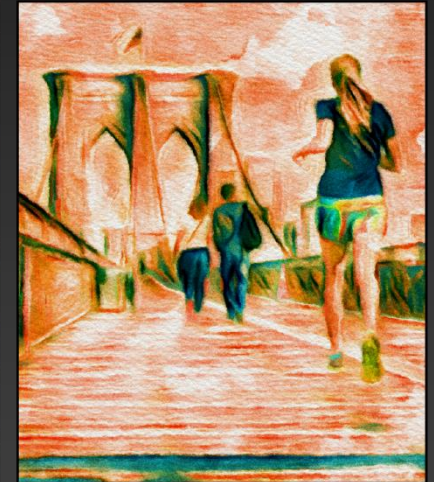
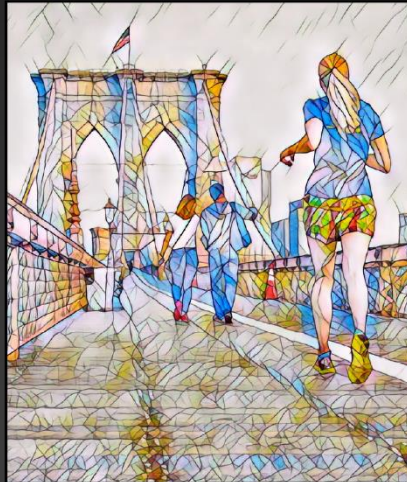


# Neural Style Transfer: A Paradigm Shift for Image-based Artistic Rendering?

AMIR SEMMO

TOBIAS ISENBERG

JÜRGEN DÖLLNER





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



Input



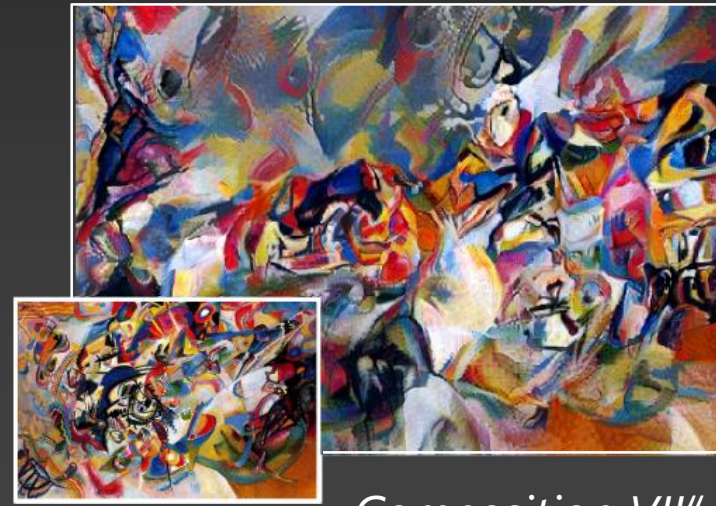
„The Starry Night“



„The Scream“



„Femme nue assis“



„Composition VII“

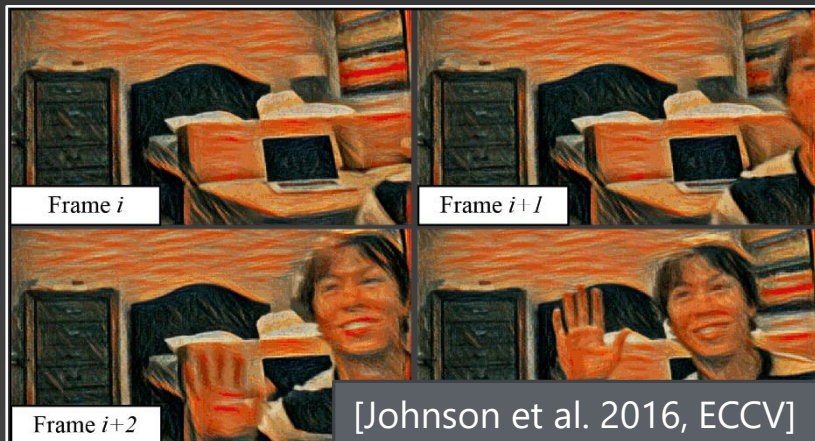


„The Shipwreck of  
the Minotaur“



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

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

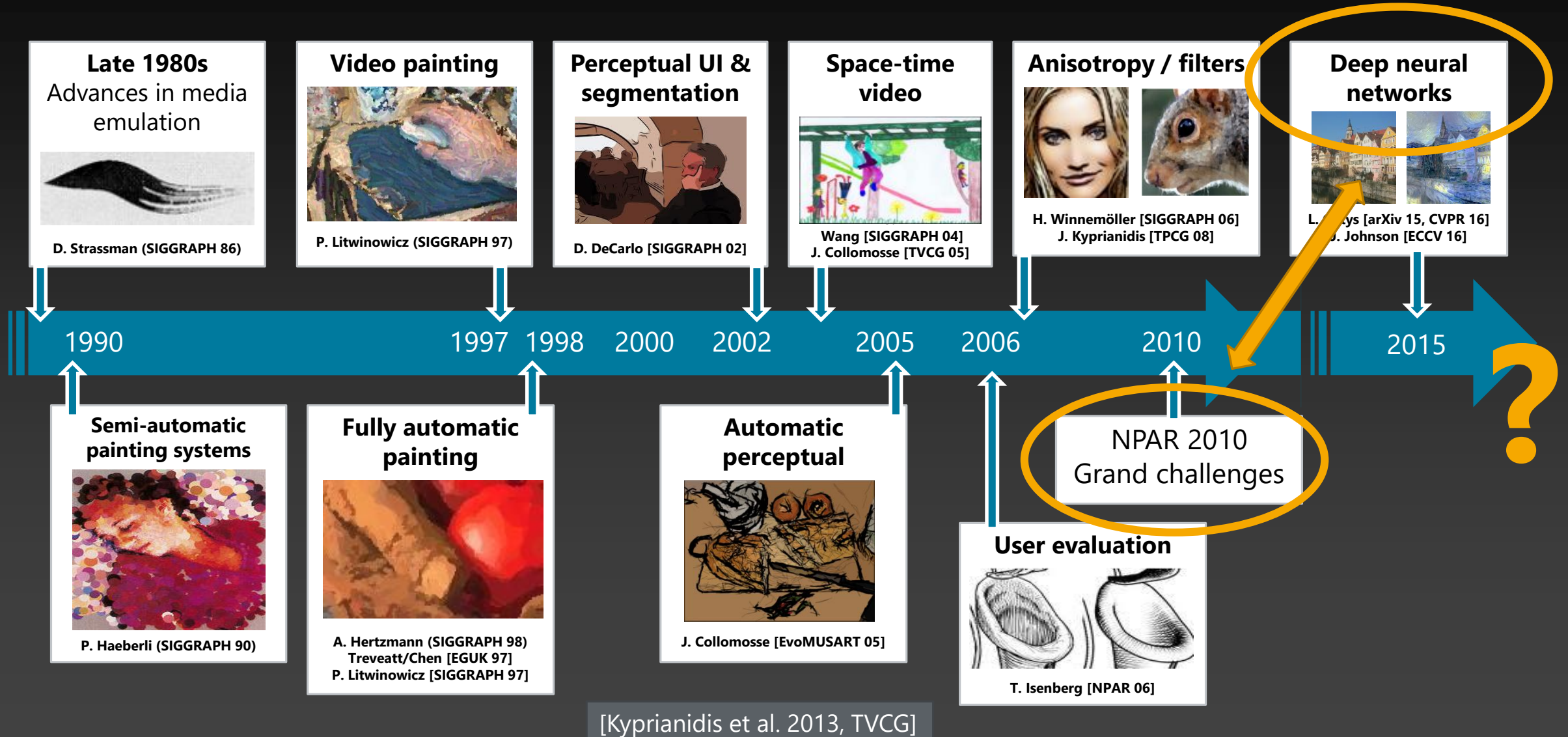


So far, primarily explored in a computer vision context ...

**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 ...



# NPAR Grand Challenges

## Non-Photorealistic Animation & Rendering: 7 Grand Challenges

David Salesin  
June 2002

[Salesin 2002, NPAR]

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

Amy A. Gooch<sup>\*</sup> University of Victoria  
Jeremy Long<sup>†</sup> University of Victoria  
Li Ji<sup>‡</sup> University of Victoria  
Anthony Estey<sup>§</sup> University of Victoria  
Bruce S. Gooch<sup>\*</sup> University of Victoria

#### Abstract

The field of non-photorealistic rendering is reaching a mature state. In its infancy, researchers explored the mimicry of methods and tools used by traditional artists to generate works of art, through techniques like watercolor or oil painting simulations. As the field has moved past mimicry, ideas from artists and artistic techniques have been adapted and altered for performance in the media of computer graphics, creating algorithmic aesthetics such as generative art or the automatic composition of objects in a scene, as well as abstraction in rendering and geometry. With these two initial stages of non-photorealistic rendering well established, the field must find new territory to cover. In this paper, we provide a high level overview of the past and current state of non-photorealistic rendering and call to arms the community to create the areas of research that make computation of non-photorealistic rendering generate never before realized results.

**CR Categories:** I.3.m [Computer Graphics]: Miscellaneous—Non-Photorealistic Rendering

**Keywords:** non-photorealistic rendering, grand challenges, meta-paper

#### 1 Introduction

There has been much discussion revolving around the current and future state of the non-photorealistic rendering (NPR) field. We survey the recent research that has been conducted in the NPR domain and discuss implications for the future. In particular, we posit on where we see NPR research in terms of the technological maturation model put forward by Robert A. Heinlein [1983]. Heinlein is credited with having anticipated many technological advances, and some say that his writing, while sometimes controversial, has been influential in provoking thought and discussion about the role and evolution of technology [Dietzman 2007]. Heinlein's model suggests that new technologies evolve over time through three stages of maturation:

1. Imitation: the new technology emulates previous work.
2. Optimization: the performance of the technology is improved.
3. Acceptance: the technology is no longer perceived as "new".

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NPAR 2010, Annex, France, June 7–10, 2010.  
© 2010 ACM 978-1-4502-0716-8/10/0008 \$10.00

While we do not agree with all of Heinlein's opinions, we find that his maturation model is an interesting lens through which to examine the state of NPR, and can serve as a useful starting point to provoke discussion on what directions should be taken into the future. We believe that NPR is currently at the second stage of the maturation model, and we outline the path we believe should be taken in order to advance the field into the third stage of maturation.

Rapid advances in computer graphics technology allow computer screens to be filled with complex visual information at near real time rates [HPG 2009]. Simulations and visualizations that once required supercomputers are now commonly run on desktop workstations or PC clusters. While Moore's law has correctly anticipated faster processors, larger disk drives and higher memory capacity, these advances have done little to help people understand the meaning of their data. The lack of understanding stems from the fact that machines process data in numerical form, while humans more easily comprehend visual data. We rely on graphs and charts that visually emphasize key features and relationships in the data to attain insight.

In the computer graphics and visualization communities, *rendering* is the process by which data is converted into an image. Photorealistic rendering denotes images based on physical simulations. The goal of photorealistic rendering is to create images indistinguishable from photographs of equivalent real world scenes. In contrast, the area of NPR is concerned with images that are guided by artistic processes. An underlying assumption in NPR is that artistic techniques developed by human artists have intrinsic merit based on the evolutionary nature of art. NPR techniques, such as illustration, are driven by aesthetic and communication constraints rather than physical simulations. Visualization is the process of using computer graphics to transform numerical data into meaningful imagery, enabling users to observe information [Yagel et al. 1991; Upson et al. 1989; Drebin et al. 1988; Senay and Ignatius 1994]. The art of non-photorealistic visualization lies in choosing visual representations of the data that maximize human understanding [Grinstein and Thuringham 1996]. The resulting display allows a viewer to detect, analyze and discover features in numerical data which may not have been recognized otherwise.

NPR images convey information more effectively by omitting extraneous detail, focusing attention on relevant features, and clarifying, simplifying, and disambiguating shape. In fact, a distinguishing feature of NPR is the concept of controlling detail in an image to enhance communication. The control of image detail is often combined with stylization to evoke the perception of complexity in an image without explicit representation, as shown in the drawings in the right two images of Figure 1. NPR images also provide a more natural vehicle for conveying information at a range of detail levels. Additional advantages of artistic imagery include:

- Communication of uncertainty – Photorealistic computer graphics imply an exactness and perfection that may overstate the fidelity of a simulation or scan.
- Communication of abstract ideas – Simple line drawings, like the force diagrams used in physics textbooks, can communicate abstract ideas in ways that a photograph cannot.

Non-Photorealistic Animation and Rendering  
Pierre Bissard and Helge Wimmerle (Editors)

EXPRESSIVE 2016

### Interactive NPR: What type of tools should we create?

Tobias Isenberg  
Isira, France

#### Abstract

*I argue that we need to increase our consideration of the interaction that is possible and/or needed for the NPR algorithms we develop. Depending on the application domain of a given algorithmic contribution, different degrees of interaction are required to make it practically useful and, thus, relevant. The spectrum of interactivity ranges from (almost) fully automatic processing to levels of control that are similar to those of traditional tools—some of the approaches even needing to support the full spectrum. Only if these considerations are first-class members of the NPR development process can we expect others to want to work with our tools and to use them on a regular basis.*

**Categories and Subject Descriptors** (according to ACM CCS): Computing methodologies [Computer Graphics]: Rendering—Non-photorealistic rendering

#### 1. Introduction

The field of non-photorealistic rendering was initially inspired (at least in part) by the insight that there is more to the idea of computer graphics than simply the dictate of the photographic camera. Starting from the iconic “first papers” of the field<sup>1</sup> such as Saito and Takahashi’s “Comprehensible Rendering of 3-D Shapes” [ST90], Haverli’s “Paint by Numbers” [Hav90], or Dooley and Cohen’s “Automatic Illustration of 3D Geometric Models” [DC96a, DC96b], NPR researchers have combined many “non-photorealistic” rendering and animation techniques. In doing so they cover the recreation or simulation of traditional artistic media, they enable completely new forms of expression, and they assist the illustration and visualization of data.

To date, while there is certainly continued interest and work in the field, it can be argued [GLP10] that researchers have created well-performing techniques for simulating many if not most of the established types of traditional media (watercolor, oil painting, pencil drawing, and many more) as well as for many ways to assist data illustration and visualization. Several books [GG01, SSC0, Gen01, RC13] survey (e.g., [LS99, Her03, RHT03, BHT11, Dac12, HGT13, KCW13, bei15, LP15]), and many years of proceedings from NPR and related conferences and journals are evidence of this extended body of work. To date, however, I argue

that most contributions to the field have concentrated on the creation of rendering (or animation) techniques. In contrast, less of a focus has been placed in the past on how to allow the targeted users of the techniques to interact, even if most NPR techniques have an interactive component. In this paper I thus analyze the state of the art of interaction with non-photorealistic rendering and propose a set of goals to work toward as we create, implement, and deploy future NPR techniques. These goals then have implications for us as researchers as we implement tools, in particular if these are to be used by real people and for real tasks.

#### 2. Discussion of Interactive NPR in the Past

The discussion of the use and design of interaction for non-photorealistic rendering was started by Salesin in his 2002 keynote [Sal02] at the annual NPAR conference. As part of his seven grand challenges for the field, he postulated as the fourth challenge: “Interactivity—How do you build tools for right-brained thinking?” Salesin argued that interactive NPR tools “should let artists and computers each do what they are good at,” “need to be simple yet flexible,” and “should support full design cycle” of creation, evaluation, and reworking. Salesin thus saw interactivity within NPR primarily from the perspective of professional artists creating artwork (such as his example of an art director working on an animated CG movie), arguably only one of several potential application domains of NPR work.

Gooch et al. [GLP10] revisited Salesin’s challenge in their meta paper at NPAR 2010, finding that “interaction is still one of the most difficult research paradigms.” In contrast to Salesin, however, they state that “interaction tools [should support] both sides of the brain.” They argue that there is a need both for interaction for artists

<sup>1</sup> I acknowledge that it can rightly be argued that there were several if not many contributions to NPAR before 1990.

<sup>2</sup> I like when how dare it is similar pointing papers [Gen01, Her03]. I use the personal pronoun “I” when I talk about my own personal views, while I write “we”/“our” when I refer to work I have done jointly with others or for referring to the NPR community as a whole.

[Gooch et al. 2010, NPAR]

[Isenberg 2016, NPAR]



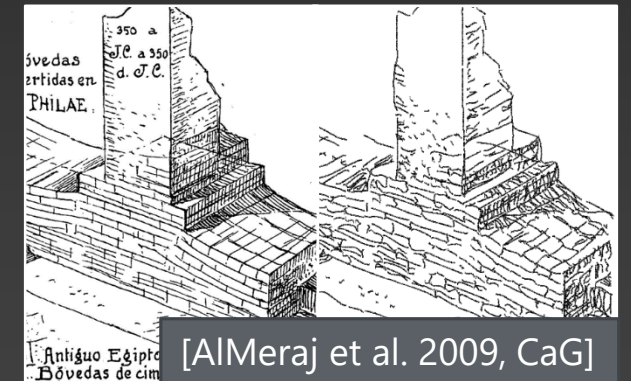
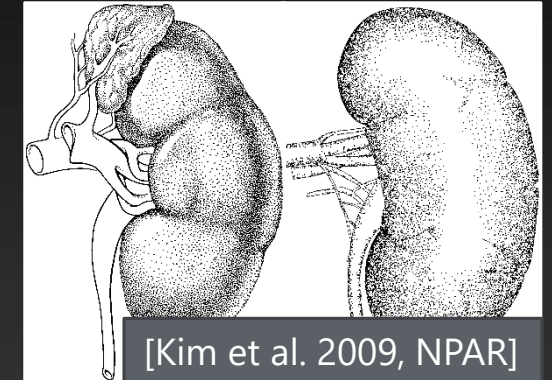
## How do you encode what makes something beautiful?

