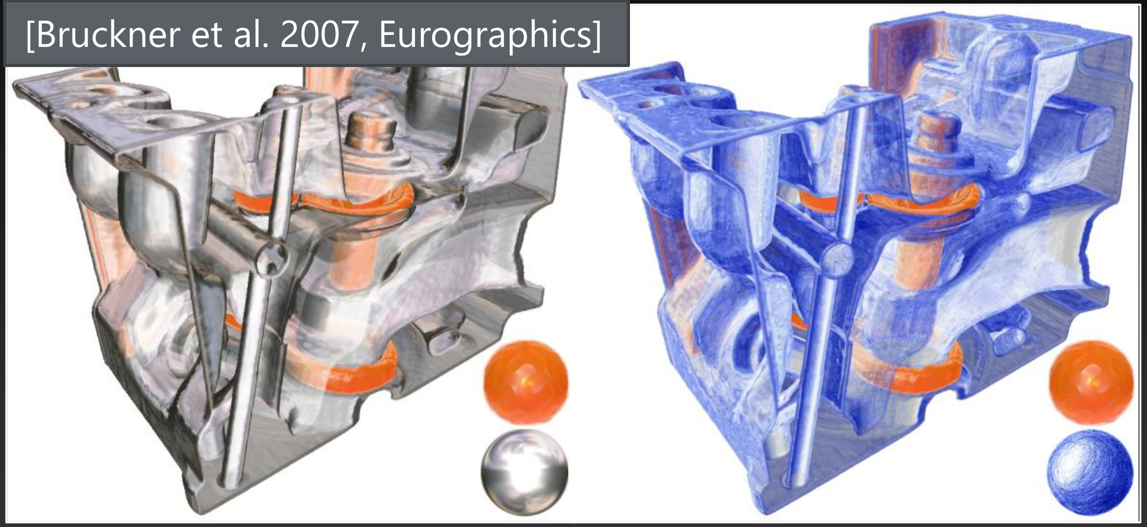
[Image by Maurice Peemen]

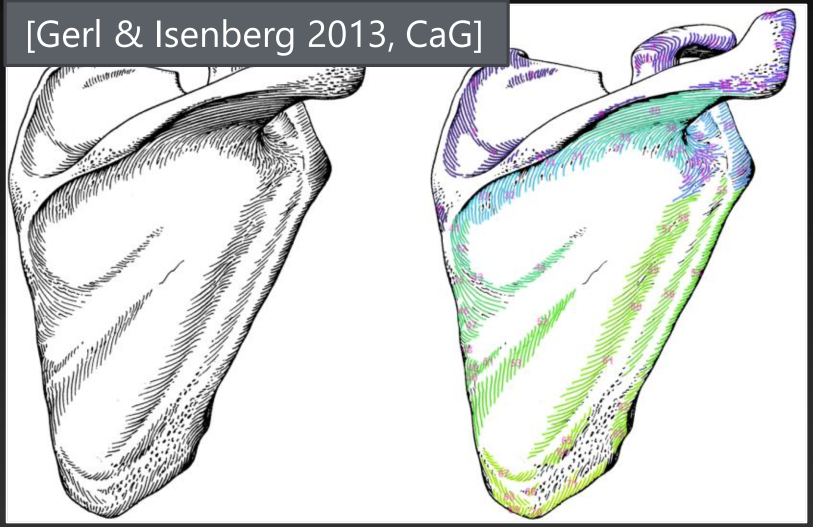
Proposal 5: Supporting Visualization Tasks

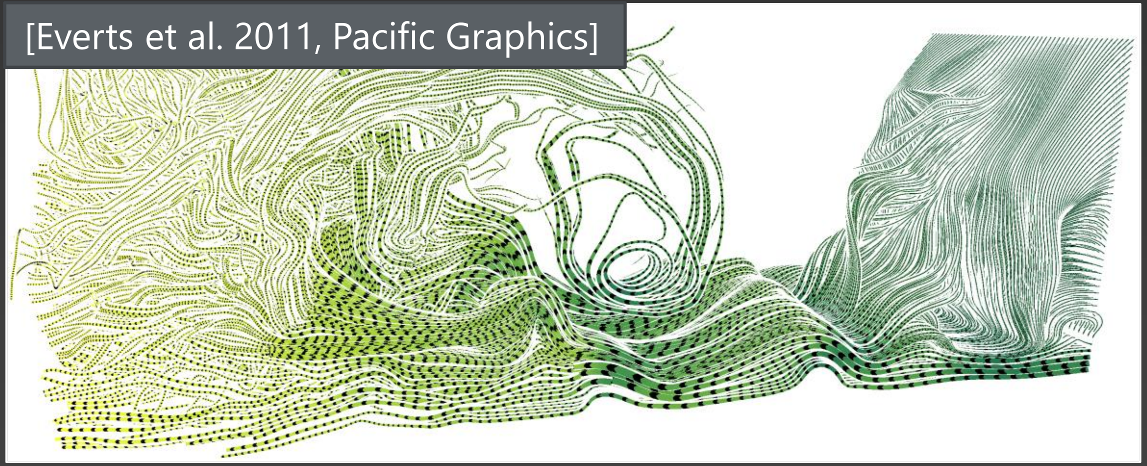


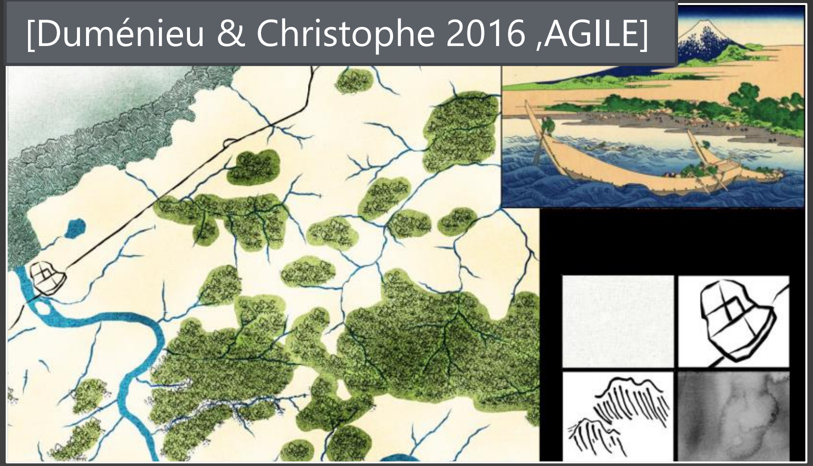
Style Image: based on work by Alphonse Mucha

