Interactive Style Space of Deep Features and Style Innovation

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1 Abstract

Stylizing images as paintings has been a popular computer vision technique for a long time. However, most studies only consider the art styles known today, and rarely have investigated styles that have not been painted yet. We fill this gap by projecting the high-dimensional style space of Convolutional Neural Network features to the latent low-dimensional style manifold space. It is worth noting that in our visualized space, simple style linear interpolation is enabled to generate new artistic styles that would revolutionize the future of art in technology. We propose a model of an Interactive Style Space (ISS) to prove that in a manifold style space, the unknown styles are obtainable through interpolation of known styles. We verify the correctness and feasibility of our Interactive Style Space (ISS) and validate style interpolation within the space.

2 Style Transfer Problem Generalization

Painting Depiction (f)

content (c): the objects in the painting…

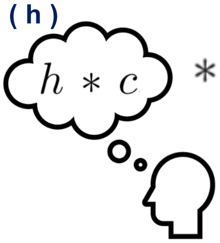
presentational form [style] (s): color, shading, stroke pattern…

$$f = s \circ c$$

Painting depiction (f)

$\circ$: Style Transfer operation

Human Perception (h)



$*$: The operation of human perception

Human perception (h) towards the content (c)

Expanded Generalization

Algorithm (t): recognize the style (s)

$$t \star f$$

$\star$: Machine's recognition operation

- For a meaningful artwork, the human perceived depiction h ∗ f should be as close as possible to the human perceived content h ∗ c:

$$\min_f \|h * f - h * c\|_a = \min_f \|h * (s \circ c) - h * c\|_a$$

- For the specific form of paintings with a style, the form recognized from the depiction t ⋆ f should be as close as to the style s:

$$\min_f \|t \star f - s\|_b = \min_f \|t \star (s \circ c) - s\|_b$$

Then, we can formulate the artistic painting depiction as a multiple objective optimization problem (Image Stylization problem):

$$f^\star = \underset{f}{argmin}\left\{\|h * f - h * c\|_a, \|t \star f - s\|_b\right\} = \underset{f}{argmin}\left\{\|h * (s \circ c) - h * c\|_a, \|t \star (s \circ c) - s\|_b\right\}$$

Add the positive constant α, the above problem can be implemented as a single objective optimization problem:

$$f^\star = \underset{f}{argmin}\left\{\|h * f - h * c\|_a + \alpha\|t \star f - s\|_b\right\} = \underset{f}{argmin}\left\{\|h * (s \circ c) - h * c\|_a + \alpha\|t \star (s \circ c) - s\|_b\right\}$$

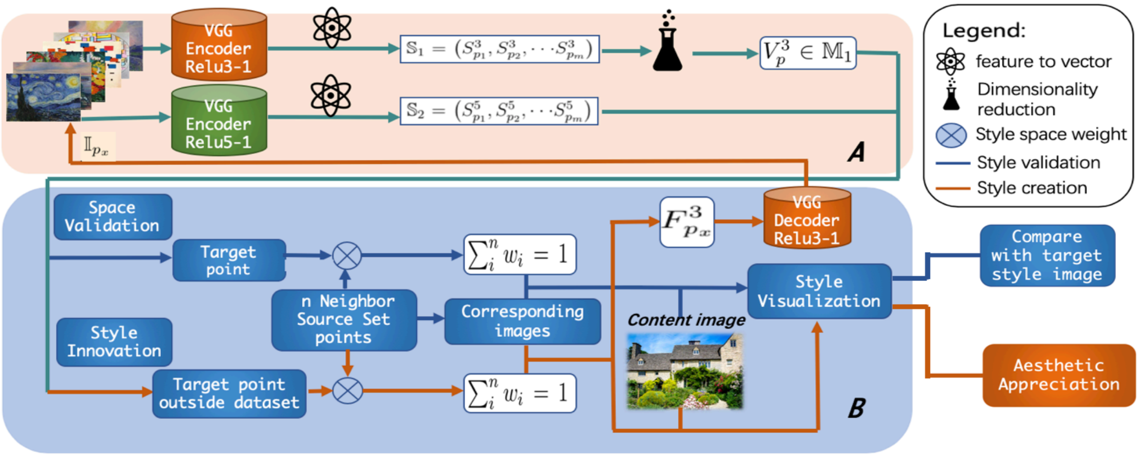
- Style Innovation problem:

To compare the similarity of styles (s1 and s2) between two images (f1 and f2) with contents (c1 and c2):

$$\|t \star f_1 - t \star f_2\|_b = \|t \star (s_1 \circ c_1) - t \star (s_2 \circ c_2)\|_b$$

$\|*\|_b$ measures the similarity/difference between two styles. For innovation problem, the difference between s1 and s2 should as large as possible.

3 The Framework of Our Method



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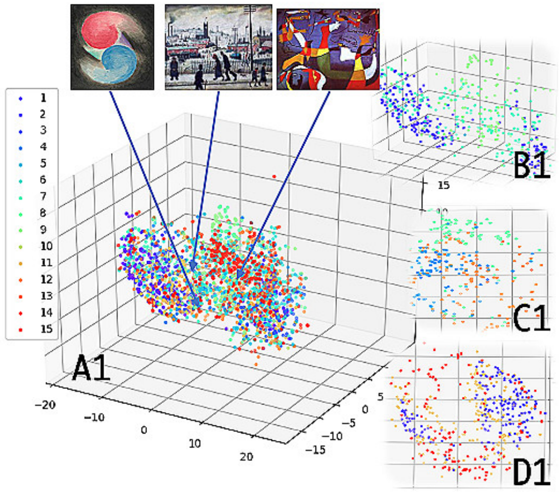
4 Interactive Style Space (ISS) Validation

Generated Interactive Style Space (ISS)



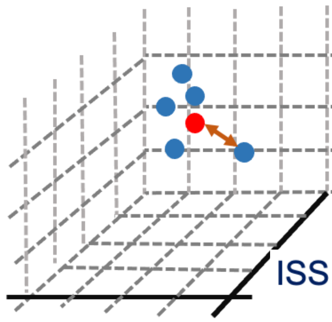
- The relationship between human depiction and style representation

For validation we should try to minimize the difference between synthesized style φ_{p_x} and target style φ_t :

$$\varphi^*_{p_x} = \underset{\varphi_{p_x}}{argmin} \left\| t \star (\varphi_{p_x} \circ c) - t \star (\varphi_t \circ c) \right\|_b$$

For style innovation we should try to maximum the difference.

Validation Method based on ISS



- Target point (pi)
- N neighbor source points (pn). (in this example, N=5)
- Euclidean distance between Target point and Source point
- S^5_N Normalized 5th layer Style Vector

$$V^n_p = \left(x^n_p, y^n_p, z^n_p\right), n = 3$$

$$d_{ix} = \alpha Dis\left(V^3_{p_i}, V^3_{p_x}\right) + \beta Dis\left(S^5_{Np_i}, S^5_{Np_x}\right),\ \alpha + \beta = 1$$

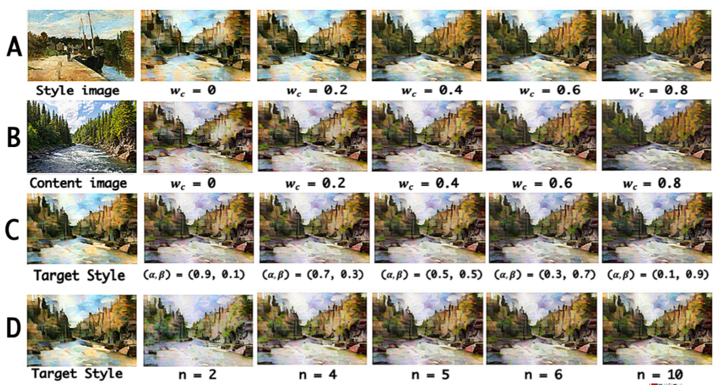
$$w_i = d^{-1}_{ix} / \left(\sum_i^n d^{-1}_{ix} \cdot (1 - w_c)\right)$$