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

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

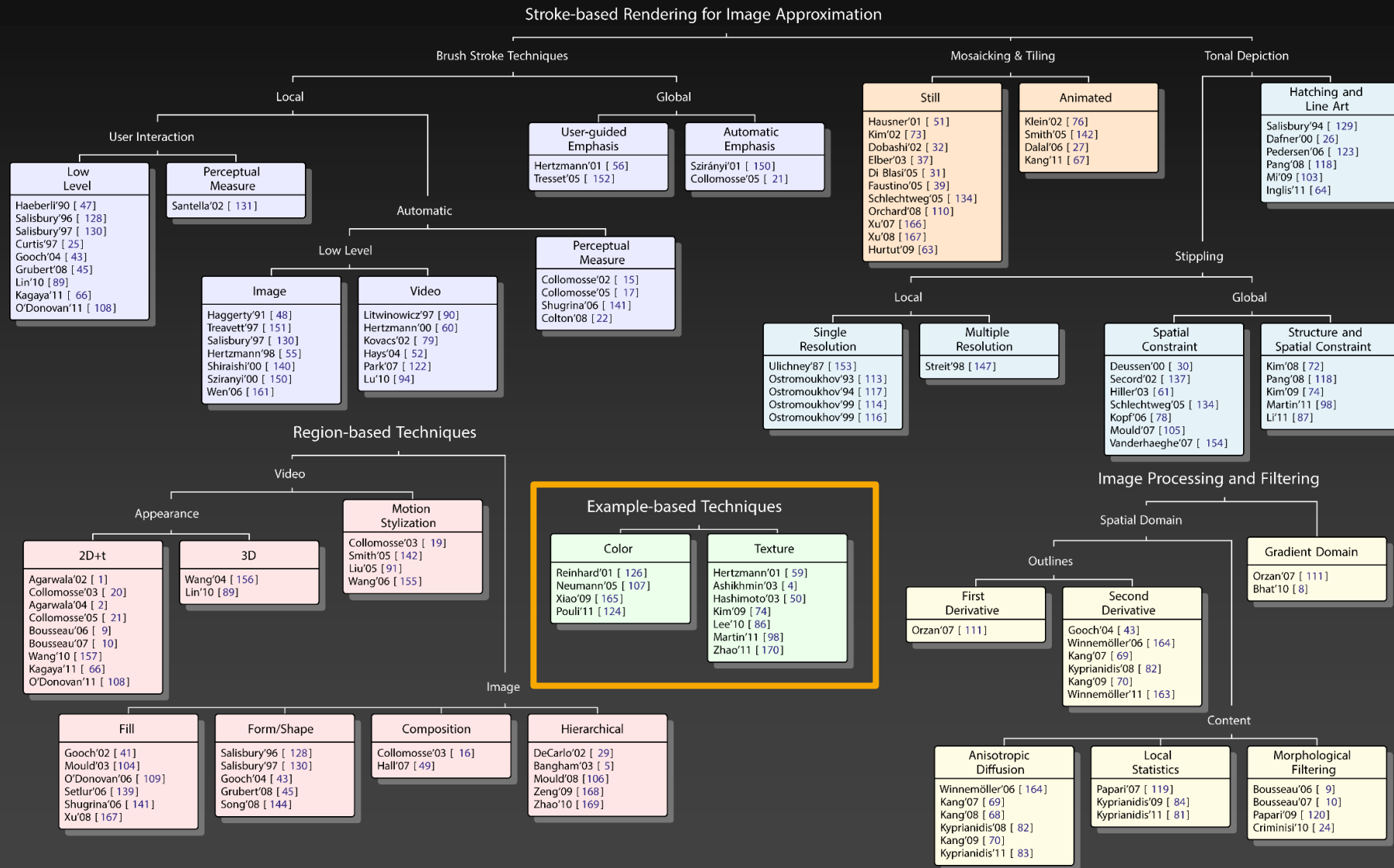
- Simulate physical process of producing a piece of artwork
- **Derive algorithmic theory that approximates the artwork itself**

# Artwork Approximation – Examples





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



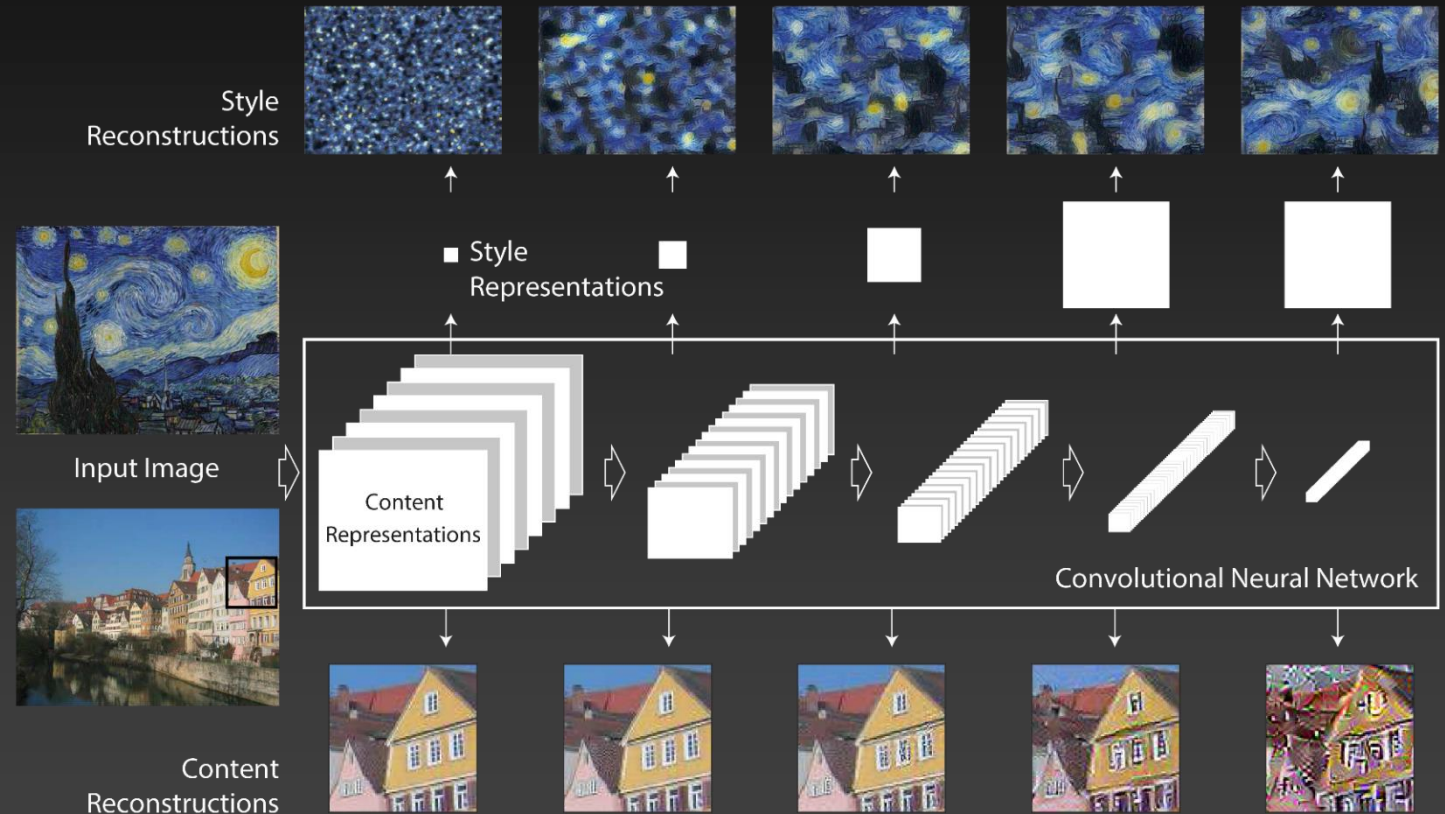


Limitations: Requires analogous style and content pairs for training, typically informs only low-level image features for texture transfer.



# 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]

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 –



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



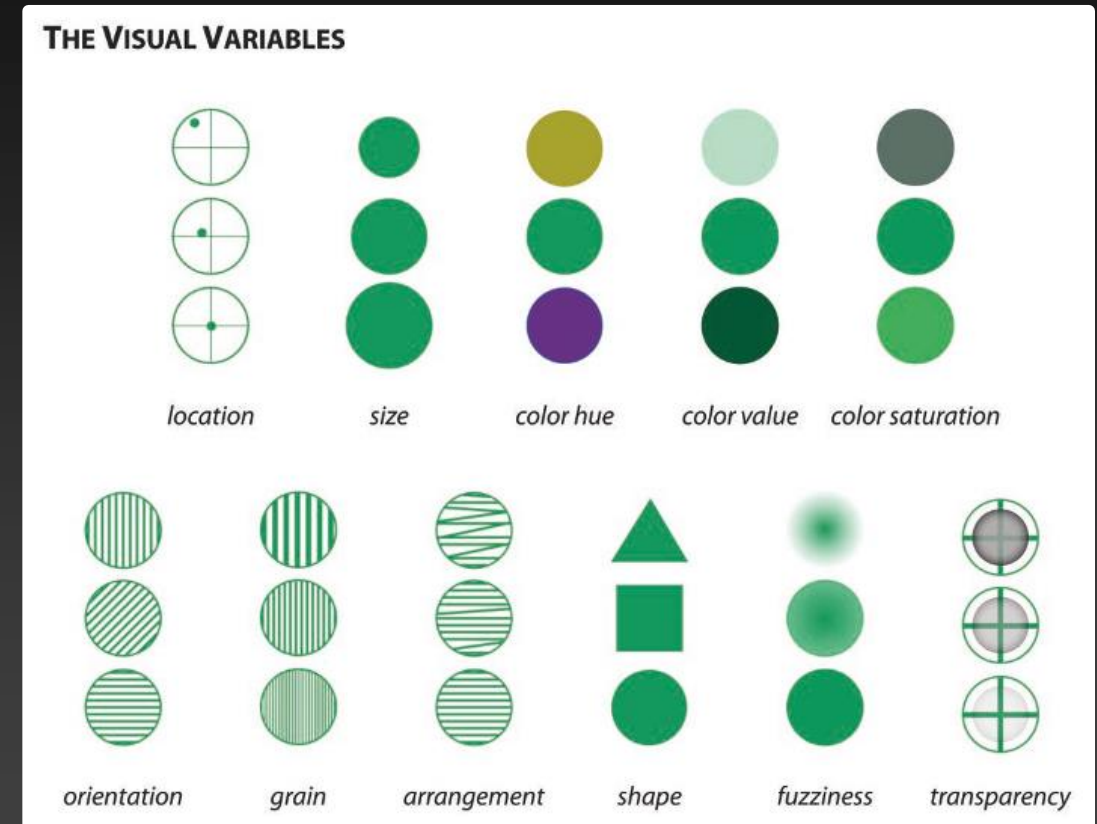
Style Image: Franz Marc – "The Tower of Blue Horses"



- 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]

## *I. Modeling Aspects*

- Color Maps
- Feature Maps
- Geometry Maps

*Color*

*Depth*



*[<http://phandroid.com>]*

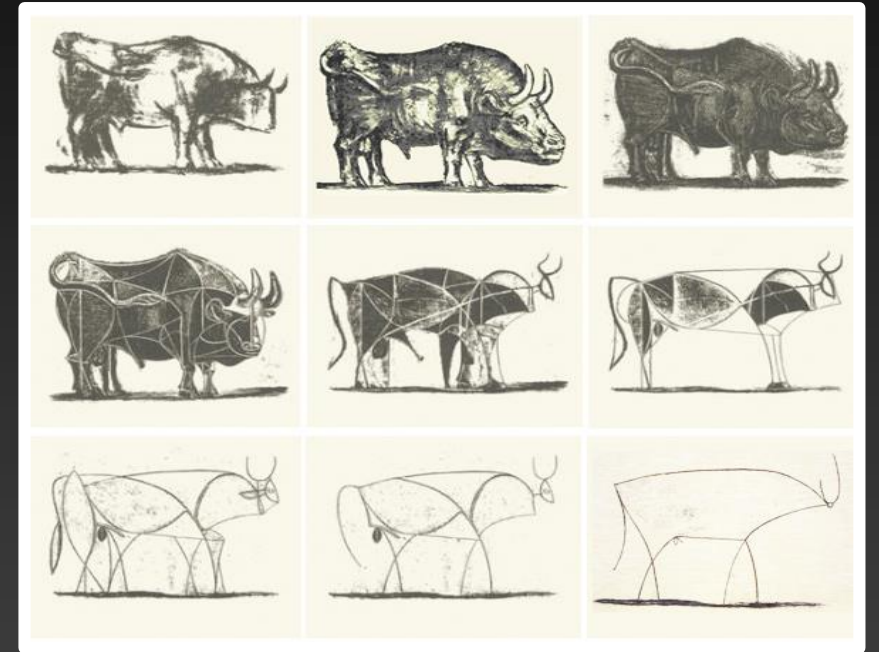


## *I. Modeling Aspects*

- Color Maps
- Feature Maps
- Geometry Maps

## *II. Filtering Aspects*

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



*Pablo Picasso [1945-46]*

## *I. Modeling Aspects*

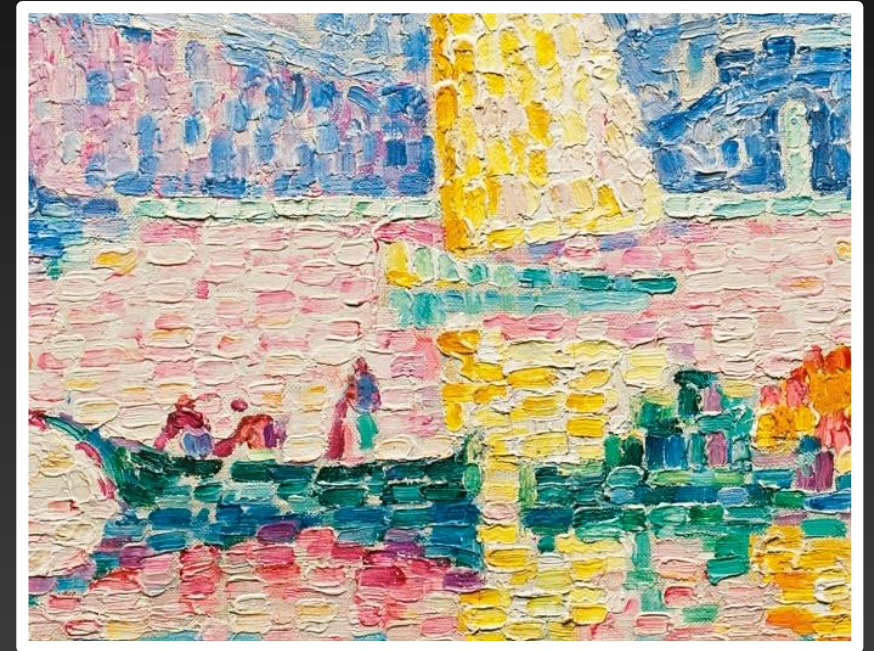
- Color Maps
- Feature Maps
- Geometry Maps

## *II. Filtering Aspects*

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

## *III. Graphical Elements*

- Point
- Line
- Area
- 2D Element



*Paul Signac [1917]*



## *I. Modeling Aspects*

- Color Maps
- Feature Maps
- Geometry Maps

## *II. Filtering Aspects*

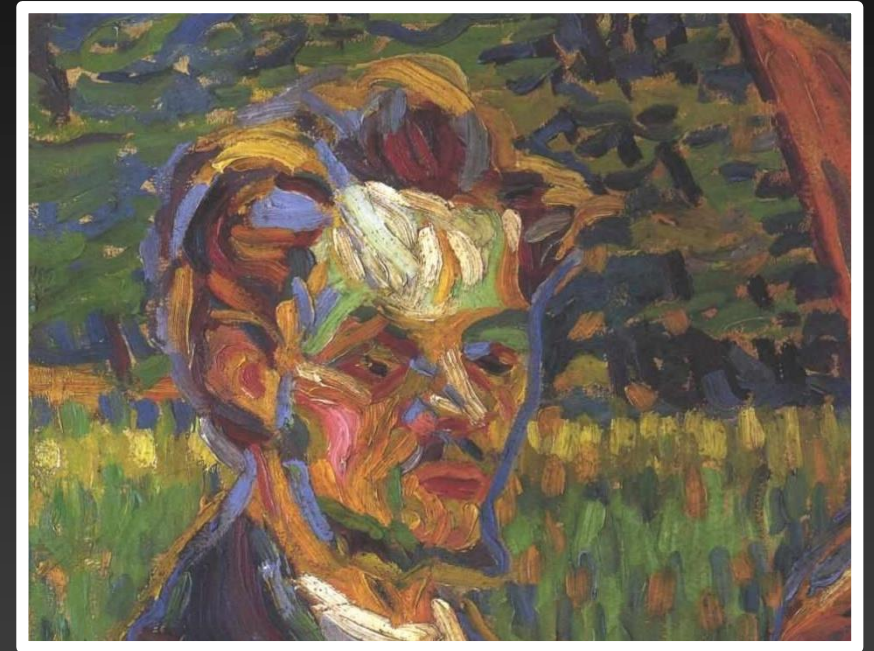
- Location-based
- Color-based
- Feature-based