Style Transfer in Illustrative Visualization


[Bruckner et al. 2007, Eurographics]


[Gerl & Isenberg 2013, CaG]


[Everts et al. 2011, Pacific Graphics]


[Duménieu & Christophe 2016 ‚AGILE]

Key concept: Level of Abstraction

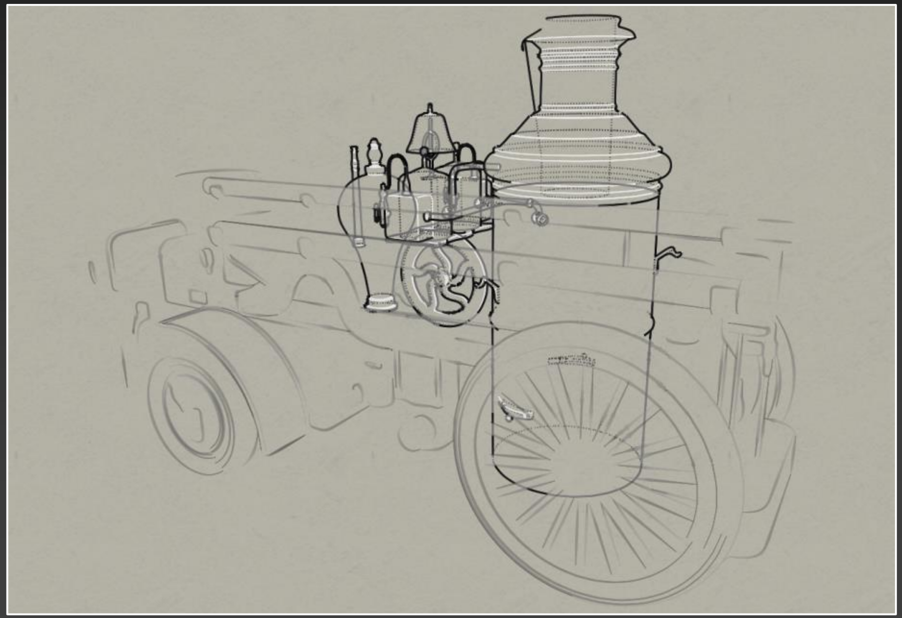
[Gatys et al. 2016, CVPR]

How to represent the spatial and thematic granularity of image contents according to user task, camera view and image resolution?

Proposal: Focus+Context Visualization

Complies with information seeking mantra: “Overview first, zoom and filter, then details-on-demand” [Shneiderman, 1996]

[DeCarlo & Santella 2002, SIGGRAPH]



[Grabli et al. 2004, EGSR]

