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

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

29.07.2017
Neural Style Transfer: A Paradigm Shift for Image-based Artistic Rendering?
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 ...

- **Late 1980s**: Advances in media emulation
  - D. Strassman (SIGGRAPH 86)

- **1990**: Semi-automatic painting systems
  - P. Haeberli (SIGGRAPH 90)

- **1997**: Video painting
  - P. Litwinowicz (SIGGRAPH 97)

- **1998**: Perceptual UI & segmentation
  - D. DeCarlo (SIGGRAPH 02)

- **2000**: Space-time video
  - J. Collomosse [TVCG 05]
  - Wang [SIGGRAPH 04]

- **2002**: Anisotropy / filters
  - J. Kyprianidis [TPCG 08]
  - H. Winnemoller [SIGGRAPH 06]

- **2005**: Fully automatic painting
  - A. Hertzmann (SIGGRAPH 98)
  - Treveatt/Chen [EGUK 97]
  - P. Litwinowicz [SIGGRAPH 97]

- **2006**: Automatic perceptual
  - J. Collomosse [EvoMUSART 05]

- **2010**: Deep neural networks
  - L. Gatys [arXiv 15, CVPR 16]
  - J. Johnson [ECCV 16]

- **2015**: User evaluation
  - T. Isenberg [NPAR 06]

- **2010**: NPAR 2010 Grand challenges

[Kyprianidis et al. 2013, TVCG]
Non-Photorealistic Animation & Rendering:

7 Grand Challenges

David Salesin
June 2002

[Salesin 2002, NPAR]

[Gooch et al. 2010, NPAR]

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


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

[MacEachren et al., 2012, TVCG]
Pictorial Semiotics – Design Aspects

1. Modeling Aspects
   - Color Maps
   - Feature Maps
   - Geometry Maps

[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

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]
Pictorial Semiotics – Design Aspects

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- Area
- 2D Element

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

Ernst Ludwig Kirchner [1907]
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- Color

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

[http://sketchingjourney.com]
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VI. Perceptual Aspects
- Flatness
- Motion Coherence
- Temporal Continuity
- Pictorial Cues

29.07.2017

Neural Style Transfer: A Paradigm Shift for Image-based Artistic Rendering?
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VI. Perceptual Aspects
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   ▪ Motion Coherence
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   ▪ Pictorial Cues

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.
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 *

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

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* Neural Style Transfer: A Paradigm Shift for Image-based Artistic Rendering? 25
Proposal 1: Semiotics-based Optimization

Style Image: Vincent van Gogh – "Starry Night"
Current Limitations

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

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
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]

Neural Style Transfer: A Paradigm Shift for Image-based Artistic Rendering?
Build tools for “right-brained” thinking [Salesin 2002, NPAR]

NPAR for artists: Control needed at multiple levels

[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

Interactive tools / devices

[Hertzmann 1998, SIGGRAPH]

[Salisbury et al. 1997, SIGGRAPH]

[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

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

"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]
Proposal 3: Combining IB-AR Paradigms
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

IPF: Noise reduction

RBT: Segmentation

[Zeng et al. 2009, ToG]  [Kyprianidis & Kang 2011, Eurographics]  [Doyle & Mould 2016, CAe]
Case Study: Combining Neural Style Transfer and Image Filtering

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

[Semmo et al. 2017, SIGGRAPH Appy Hour]
Case Study: Combining Neural Style Transfer and Image Filtering
Further Additions: Physically-based and Distortion Effects

Substrate-based Effects

Image Warping

[Montesdeoca et al. 2017, NPAR]

[Li & Mould et al. 2015, CAe]
Proposal 4: New Forms of Art
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
"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
Proposal 5: Supporting Visualization Tasks
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

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

[Gatys et al. 2016, CVPR]

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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
Comparing Hand-Made Images with Computer-Generated NPR

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

[Artist C]

[Others]

[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

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

[“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)
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

29.07.2017
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**
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- **Tobias Isenberg**
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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

29.07.2017

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

“Artistic style transfer for videos”
- Introduce a temporal consistency loss function using optical flow information
Iterative vs. Feed-forward Neural Style Transfer

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

[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)