## *III. Graphical Elements*

- Point
- Line
- Area
- 2D Element

## *IV. Graphical Variables*

- Form
- Shape
- Size
- Color



*Ernst Ludwig Kirchner [1907]*

## *I. Modeling Aspects*

- Color Maps
- Feature Maps
- Geometry Maps

## *II. Filtering Aspects*

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

## *III. Graphical Elements*

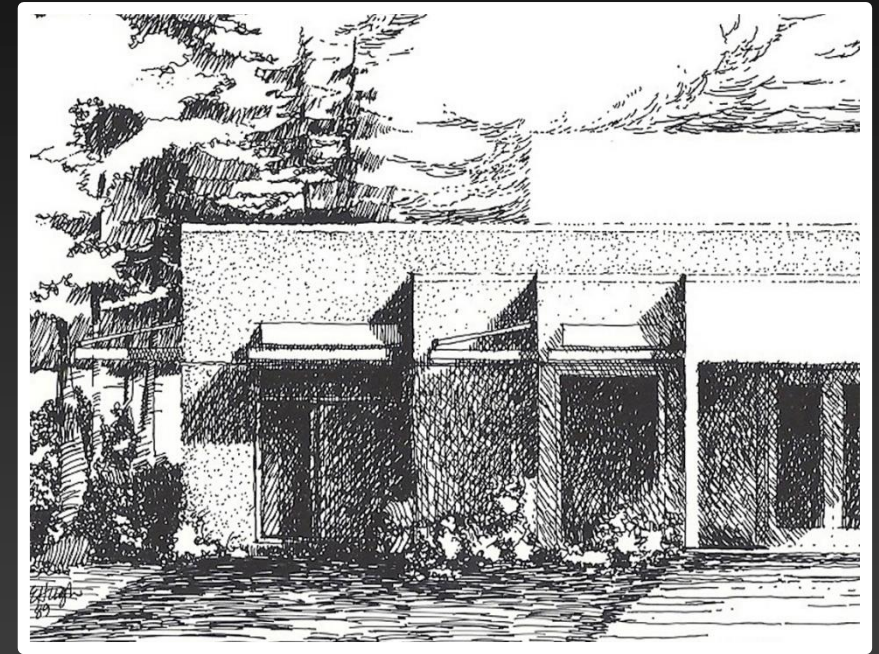
- Point
- Line
- Area
- 2D Element

## *IV. Graphical Variables*

- Form
- Size
- Shape
- Color

## *V. Design Mechanisms*

- Space/Texture
- Transparency/Blending
- Shading
- Shadows
- Crispness
- Resolution



[<http://sketchingjourney.com>]

## *I. Modeling Aspects*

- Color Maps
- Feature Maps
- Geometry Maps

## *II. Filtering Aspects*

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

## *III. Graphical Elements*

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- Line
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- Form
- Size
- Shape
- Color

## *V. Design Mechanisms*

- Space/Texture
- Transparency/Blending
- Shading
- Shadows
- Crispness
- Resolution

## *VI. Perceptual Aspects*

- Flatness
- Motion Coherence
- Temporal Continuity
- Pictorial Cues



*Gustave Caillebotte [1877]*



## I. Modeling Aspects

- Color Maps
- Feature Maps
- Geometry Maps

## II. Filtering Aspects

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

## III. Graphical Elements

- Point
- Line
- Area
- 2D Element

## IV. Graphical Variables

- Form
- Size
- Shape
- Color

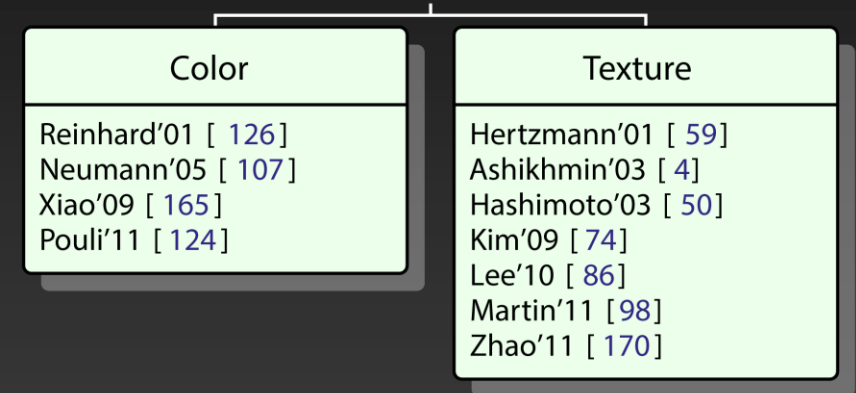
## V. Design Mechanisms

- Space/Texture
- Transparency/Blending
- Shading
- Shadows
- Crispness
- Resolution

## VI. Perceptual Aspects

- Flatness
- Motion Coherence
- Temporal Continuity
- Pictorial Cues

### Example-based Techniques

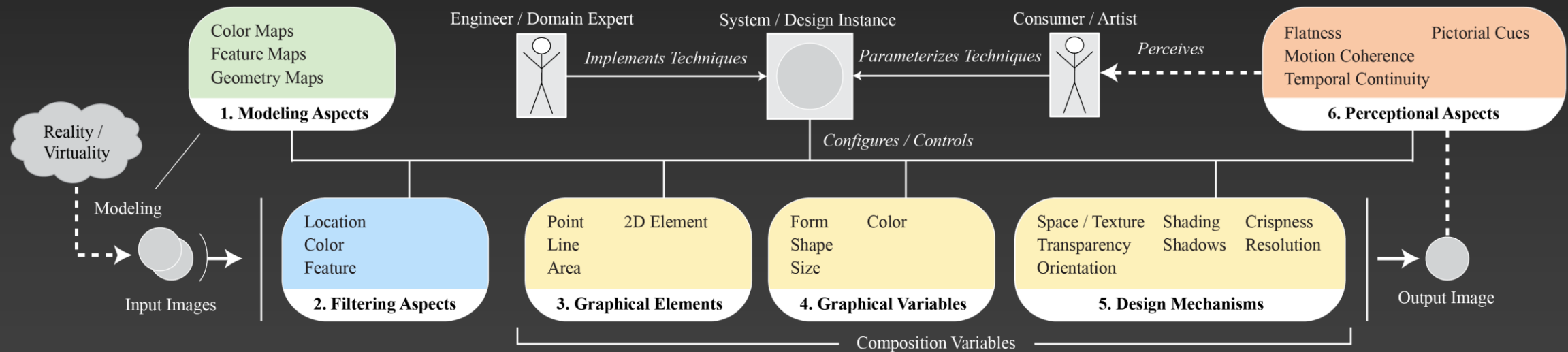


[Kyprianidis et al. 2013, TVCG]

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]	x	x				x		x		x					x		x
	Chang et al. [2015]	x	x				x		x									x
	Kim et al. [2009]	x				x		x	x	x	x			x	x			
	Maciejewski et al. [2008]	x				x		x	x	x	x			x	x			
	Martín et al. [2011]	x				x		x	x	x	x			x	x			x
	Neumann Broth. [2005]	x							x									
	Pouli & Reinhard [2011]	x							x									x
	Reinhard et al. [2001]	x							x									
	Wu et al. [2013]	x	x						x									
	Xiao & Ma [2009]	x	x						x									
Image Analogies	Yang et al. [2017]	x	x						x									
	Ashikhmin [2003]	x	x								x							x
	Bénard et al. [2013]	x	x	x			x			x	x	x		x		x	x	x
	Berger et al. [2013]	x			x		x	x										
	Efros & Freeman [2001]	x									x							
	Fiser et al. [2016]	x		x							x			x			x	x
	Hashimoto et al. [2003]	x	x								x					x		
	Hertzmann [2001]	x									x							
	Hertzmann et al. [2002]	x			x		x	x										
	Lee et al. [2011]	x	x	x							x							
	Wang et al. [2013]	x						x			x							
	Zhao & Zhu [2011]	x			x		x	x										

	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]	x	x								x					x		
	Champanand [2016]	x	x		x		x				x							
	Chen & Schmidt [2016]	x									x							
	Dumoulin et al. [2017]	x									x							
	Gatys et al. [2016a]	x				x					x							
	Gatys et al. [2016b]	x				x					x							
	Gatys et al. [2016c; 2017]	x	x		x	x			x		x							
	Gupta et al. [2017]	x	x								x					x		
	Huang & Belongie [2017]	x									x				x			
	Iizuka et al. [2016]	x							x		x							
	Johnson et al. [2016a]	x									x				x			
	Li & Wand [2016]	x									x							
	Liu et al. [2017]	x		x	x		x				x						x	
	Risser et al. [2017]	x	x		x		x				x							
	Ruder et al. [2016]	x	x								x					x		
	Selim et al. [2016]	x	x				x			x	x					x		
	Taigman et al. [2016]	x									x							
	Ulyanov et al. [2016a]	x									x							
	Ulyanov et al. [2017a]	x	x				x				x							
	Ulyanov et al. [2016b]	x									x							

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



# Proposal 1: Semiotics-based Optimization



Style Image: Vincent van Gogh – “Starry Night”



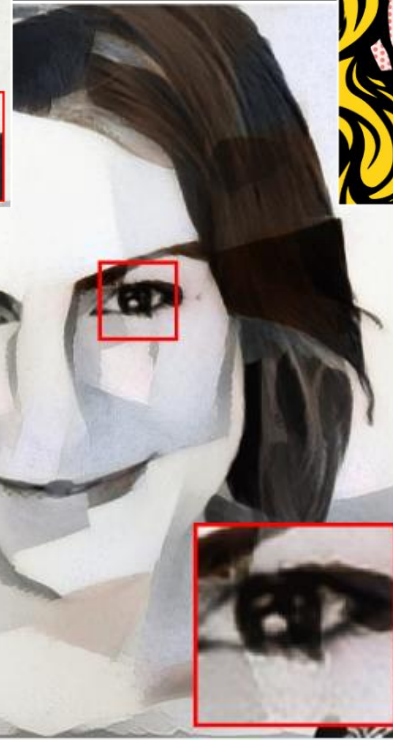
# Current Limitations



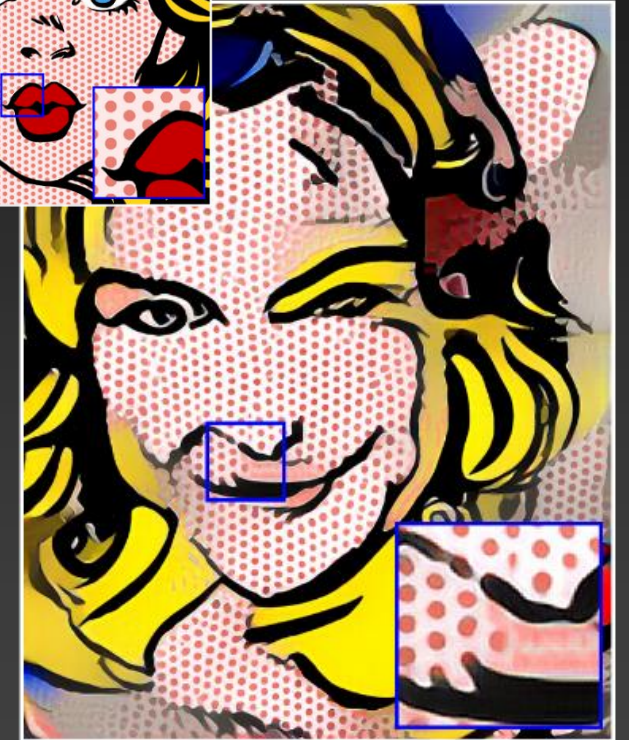
Content Image



Neural Style Transfer



Neural Style Transfer



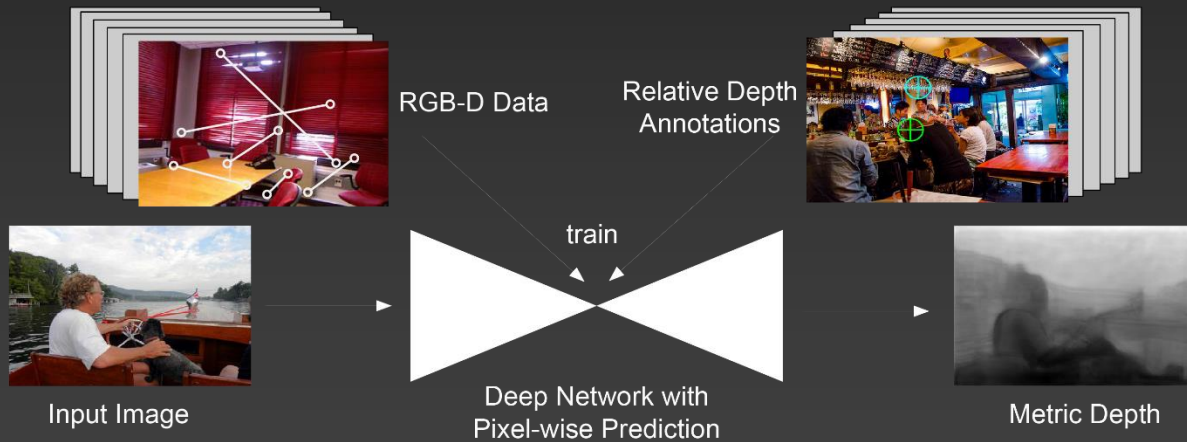
Neural Style Transfer



# 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]

## “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*

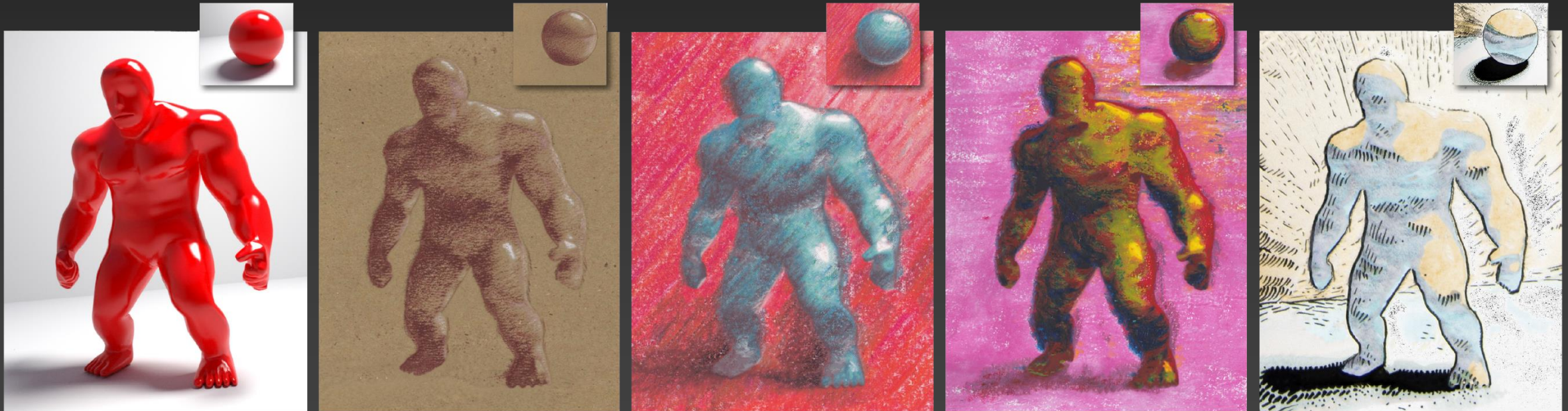


*Size Control*



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

- Illuminations-specific guidance is necessary for faithful style transfer





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?