Proposal: Toolboxes of Illustration Styles

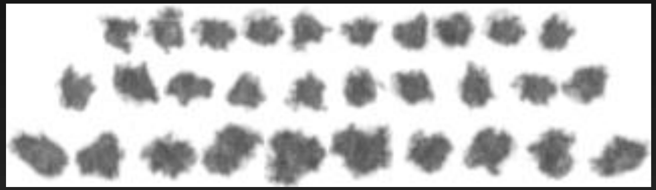
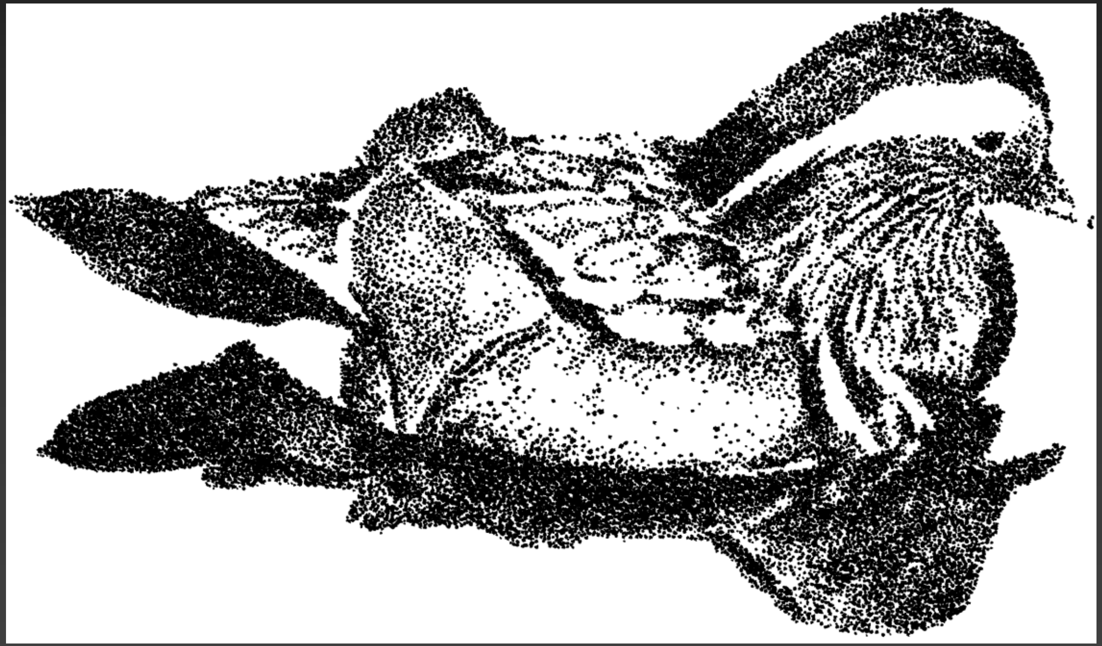
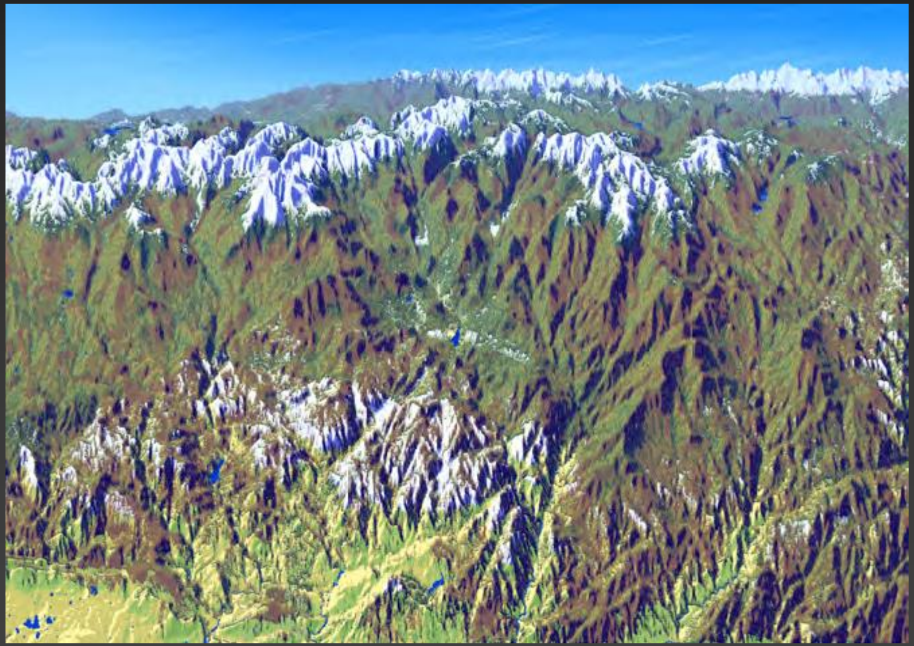


Illustration Styles /
Texture Marks



[Martín et al. 2011, CaG]



[Bratkova et al. 2009, Tog]

Proposal 6: Evaluation

Style Image: Hokusai – "The Great Wave off Kanagawa"

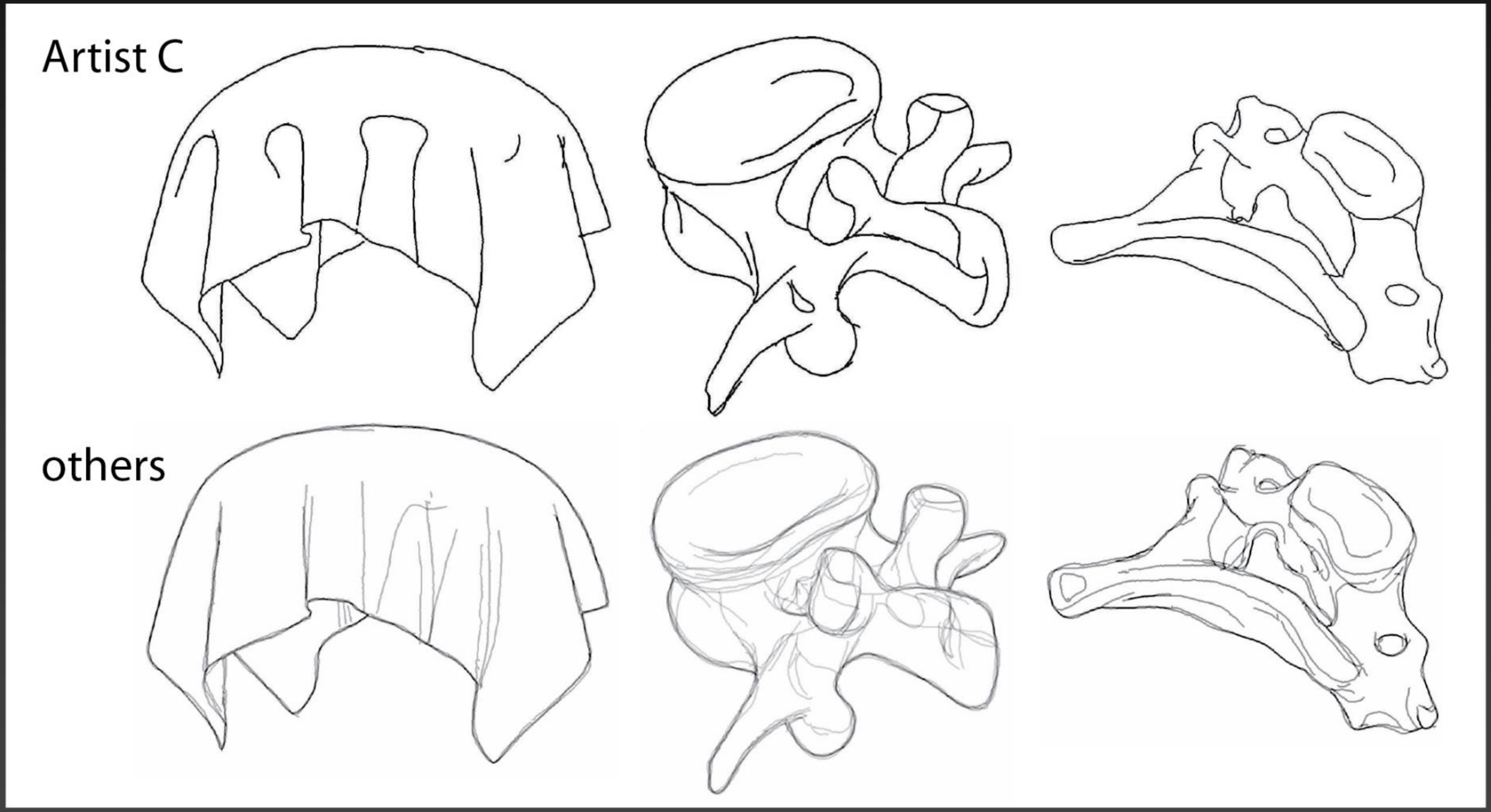
Visual Turing Test – Preliminary Choice Experiment