- Style visualization: Wasserstein Style Transfer [1]:

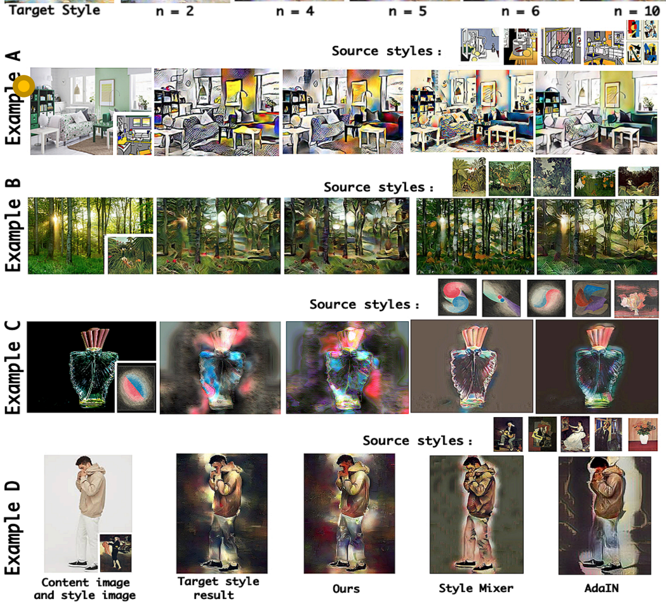
$$T^{\mathfrak{W}}_{F^n_c \to F^n_{p_x}}(x) = m^n_{p_x} + (\sigma^n_c)^{-\frac{1}{2}} \left[(\sigma^n_c)^{\frac{1}{2}} \left(\sigma^n_{p_x}\right) (\sigma^n_c)^{\frac{1}{2}}\right] (\sigma^n_c)^{-\frac{1}{2}} \cdot (x - m^n_c)$$

$$I^n_{p_x} = D^n\left(T^{\mathfrak{W}}_{F^n_c \to F^n_{p_x}}\left(E^n(I_c)\right)\right)$$

Quantitative Evaluation and Comparison of Validation Results



Evaluation Quality		Pixel-wise Mse	Wasserstein Distance	Style vector ReLU3-1	Style vector ReLU5-1
Evaluation Examples	Image 1	9.2958	0.0112	0.1484	0.4666
	Image 2	12.0209	0.0145	0.1256	0.5684
	Image 3	10.3374	0.0104	0.1883	0.4888
	Image 4	40.3908	0.2044	0.4748	0.7733
	Image 5	42.5435	0.1725	0.3391	0.7003
	Image 6	43.0349	0.2319	0.7763	0.8544
(α, β)	(0.9,0.1)	1.9675	0.0196	0.0334	0.1656
	(0.7,0.3)	**1.9626**	0.0196	0.0328	0.1674
	(0.5,0.5)	1.9669	0.0196	0.0338	0.1659
	(0.3,0.7)	2.2530	0.0189	0.0325	0.1541
	(0.1,0.9)	2.2148	0.0205	0.0255	0.1329
n	2	3.6548	0.0242	0.0542	0.1684
	4	2.3035	0.0206	0.0394	0.1879
	5	**1.9626**	0.0196	0.0338	0.1674
	6	1.9683	0.0195	0.0299	0.1537
	10	2.3225	0.0217	0.0293	0.1481



5 Style Innovation examples

Reference

[1] Y. Mroueh, "Wasserstein style transfer," *arXiv preprint arXiv:1905.12828*, 2019.