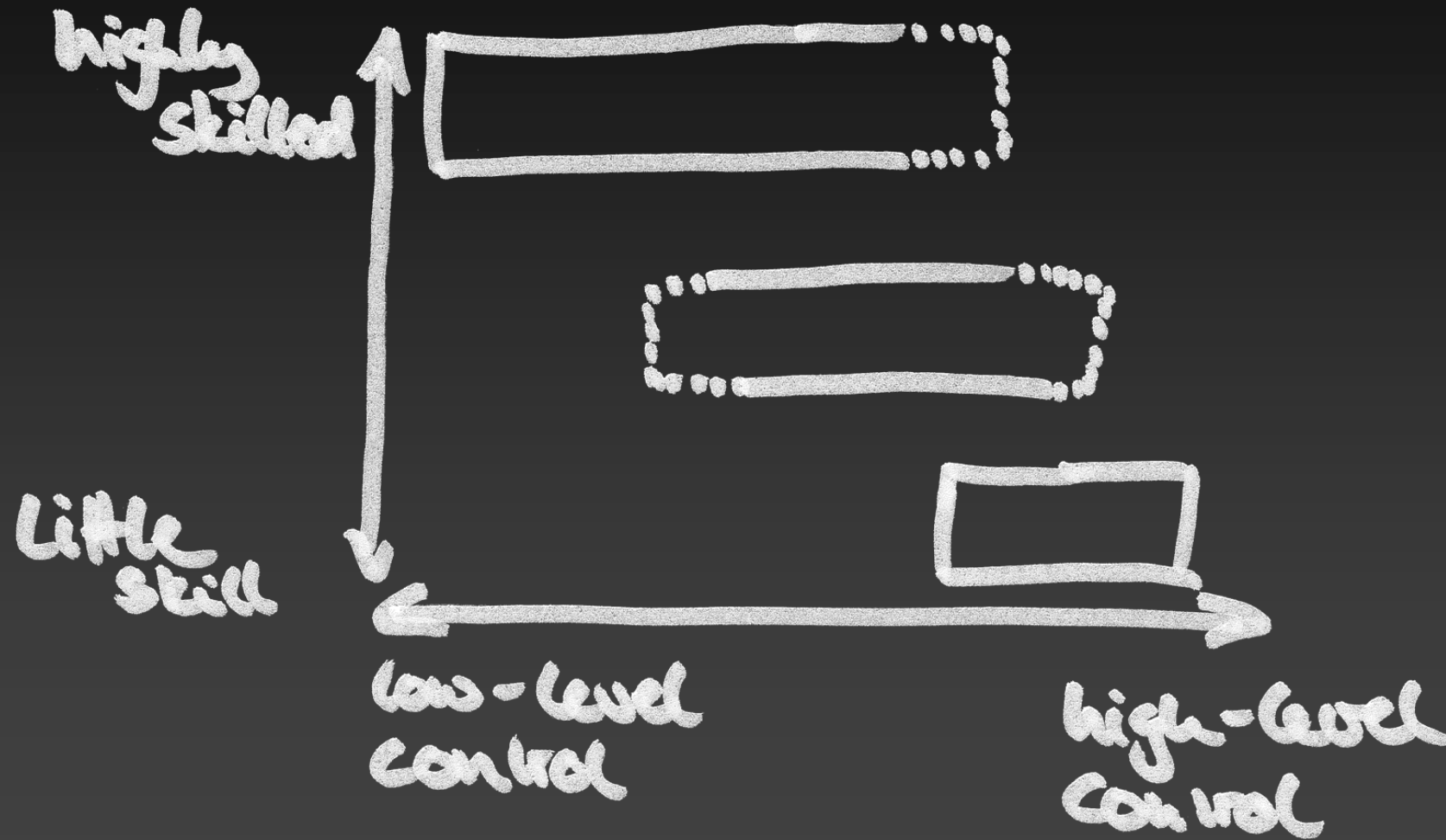


## Proposal 2: Providing Interactivity

HOLLYWOOD



# 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]

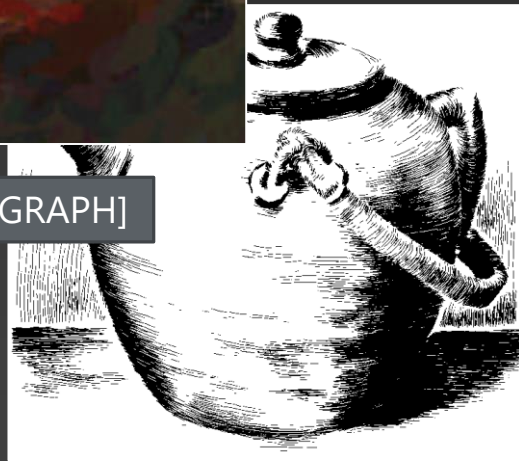
# Build tools for “right-brained” thinking [Salesin 2002, NPAR]

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

### *Techniques*

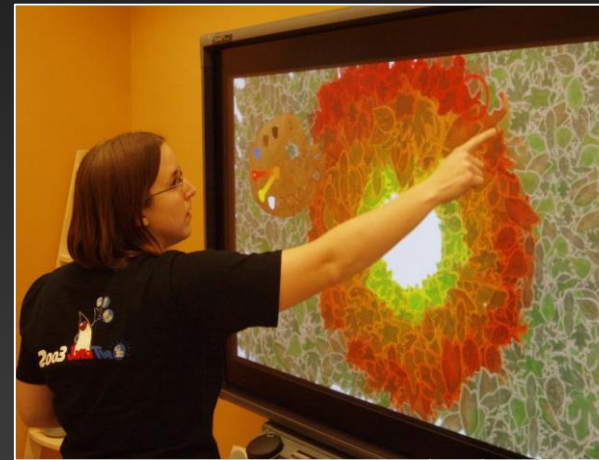


[Hertzmann 1998, SIGGRAPH]



[Salisbury et al. 1997, SIGGRAPH]

### *Interactive tools / devices*



[Schwarz et al. 2007, NPAR]



[Adobe PaintCan]

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

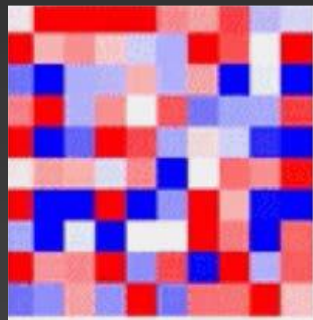




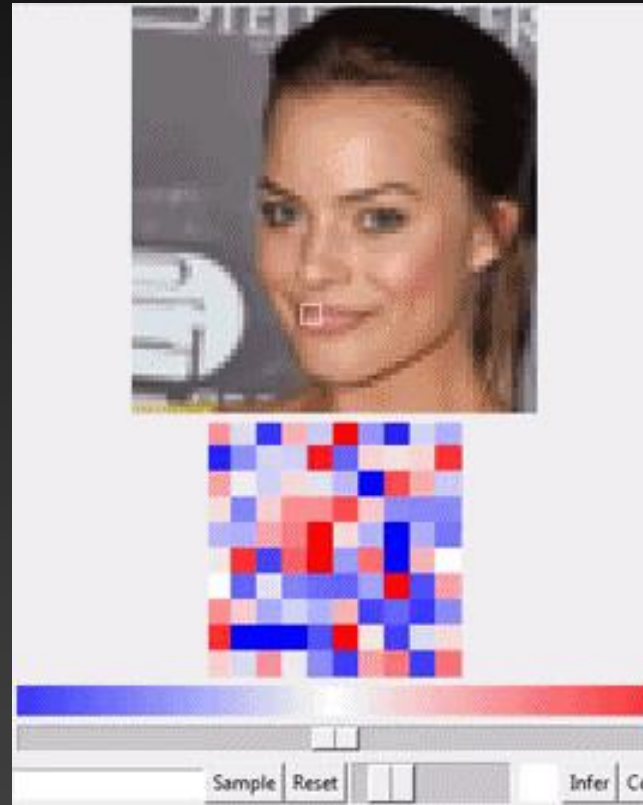
How to locally adjust design aspects such as color, orientation, scale per „rendering primitive“ to adjust the final output ?

# Proposal – Modifying a Latent Encoding of Style

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



*Latent encoding for a Monet painting*

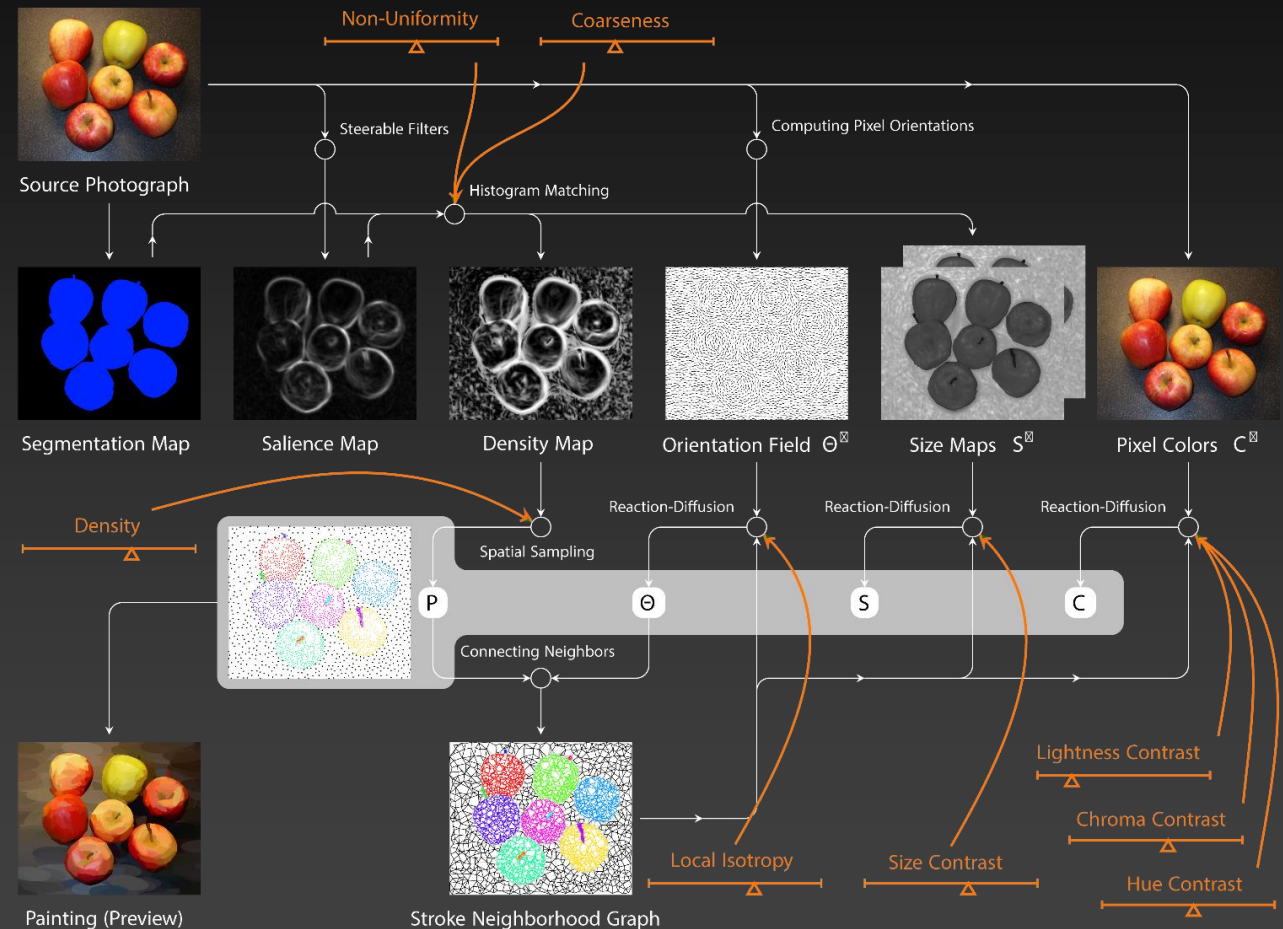


[„Neural Photo Editing with Introspective Adversarial Networks“, Brock et al. 2016, arXiv.org report]



# Proposal – Parameter Maps

- Feed parameter maps into optimization stage as additional constraints
- Example: 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

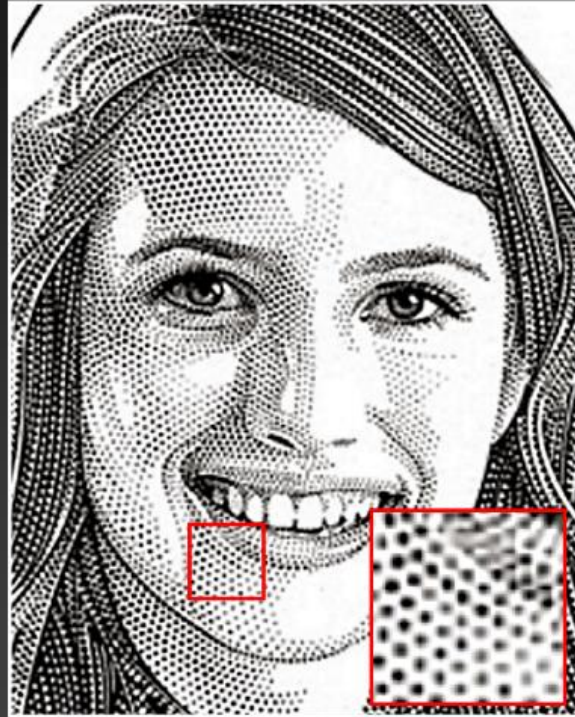
Style Image: Gilles Vranckx – “Heisenberg”



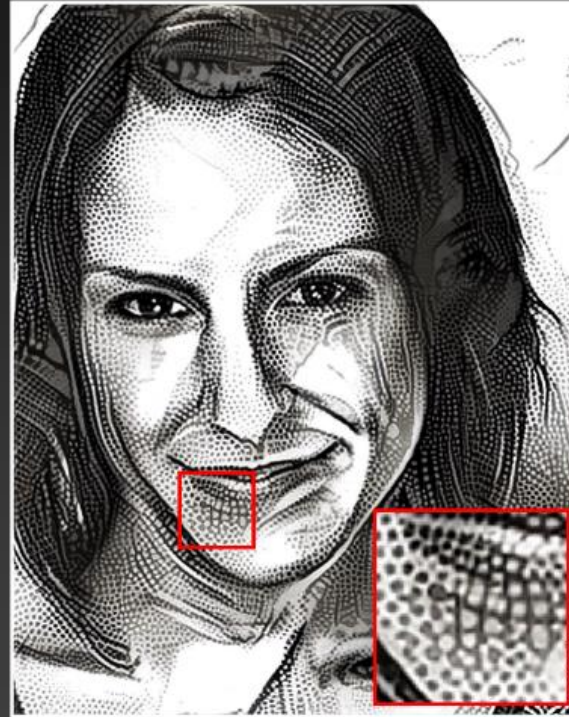
# Limitations – Example: Image Stippling



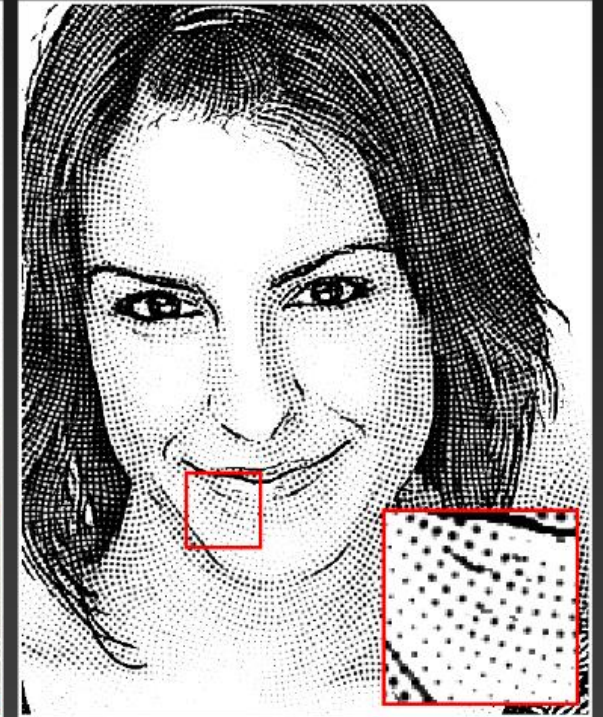
[Content Image]



[Style Image by Randy Glass]



[Neural Style Transfer, Pikazo]

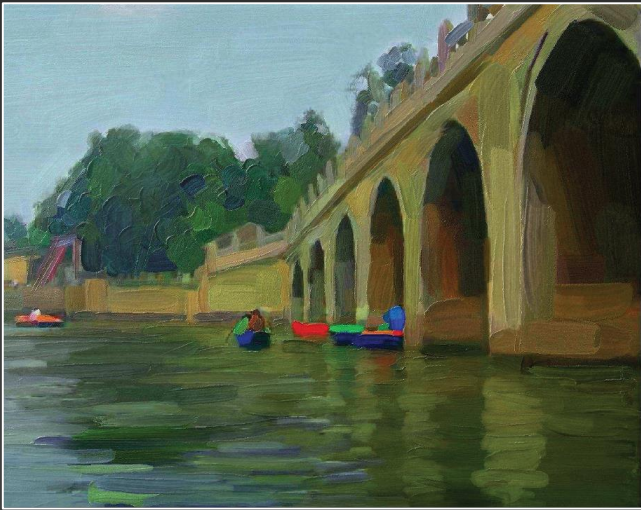
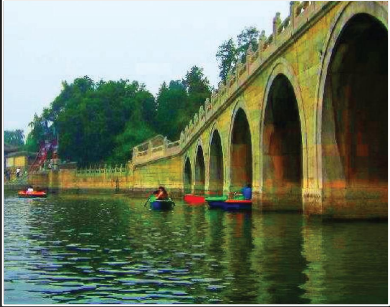


[Son et al. 2011, Graphical Models]