- Participants had to select hand-painted images from 10 pairs with NST results
- Average of 45,000 participants answered 6.1 image pairs correctly

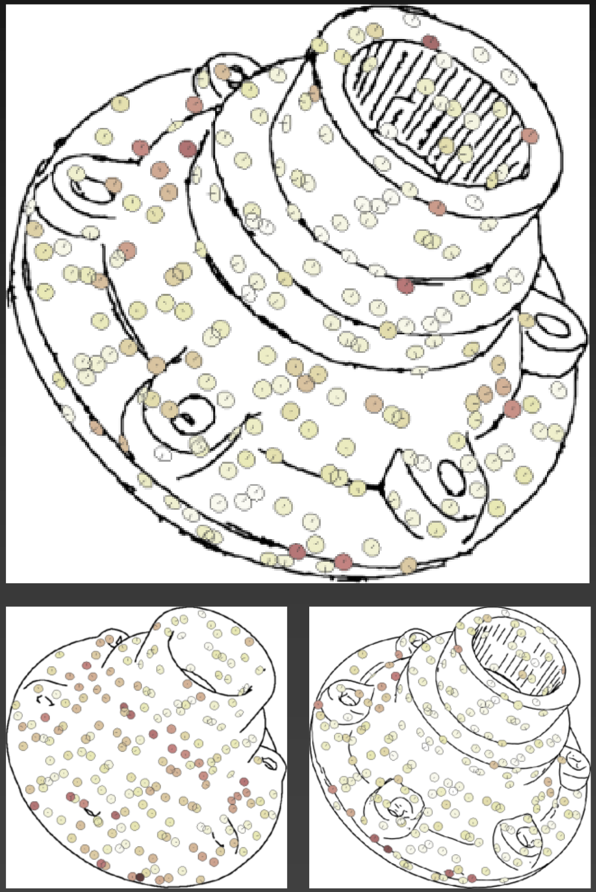
[turing.deepart.io]

Comparing Hand-Made Images with Computer-Generated NPR

How to feed-back gained knowledge into optimization process of style transfers?



[Cole et al. 2008, SIGGRAPH]



[Cole et al. 2009, SIGGRAPH]

Make Use of Benchmark Image Sets for Comparison!

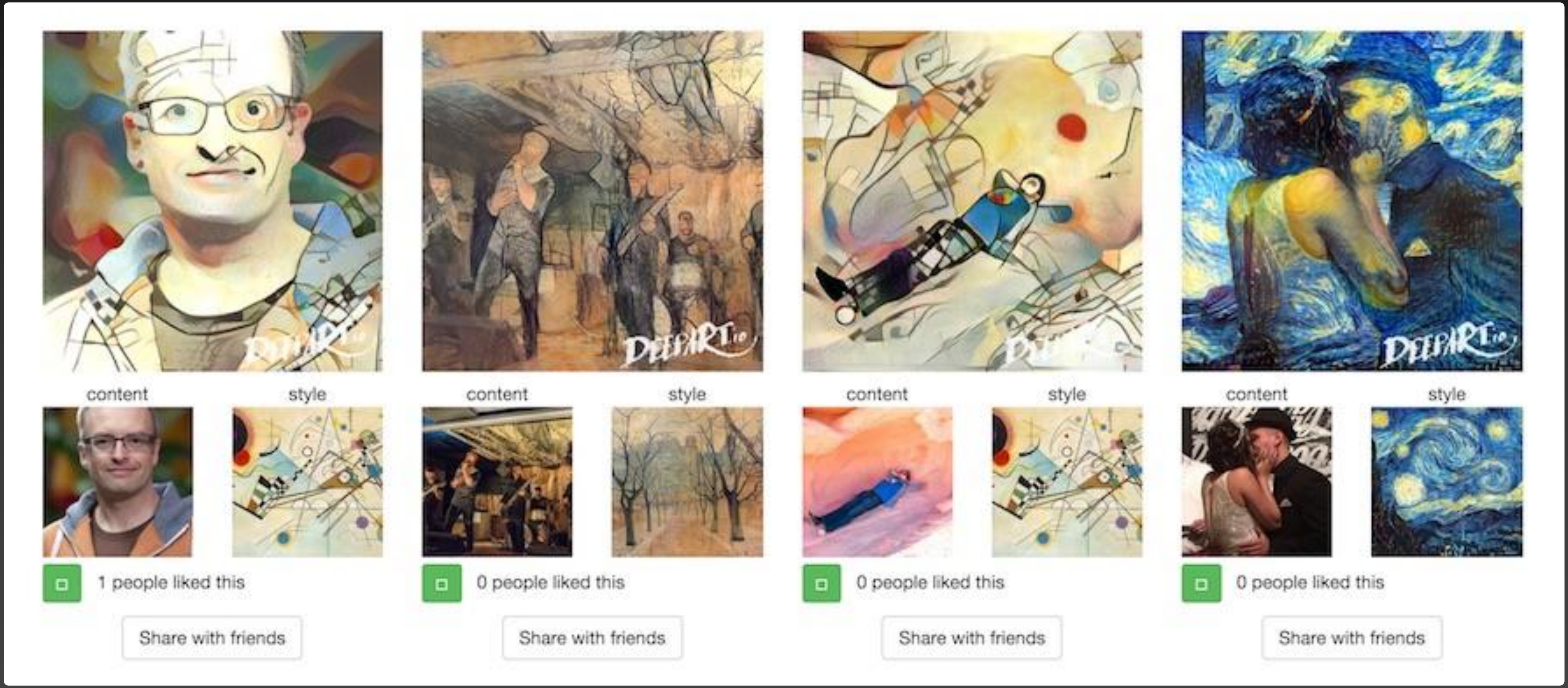
[Mould and Rosin 2016, NPAR]

Applications

Style Image: Prisma – “Dreams”

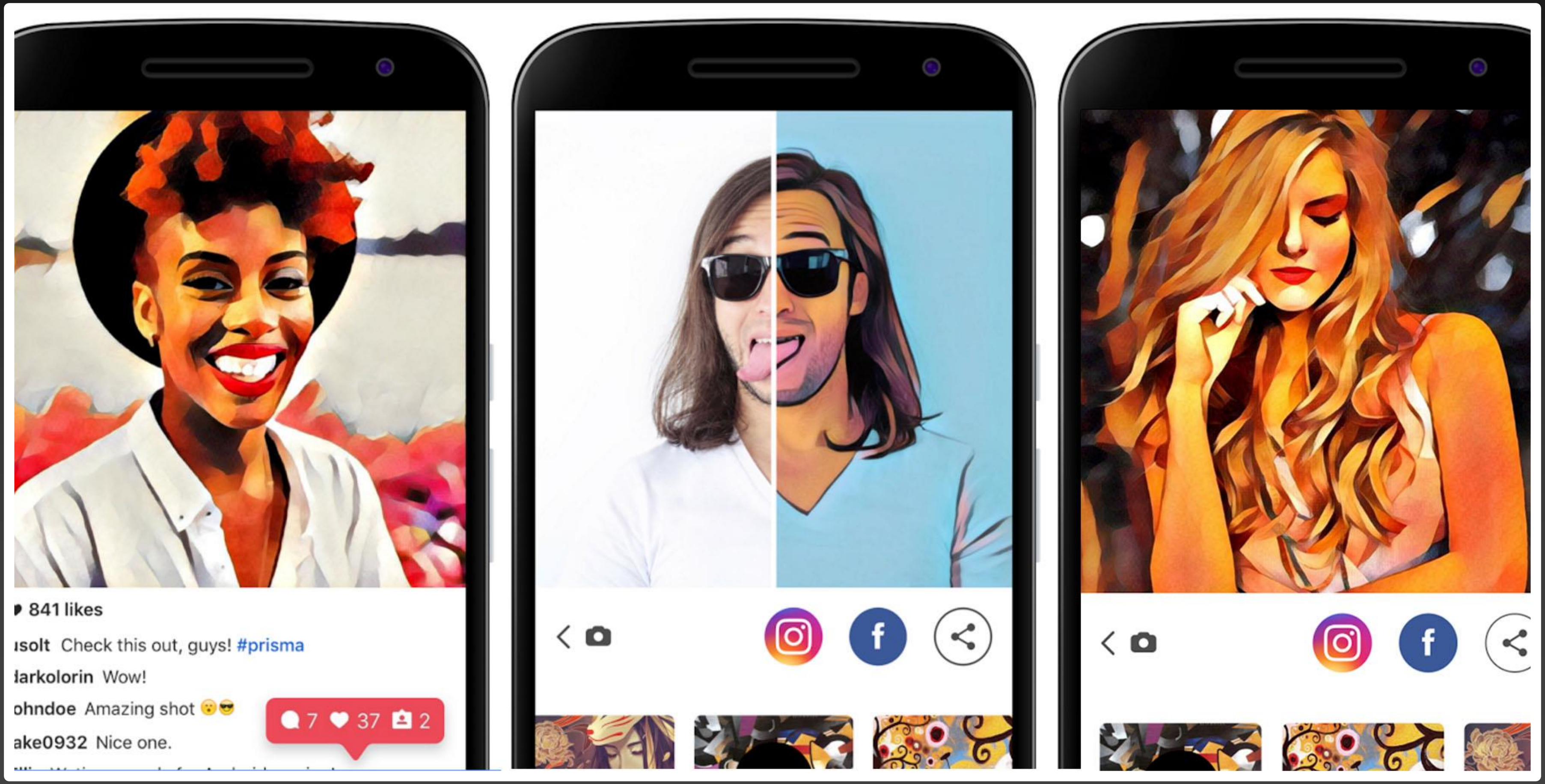
1. Casual Creativity

deepart.io

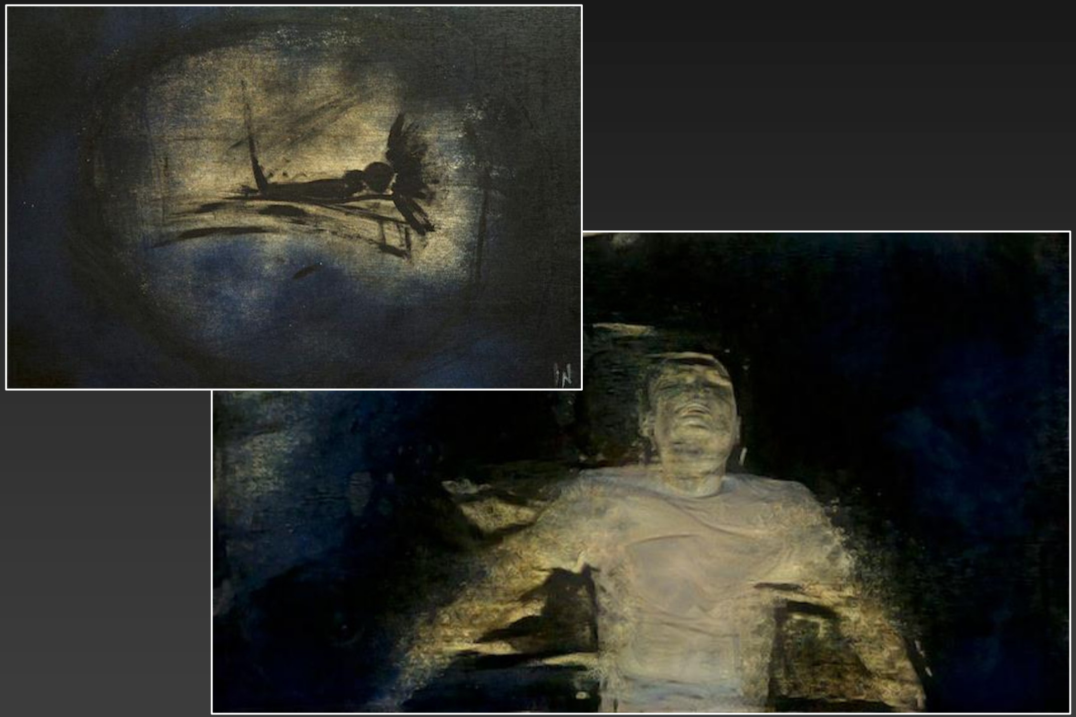


1. Casual Creativity

Prisma (60 million new users in three weeks)



2. Art Productions



[„Come Swim“, Joshi et al. 2016, arXiv]