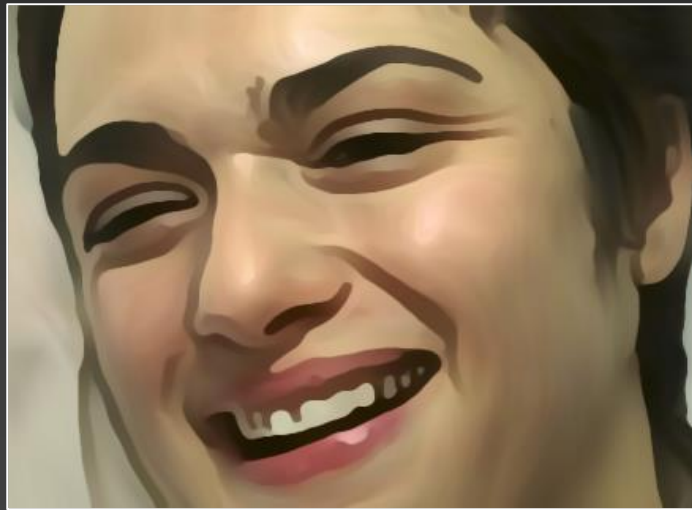
# Proposal: Use IB-AR Paradigms for Tasks They Are Good At

SBR: Blending, layering



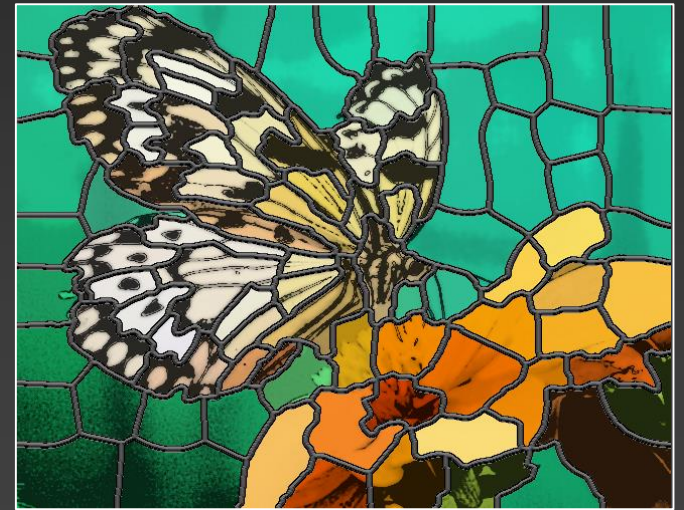
[Zeng et al. 2009, ToG]

IPF: Noise reduction



[Kyprianidis & Kang 2011, Eurographics]

RBT: Segmentation



[Doyle & Mould 2016, CAe]



# Case Study: Combining Neural Style Transfer and Image Filtering



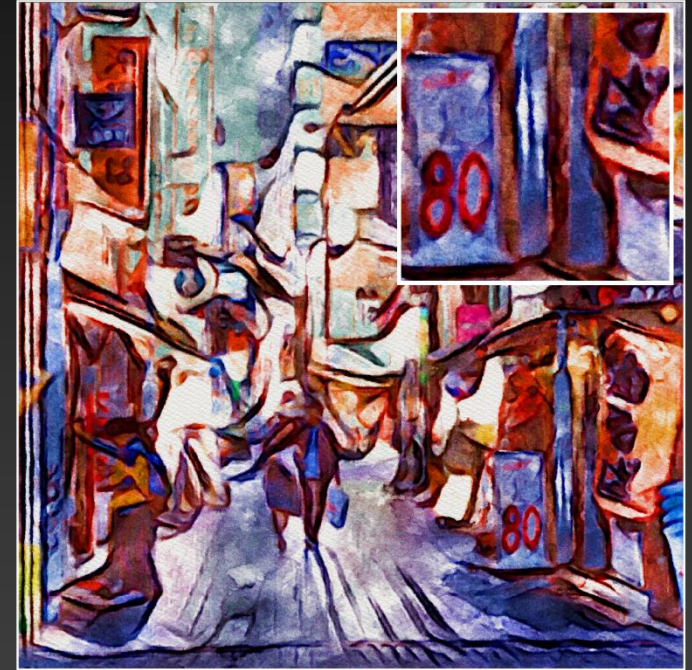
Content Image



NST (FJBU as closeup)



NST with Post-process Oil Paint Filtering



NST with Post-process Watercolor Rendering

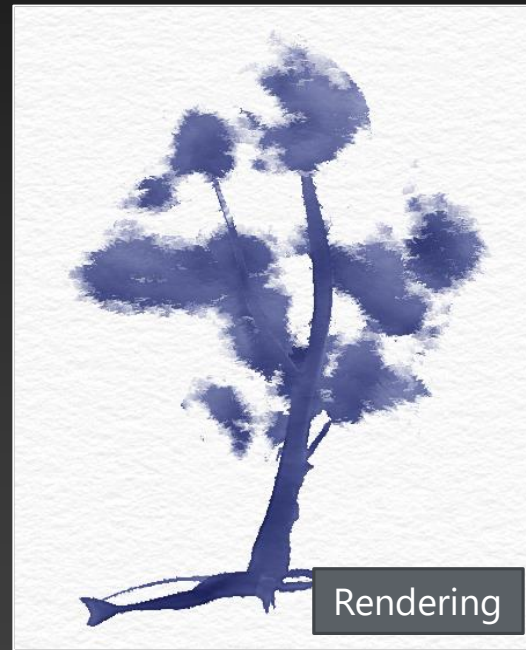
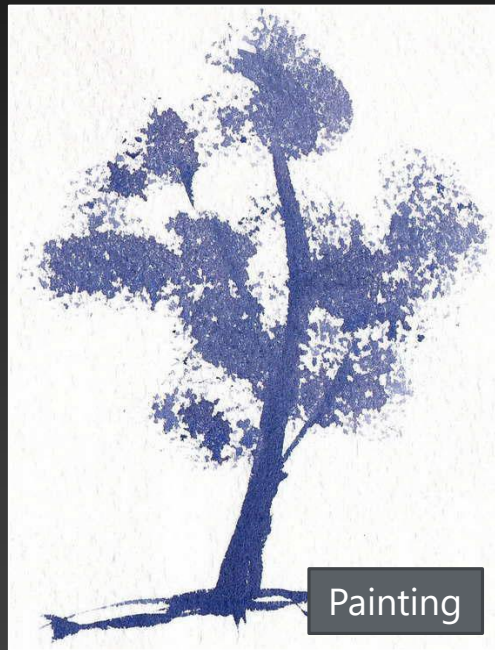
[Semmo et al. 2017, SIGGRAPH Appy Hour]

# Case Study: Combining Neural Style Transfer and Image Filtering



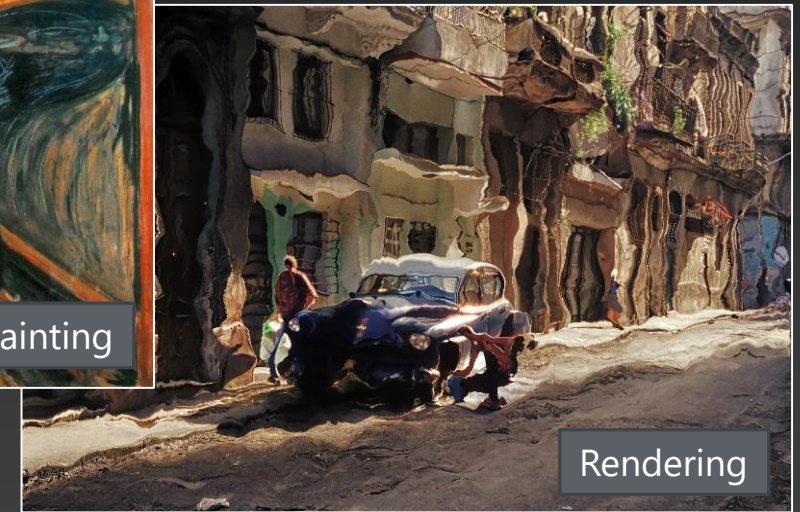
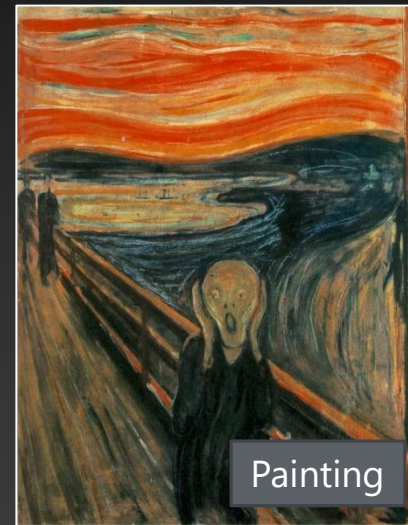


## Substrate-based Effects



[Montesdeoca et al. 2017, NPAR]

## Image Warping



[Li & Mould et al. 2015, CAe]



## Proposal 4: New Forms of Art



Style Image: Francis Picabia – "Udnie"

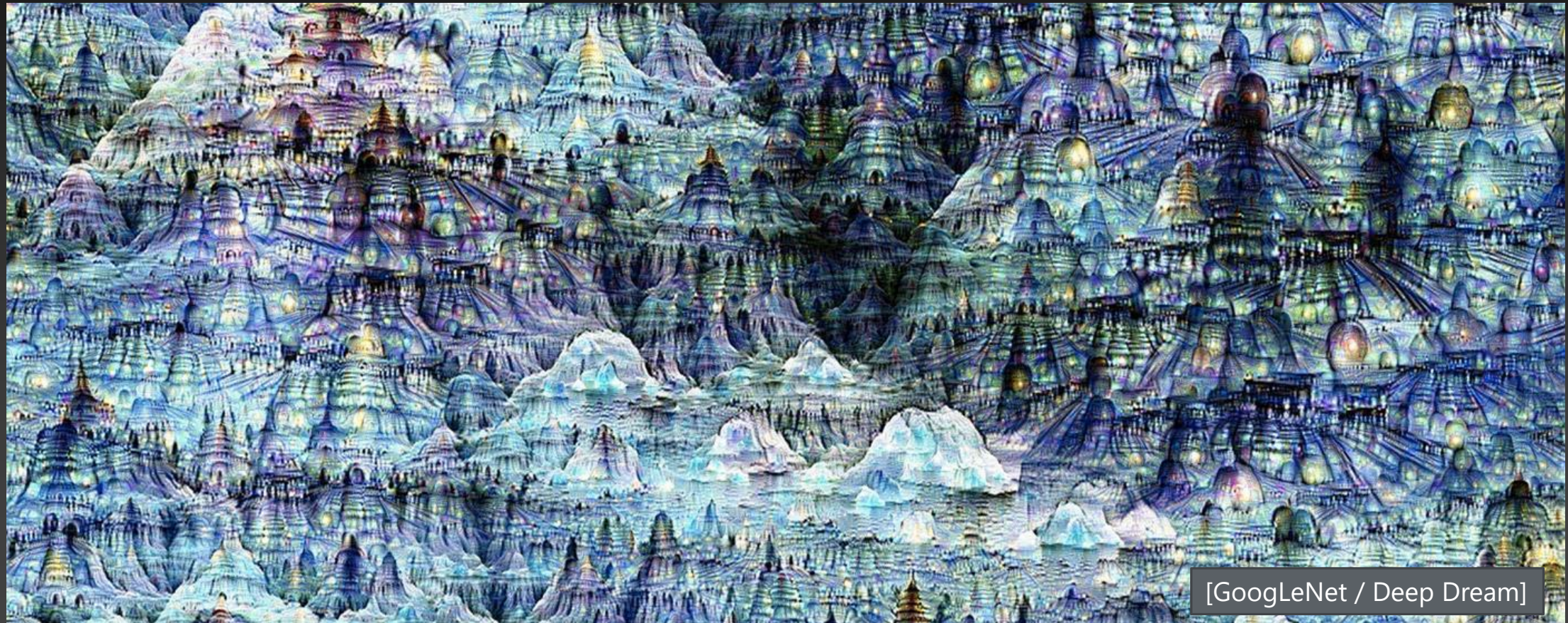


## Challenge:

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

[Salesin 2002, NPAR]

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



[GoogLeNet / Deep Dream]



## “Recognition AI” (Tate IK 2016): Matches old British art to new photojournalism

DATE: 17/08/16  
TITLE: Eunuchs apply make-up before Raksha Bandhan festival celebrations in a red light area in Mumbai  
AUTHOR: DANISH SIDDIQUI  
SOURCE: REUTERS

□ OBJECTS 52%

- 1 WOMAN WEARING A DRESS
- 2 WOMAN WEARING A BLACK SHIRT
- 3 A BLACK BAG ON THE FLOOR
- 4 A GREEN AND YELLOW BAG

○ FACES 35.6%

SUBJECT 1


AGE: 23  
GENDER: Female  
EMOTION: Neutral 89%

△ COMPOSITION 41.2%

DOMINANT COLOUR: #850203  
ACCENT COLOUR: #D99B81

≡ CONTEXT 12%

DESCRIPTION  
Eunuchs apply make-up before Raksha Bandhan festival celebrations in a red light area in Mumbai.



DATE: C.1660  
TITLE: Two Ladies of the Lake  
Family  
AUTHOR: Sir Peter Lely  
SOURCE: TATE

□ OBJECTS 52%

- 1 WOMAN IN A BROWN JACKET
- 2 WOMAN WEARING A WHITE SHIRT
- 3 WOMAN SITTING ON A BENCH
- 4 BLUE JEANS ON THE PERSON

○ FACES 35.6%

SUBJECT 1


AGE: 32  
GENDER: FEMALE  
EMOTION: Neutral 90%

△ COMPOSITION 41.2%

DOMINANT COLOUR: #024920  
ACCENT COLOUR: #555054

≡ CONTEXT 12%

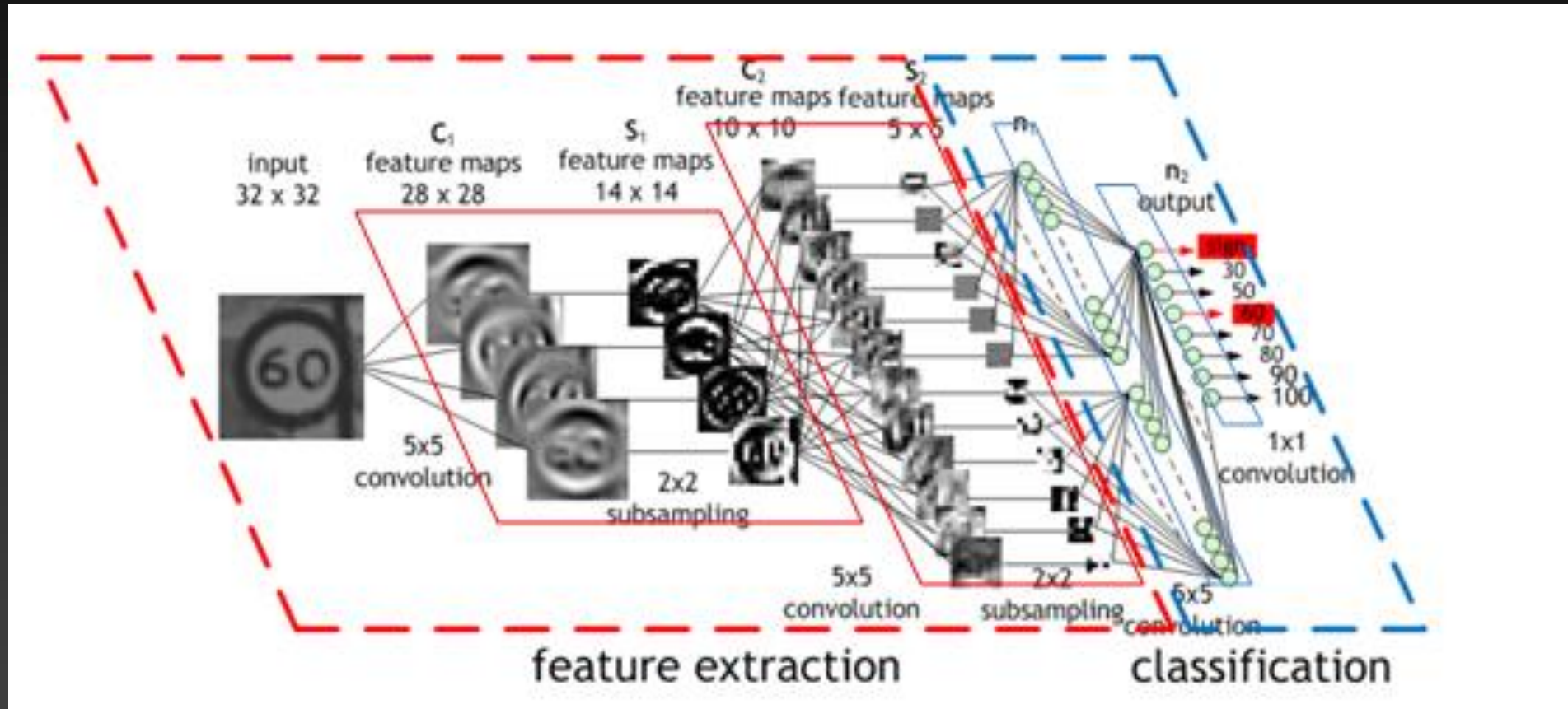
TAGS  
EMOTIONS, CONCEPTS AND IDEAS, UNIVERSAL CONCEPTS, BEAUTY, LEISURE AND PASTIMES, MUSIC AND ENTERTAINMENT, MUSIC, OBJECTS, FINE ARTS AND MUSIC, INSTRUMENT, GUITAR, FURNISHINGS