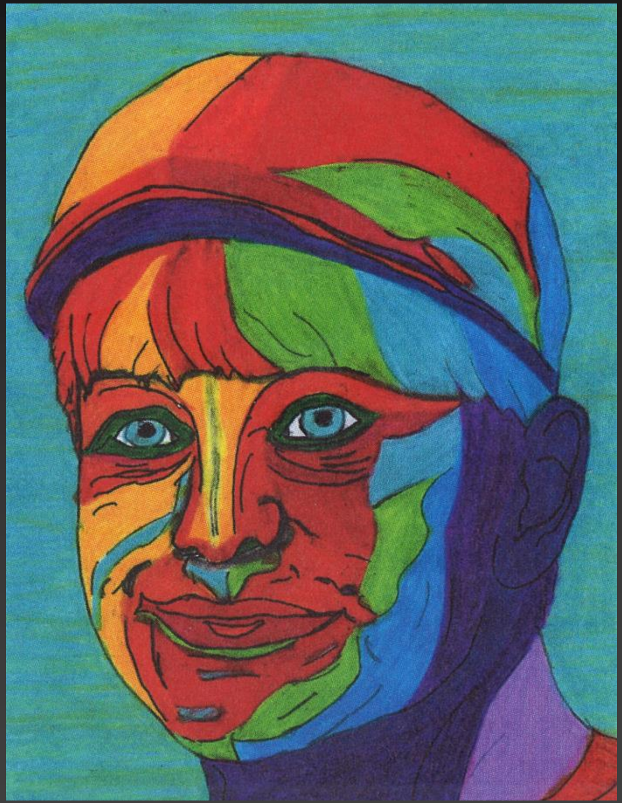
Painting from ‘Loving Vincent’ Style transfer from deepart.io

[„Loving Vincent“, BreakThru Films]

3. Teaching Art Classes

Color Analysis (11-12 years)

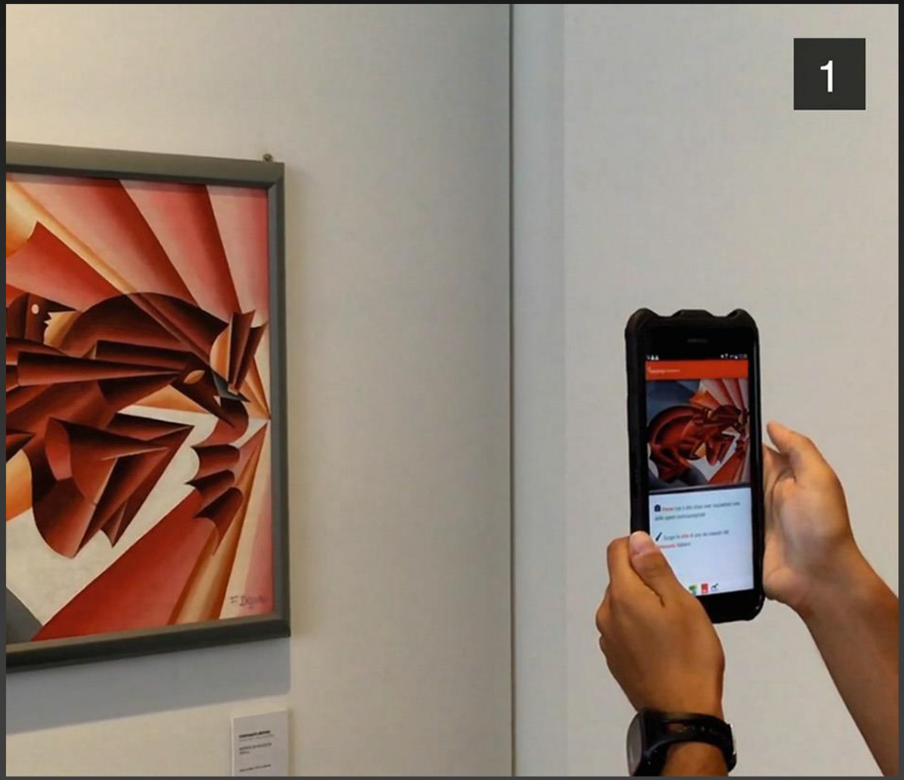
Style Analysis (13-14 years)