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

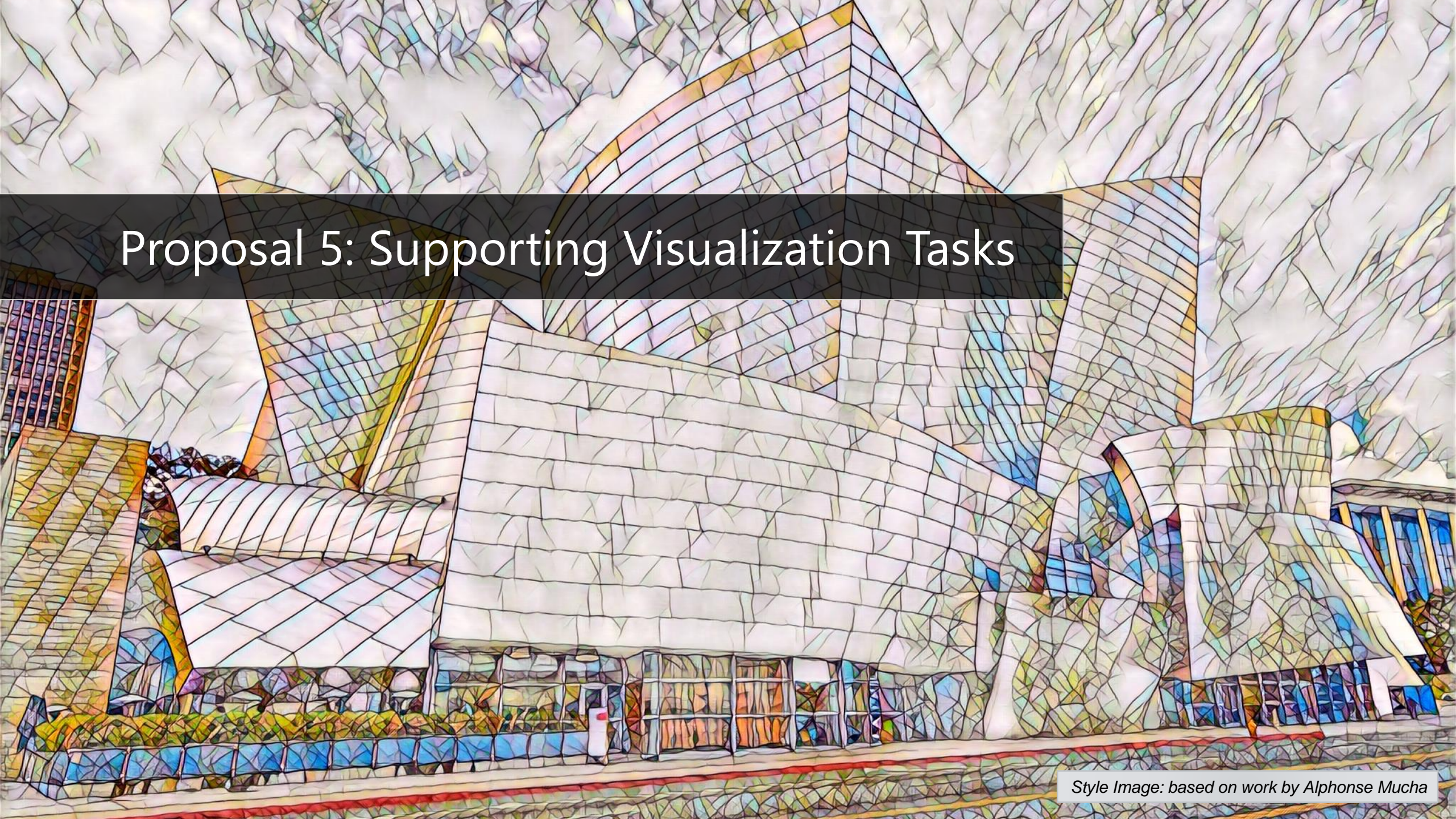


# Proposal: Use Classification to Inject Custom Style Representations



[Image by Maurice Peemen]



The background of the slide is a stylized, stained-glass illustration of the Walt Disney Concert Hall in Los Angeles. The building's iconic, undulating, metallic surfaces are rendered in a mosaic of colorful, irregular shapes, primarily in shades of white, grey, and blue, with accents of yellow, orange, and red. The sky above is a complex, swirling pattern of light and dark tones, also in a stained-glass style. The overall effect is a vibrant, artistic representation of the building's architecture.

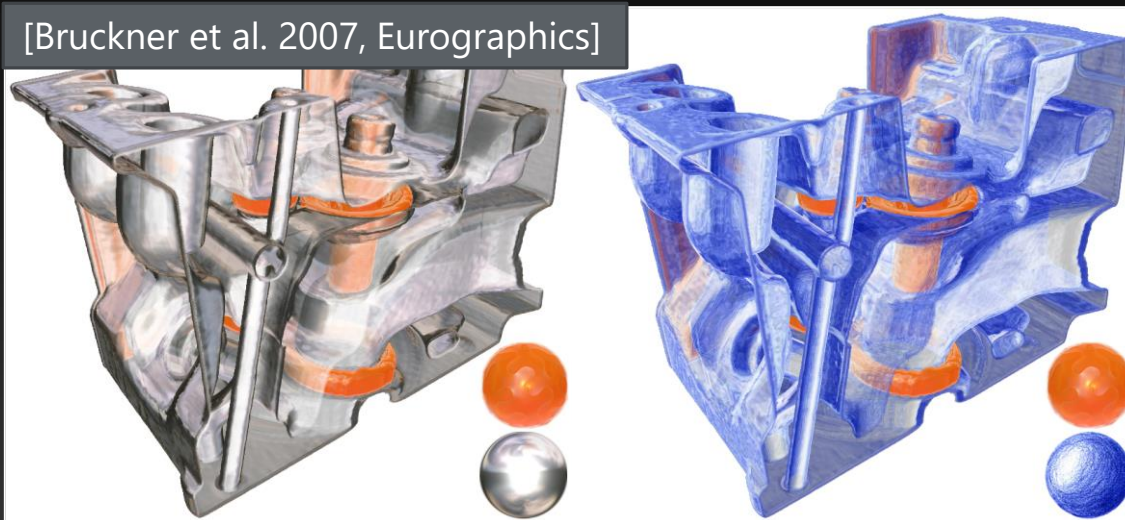
# Proposal 5: Supporting Visualization Tasks

*Style Image: based on work by Alphonse Mucha*

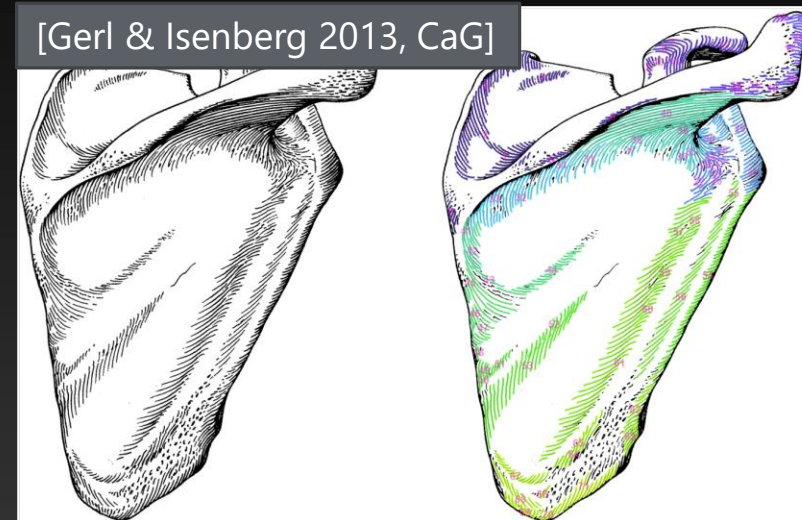


# Style Transfer in Illustrative Visualization

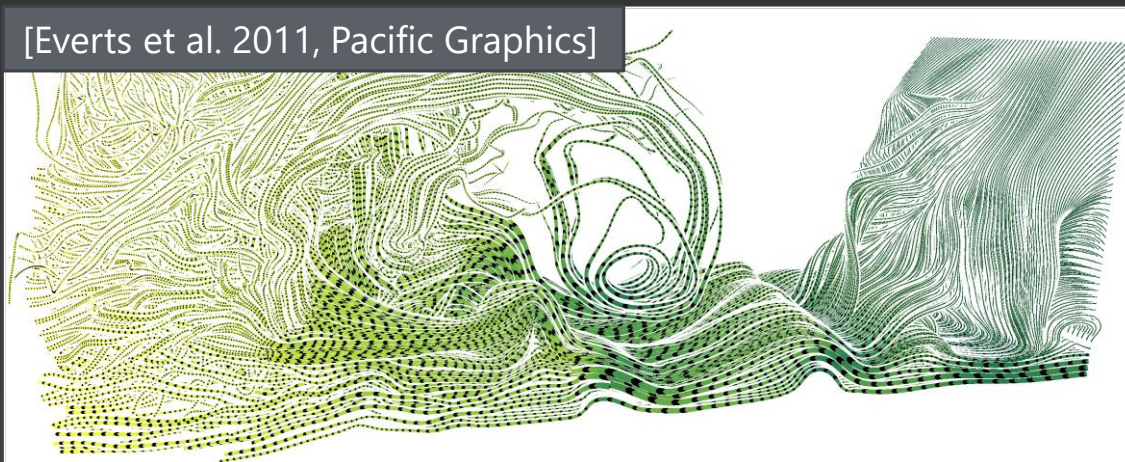
[Bruckner et al. 2007, Eurographics]



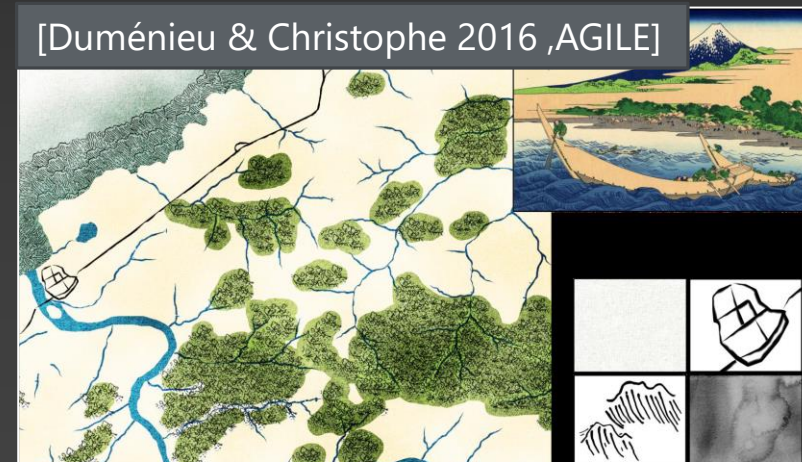
[Gerl & Isenberg 2013, CaG]



[Everts et al. 2011, Pacific Graphics]



[Duménieu & Christophe 2016 ,AGILE]





# Key concept: Level of Abstraction



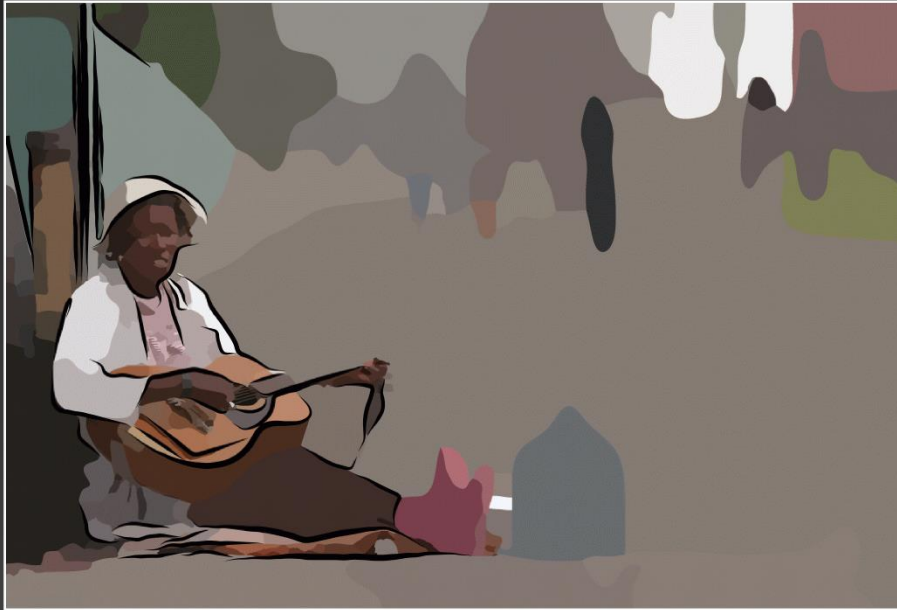
[Gatys et al. 2016, CVPR]



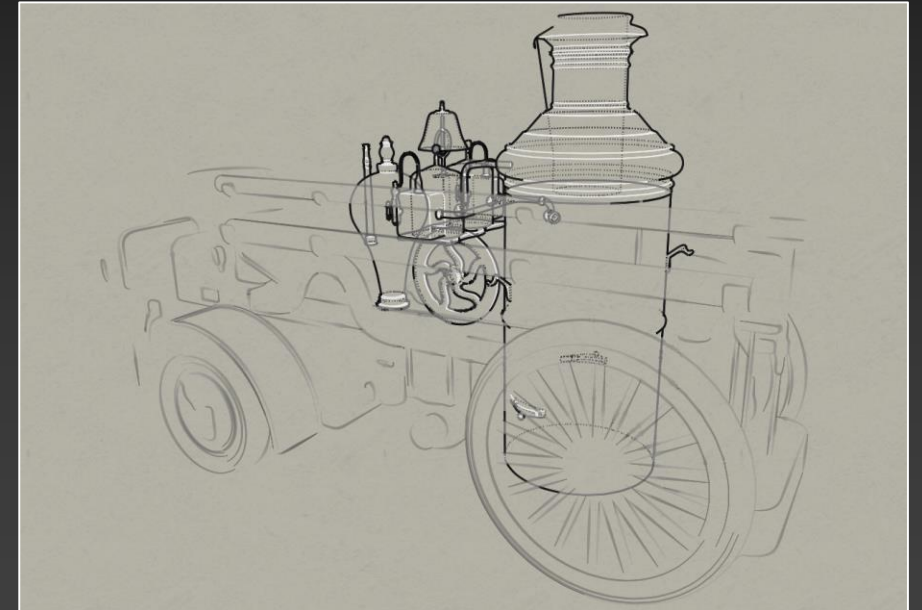
How to represent the spatial and thematic granularity of image contents according to user task, camera view and image resolution?

# 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

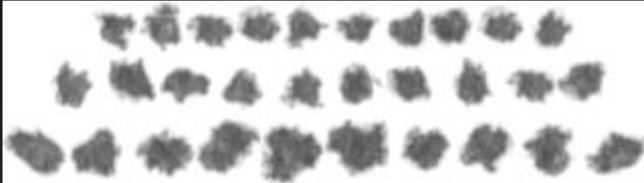
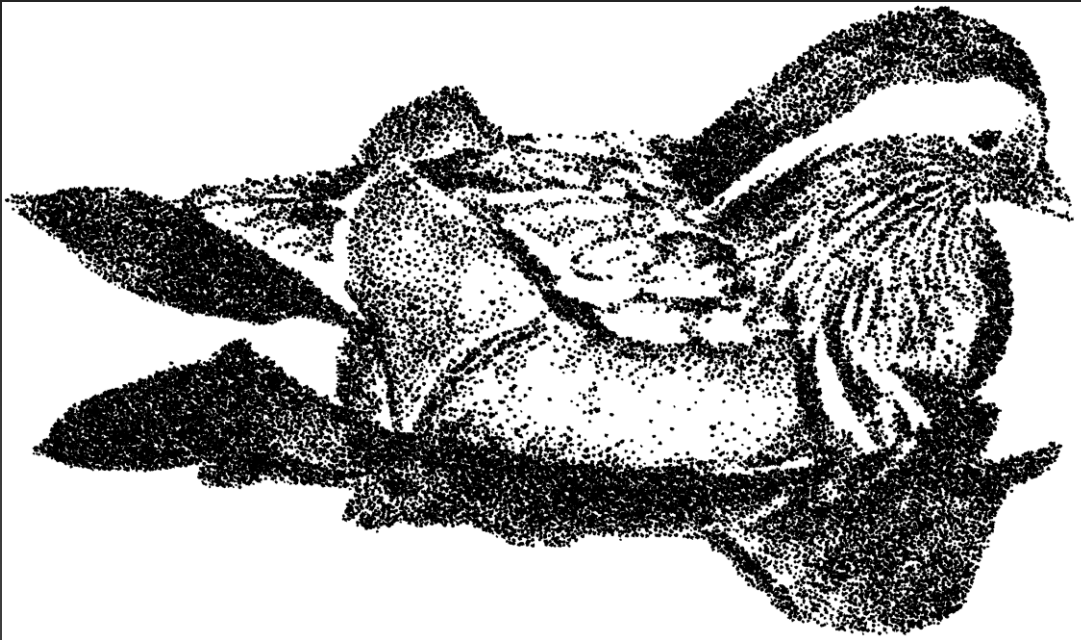
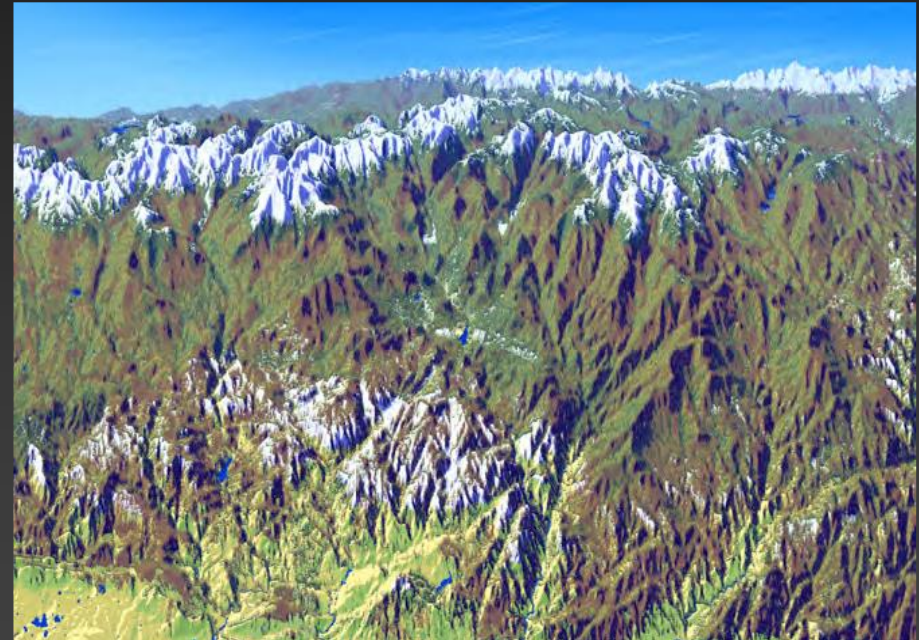