[Left: Color Analysis of Henri de Toulouse-Lautrec, Right: Portrait in Style of Martin Kippenberger by Nele Zeyn. In „Hands on: Kunstgeschichte“, 2017, Joachim Penzel (eds.)]

4. Exhibitions and Art Installations

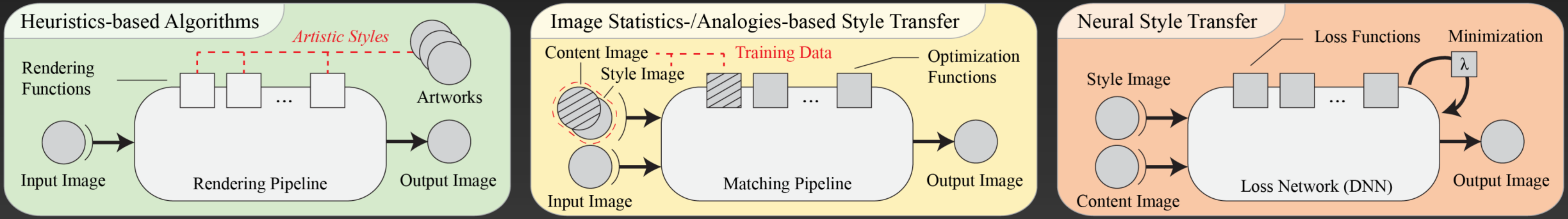
[Adobe *Artistic Eye*]



[„Imaging Novecento“, Becattini et al. 2016, EuroMed]

Wrap-up

- **Conceptual Shift in Artistic Style Transfer and Example-based Rendering**
  - Generalized style transfer that only depends on single style and content images



- **A Semiotic Structure for Artistic Style Transfer**
- **6 Proposals for NPAR Research**
  - Semiotics, Interactivity, Paradigm Combination, New Forms of Art, Visualization, Evaluation

Shift in the Engineering Approach

« Smerity.com

In deep learning, architecture engineering is the new feature engineering

June 11, 2016

Two of the most important aspects of machine learning models are feature extraction and feature engineering. Those features are what supply relevant information to the machine learning models.

Thank You For Your Attention!

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  Faculty of Digital Engineering
  University of Potsdam

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project 01IS15041B

- **Tobias Isenberg**
  Inria & Université Paris-Saclay

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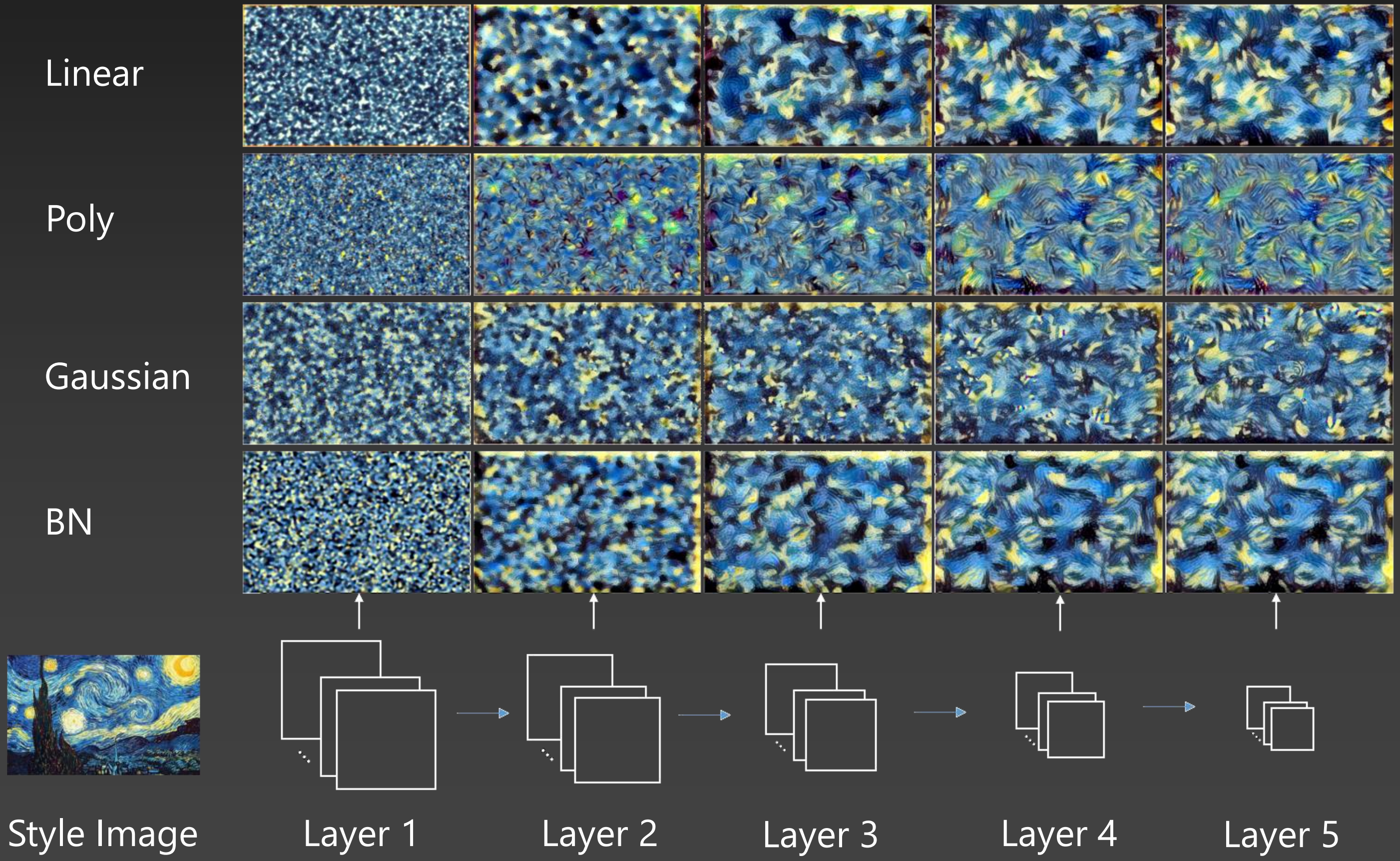
BACKUP SLIDES

How to represent artistic style? [Li et al. 2017, arXiv]

- Matching the *Gram matrices* of the neural activations can be seen as minimizing a specific Maximum Mean Discrepancy (MMD)



arXiv:1701.01036v2 [cs.CV] 1 Jul 2017

Demystifying Neural Style Transfer

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Abstract

Neural Style Transfer [Gatys *et al.*, 2016] has recently demonstrated very exciting results which catches eyes in both academia and industry. Despite the amazing results, the principle of neural style transfer, especially why the Gram matrices could represent style remains unclear. In this paper, we propose a novel interpretation of neural style transfer by treating it as a domain adaptation problem. Specifically, we theoretically show that matching the Gram matrices of feature maps is equivalent to minimize the Maximum Mean Discrepancy (MMD) with the second order polynomial kernel. Thus, we argue that the essence of neural style transfer is to match the feature distributions between the style images and the generated images. To further support our standpoint, we experiment with several other distribution alignment methods, and achieve appealing results. We believe this novel interpretation connects these two important research fields, and could enlighten future researches.

1 Introduction

Transferring the style from one image to another image is an interesting yet difficult problem. There have been many efforts to develop efficient methods for automatic style transfer [Hertzmann *et al.*, 2001; Efros and Freeman, 2001; Efros and Leung, 1999; Shih *et al.*, 2014; Kwatra *et al.*, 2005]. Recently, Gatys *et al.* proposed a seminal work [Gatys *et al.*, 2016]: It captures the style of artistic images and transfer it to other images using Convolutional Neural Networks (CNN). This work formulated the problem as finding an image that matching both the content and style statistics based on the neural activations of each layer in CNN. It achieved impressive results and several follow-up works improved upon this innovative approaches [Johnson *et al.*, 2016; Ulyanov *et al.*, 2016; Ruder *et al.*, 2016; Ledig *et al.*, 2016]. Despite the fact that this work has drawn lots of attention, the fundamental element of style representation: the Gram matrix in [Gatys *et al.*, 2016] is not fully explained. The reason why Gram matrix can represent artistic style still remains a mystery.

In this paper, we propose a novel interpretation of neural style transfer by casting it as a special domain adaptation [Beijbom, 2012; Patel *et al.*, 2015] problem. We theoretically prove that matching the Gram matrices of the neural activations can be seen as minimizing a specific Maximum Mean Discrepancy (MMD) [Gretton *et al.*, 2012a]. This reveals that neural style transfer is intrinsically a process of distribution alignment of the neural activations between images. Based on this illuminating analysis, we also experiment with other distribution alignment methods, including MMD with different kernels and a simplified moment matching method. These methods achieve diverse but all reasonable style transfer results. Specifically, a transfer method by MMD with linear kernel achieves comparable visual results yet with a lower complexity. Thus, the second order interaction in Gram matrix is not a must for style transfer. Our interpretation provides a promising direction to design style transfer methods with different visual results. To summarize, our contributions are shown as follows:

1. First, we demonstrate that matching Gram matrices in neural style transfer [Gatys *et al.*, 2016] can be reformulated as minimizing MMD with the second order polynomial kernel.
2. Second, we extend the original neural style transfer with different distribution alignment methods based on our novel interpretation.

2 Related Work

In this section, we briefly review some closely related works and the key concept MMD in our interpretation.

Style Transfer Style transfer is an active topic in both academia and industry. Traditional methods mainly focus on the non-parametric patch-based texture synthesis and transfer, which resamples pixels or patches from the original source texture images [Hertzmann *et al.*, 2001; Efros and Freeman, 2001; Efros and Leung, 1999; Liang *et al.*, 2001]. Different methods were proposed to improve the quality of the patch-based synthesis and constrain the structure of the target image. For example, the image quilting algorithm based on dynamic programming was proposed to find optimal texture

*Corresponding author

Combine Deep Learning with Image Analogies

A (input) | A′ (output) | B (output) | B′ (input)

[„Visual Attribute Transfer through Deep Image Analogy“, Liao et al. 2017, SIGGRAPH]

Example – Image Flow [Ruder et al. 2016, GCPR]

“Artistic style transfer for videos”

- Introduce a temporal consistency loss function using optical flow information

Initialization | Optical Flow | Uncertainty | After Optimization

Iterative vs. Feed-forward Neural Style Transfer

[deepart.io] [Pikazo] [Feed-forward Style Transfer, Ulyanov et al. 2017, arXiv]

Feed-forward Neural Style Transfer [Johnson et al. 2016, ECCV]

Train feed-forward neural networks using test image sets (e.g., MS-COCO)