Illustration Styles /  
Texture Marks



[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

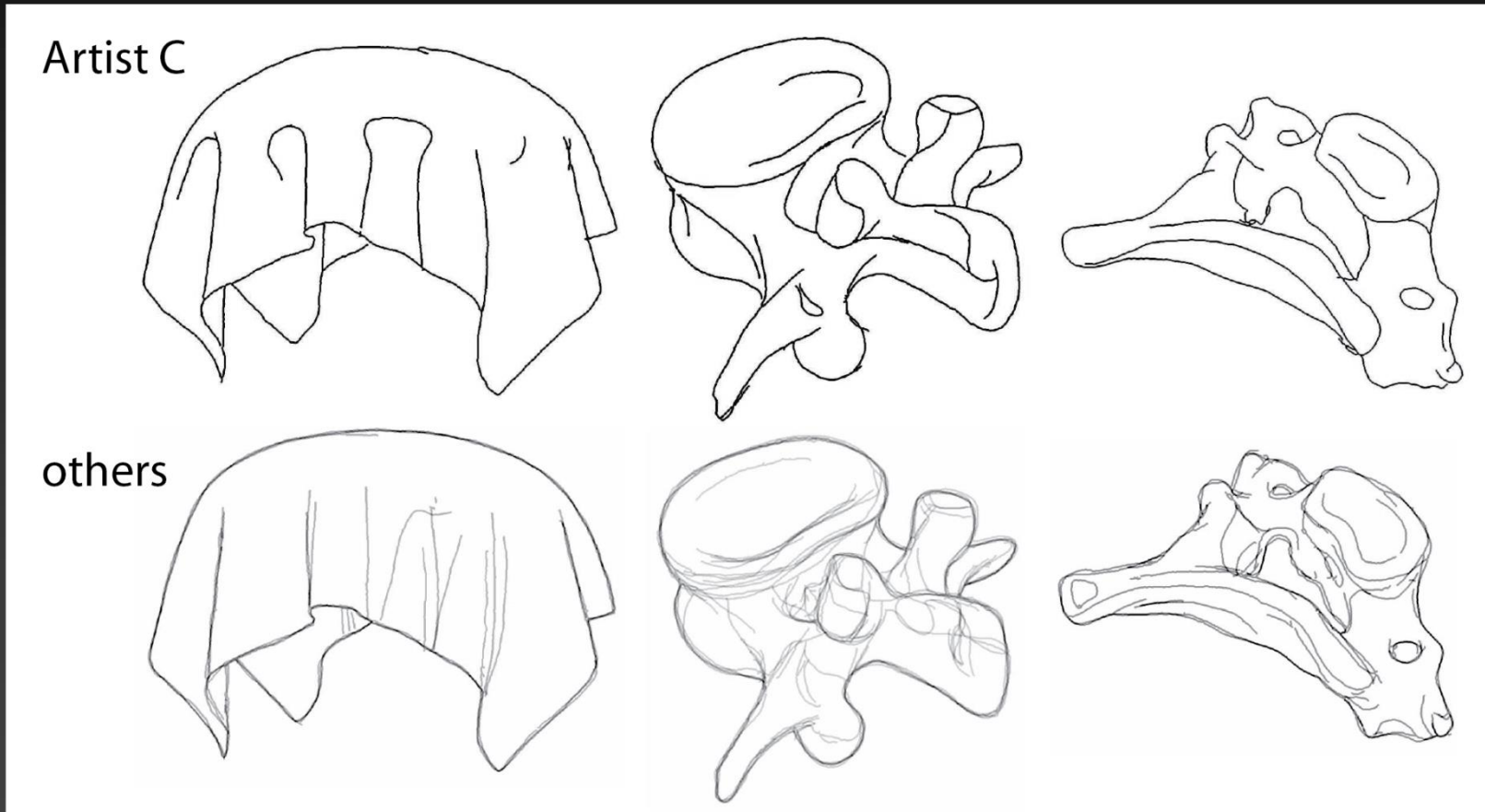
- Participants had to select hand-painted images from 10 pairs with NST results
- Average of 45,000 participants answered 6.1 image pairs correctly



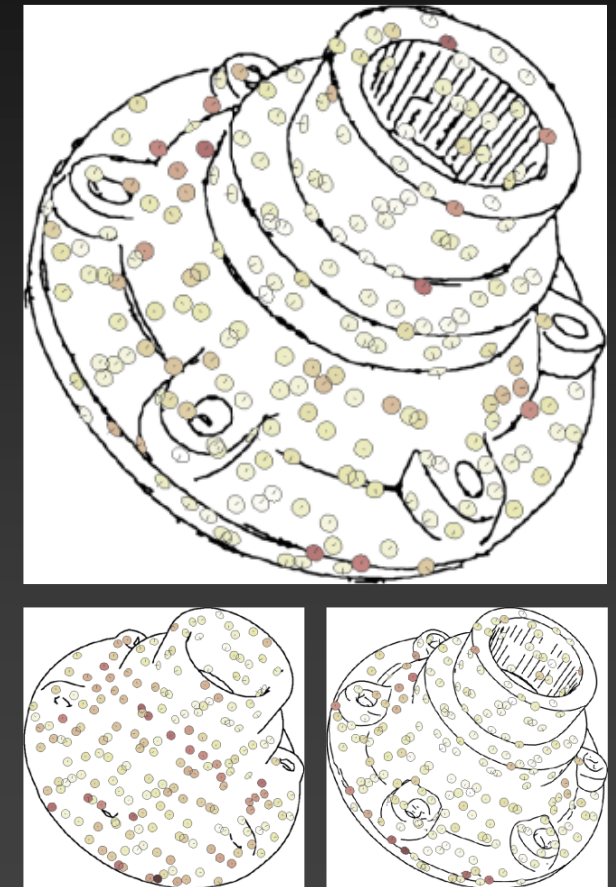
[[turing.deepart.io](https://turing.deepart.io)]

# 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]



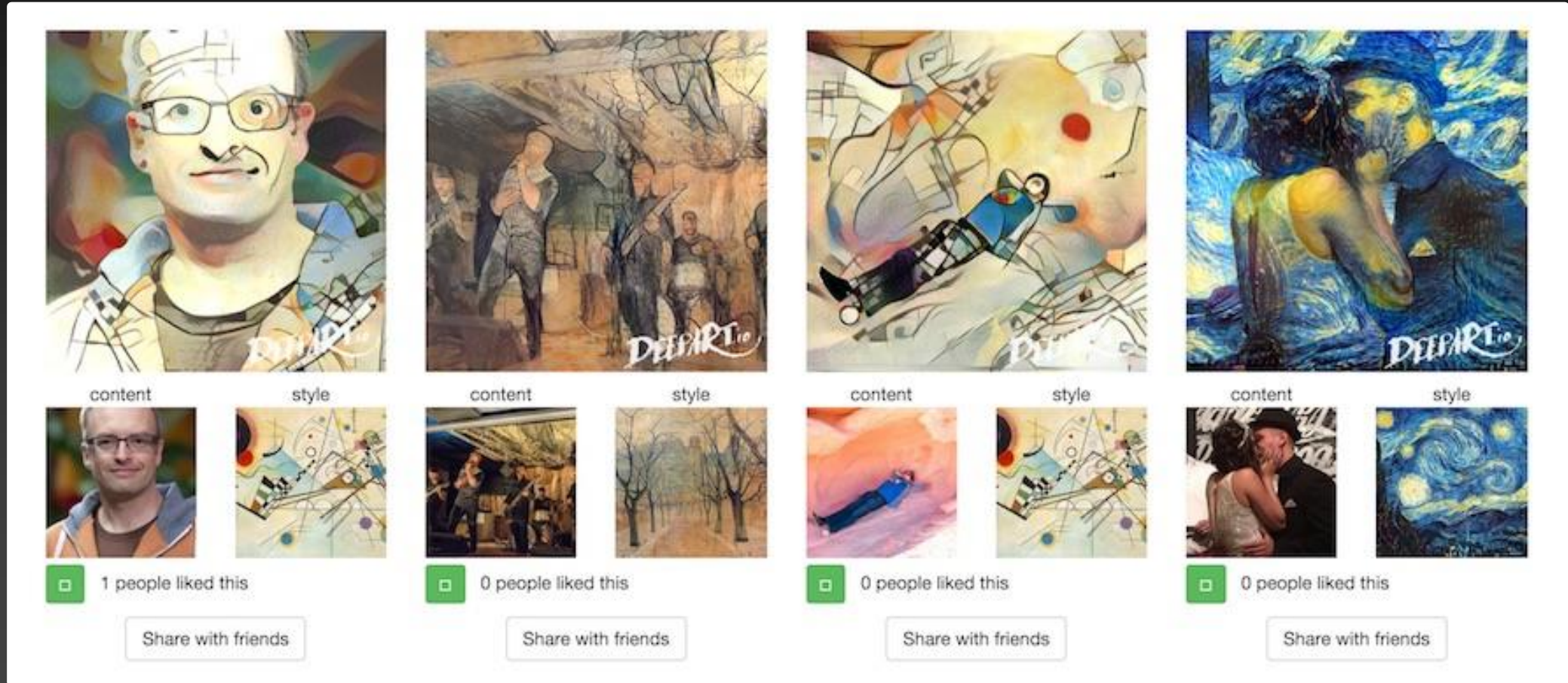
# Applications





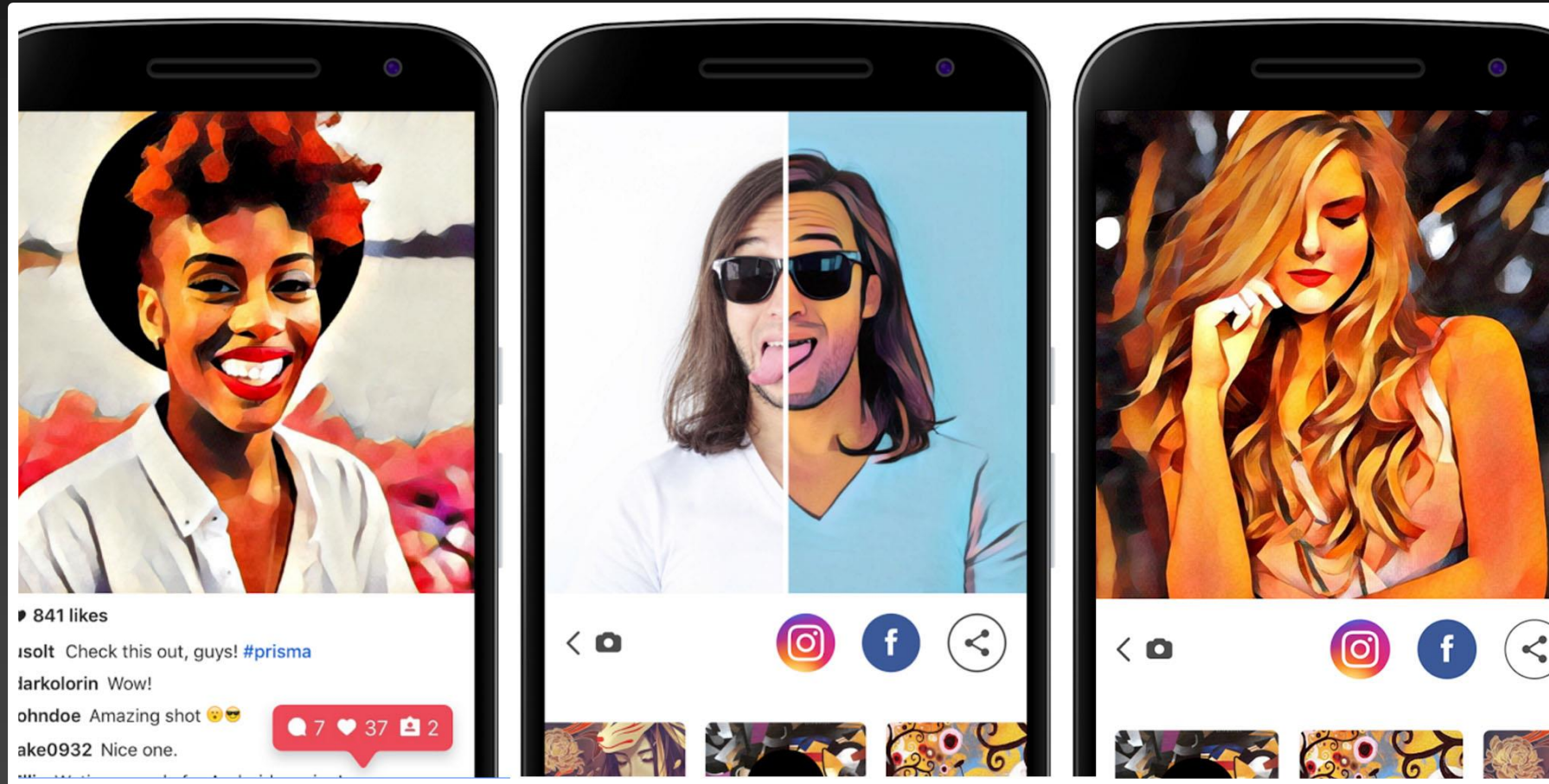
# 1. Casual Creativity

deepart.io



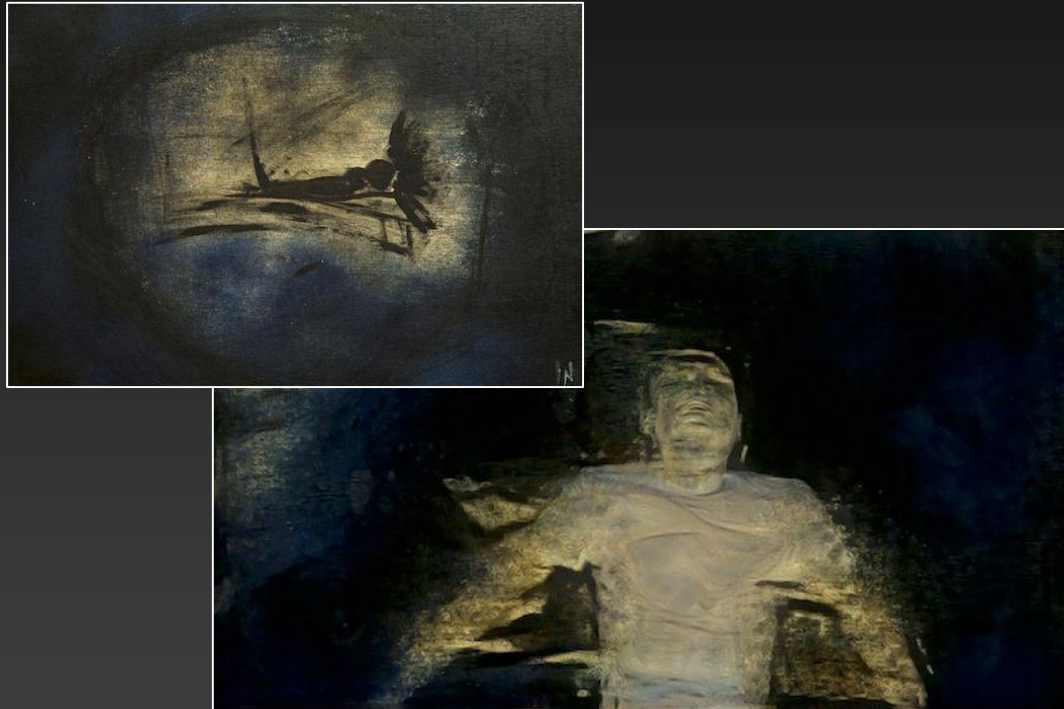
# 1. Casual Creativity

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

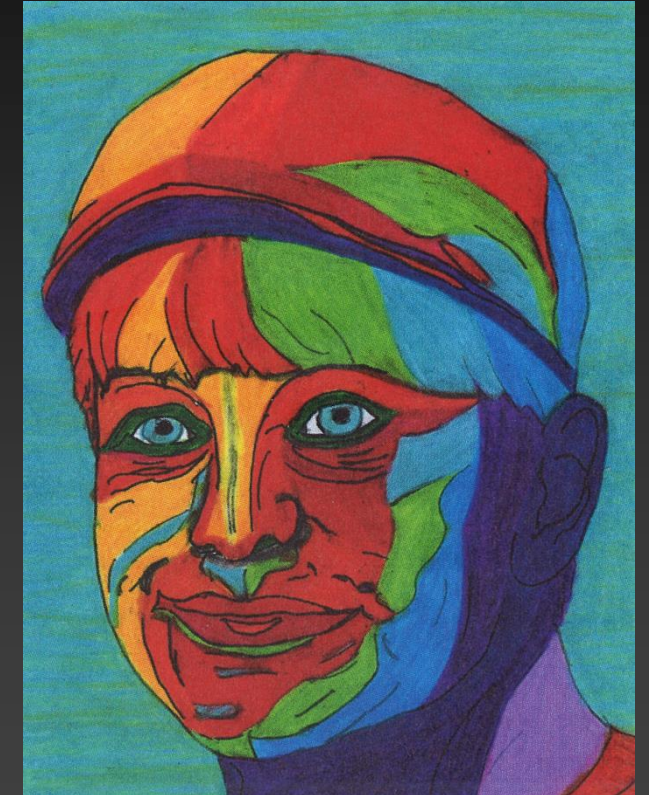
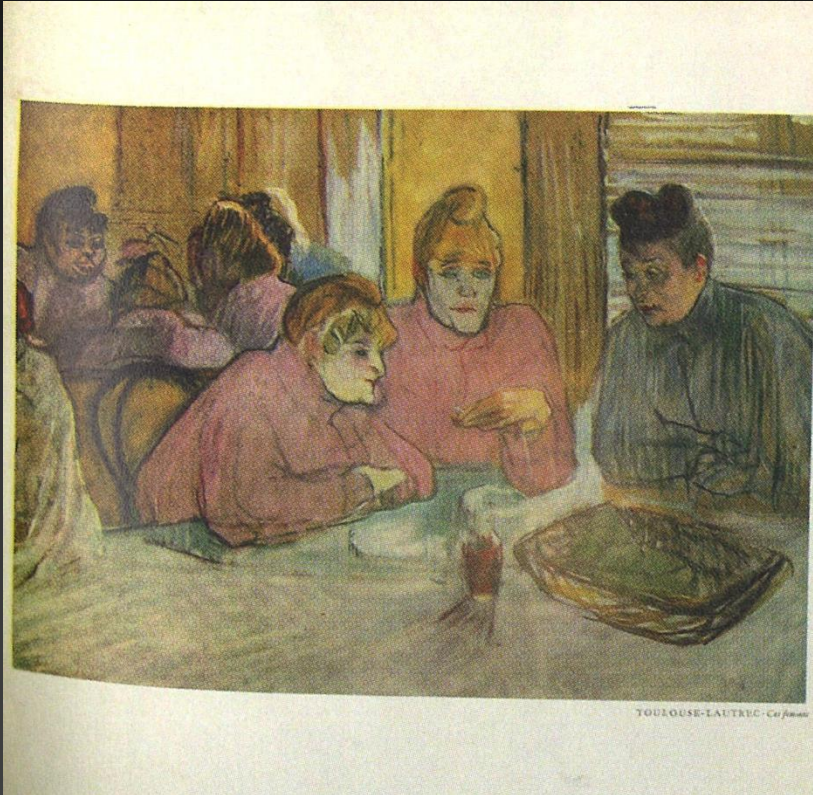
[„Loving Vincent“, BreakThru Films]



### 3. Teaching Art Classes

#### Color Analysis (11-12 years)

#### Style Analysis (13-14 years)



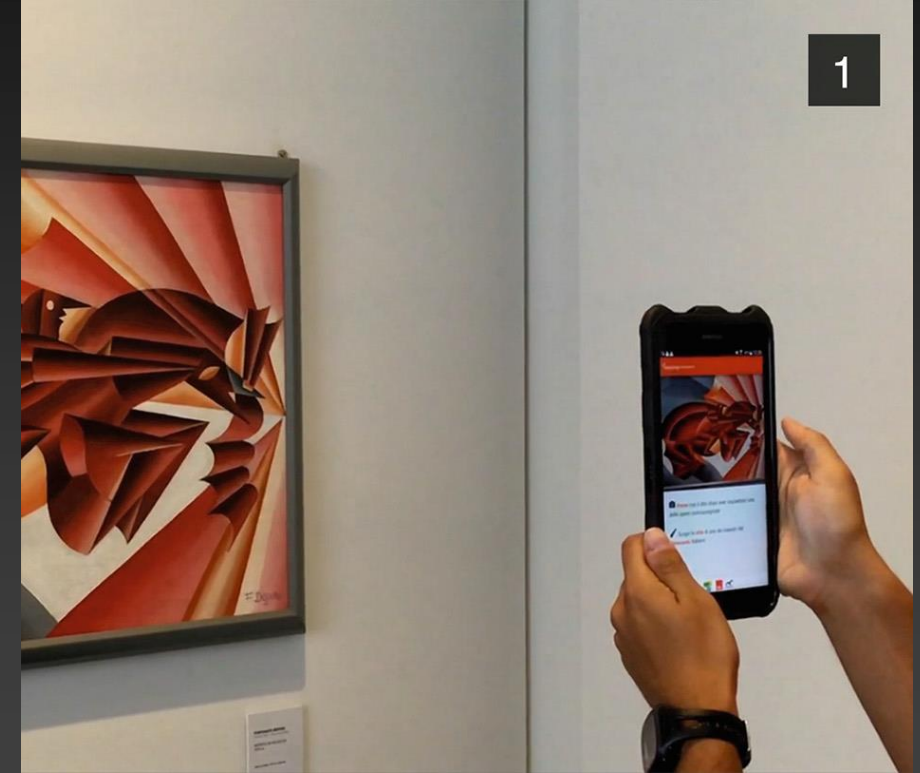
[Left: Color Analysis of Henri de Toulouse-Lautrec, Right: Portrait in Style of Martin Kippenberger by Nele Zeyn. In „Hands on: Kunstgeschichte“, 2017, Joachim Penzel (eds.)]



## 4. Exhibitions and Art Installations



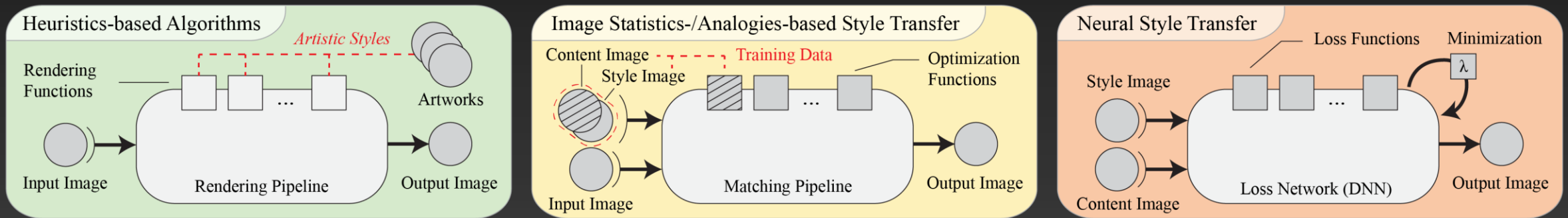
[Adobe Artistic Eye]



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

## ■ 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



« 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!

- **Amir Semmo and Jürgen Döllner**

Hasso-Plattner-Institut,  
Faculty of Digital Engineering  
University of Potsdam

hpi3d.de | amirsemmo.de



- **Tobias Isenberg**

Inria & Université Paris-Saclay

aviz.fr | tobias.isenberg.cc

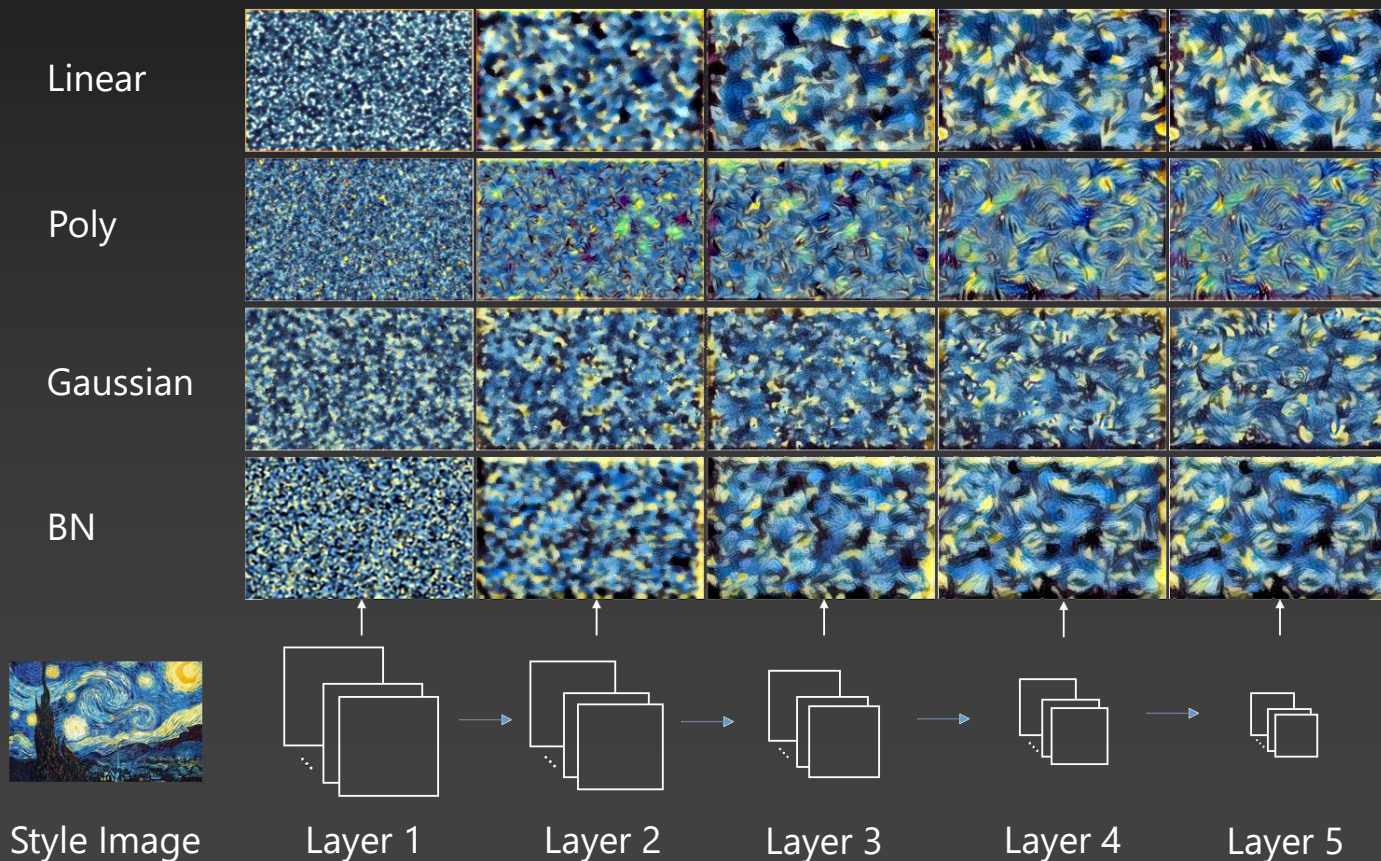




# BACKUP SLIDES

# 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)





# Combine Deep Learning with Image Analogies



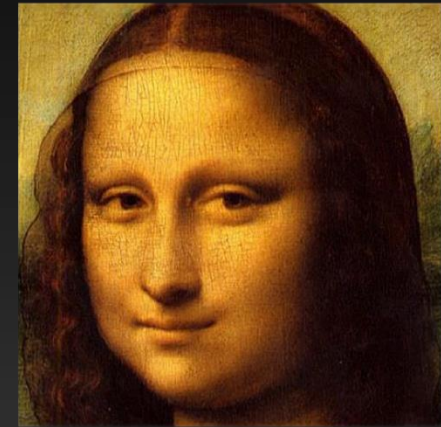
:



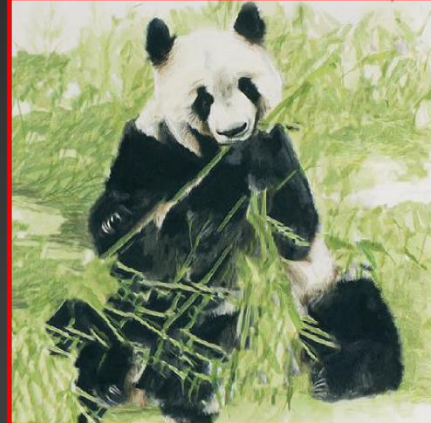
::



:



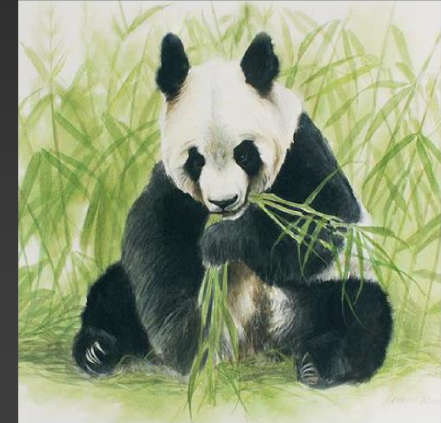
:



::



:



A (input)

A' (output)

B (output)

B' (input)

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

## “Artistic style transfer for videos”

- Introduce a temporal consistency loss function using optical flow information



Initialization

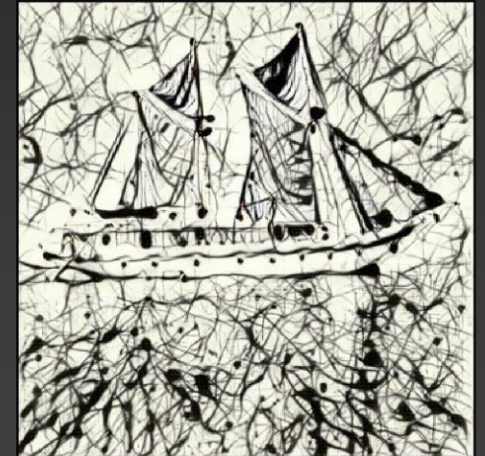
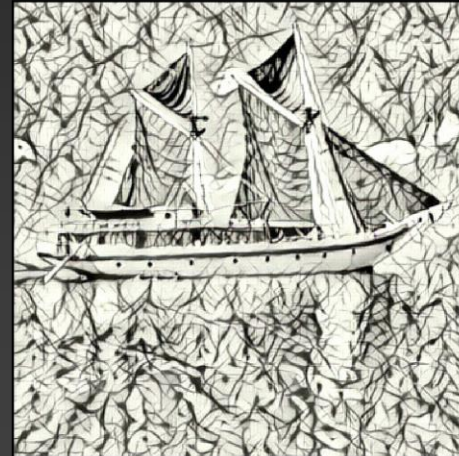
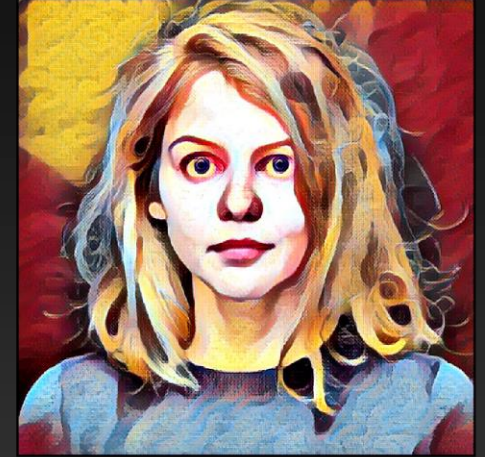
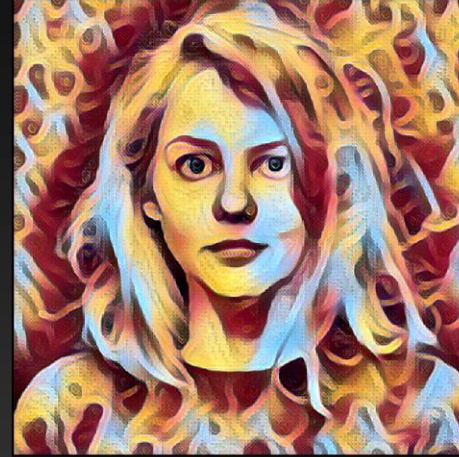
Optical Flow

Uncertainty

After Optimization



# Iterative vs. Feed-forward Neural Style Transfer



[deepart.io]

[Pikazo]

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



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

