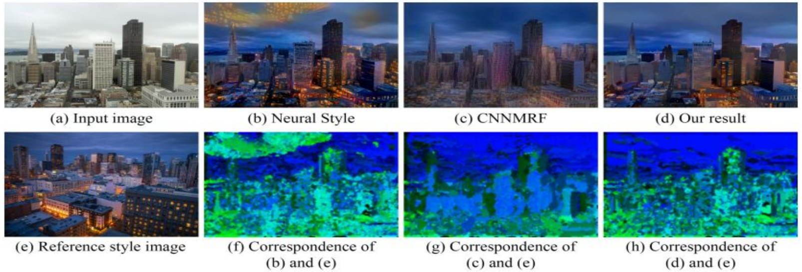
Photo Realistic Style Transfer - Recent work in transferring style between images.

What is the problem?

Photographic style transfer aims to apply a reference image style to an input photo while maintaining photorealism. Existing methods either introduce distortions or offer limited global adjustments. The challenge is preserving the input's structure while allowing local, context-aware changes. Key difficulties include avoiding content-mismatch artifacts, handling semantic differences, and creating a versatile solution for various scenarios like time-of-day changes and artistic edits.

What has been done earlier?

- Global color transfer methods - match overall color statistics but lack local adaptation
- Neural style transfer - produces artistic results but introduces distortions and ignores semantic context
- CNNMRF - uses patch-based matching but often results in partial transfers
- Content-aware methods for specific scenarios - limited to particular applications



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What are the remaining challenges? What novel solution proposed by the authors to solve the problem?

Remaining challenges:

1. **Preserving photorealism while allowing local, context-aware style changes**
   a. Avoiding painting-like distortions that occur in neural style transfer
   b. Maintaining straight edges, regular patterns, and overall image structure
2. **Avoiding content-mismatch artifacts ("spillover" effects)**
   a. Preventing style transfer between semantically different regions (e.g. sky style applied to buildings)
   b. Handling differences in content distribution between input and style images
3. **Achieving faithful style transfer for a wide range of scenarios**
   a. Creating a general method that works for various style transfer tasks without scenario-specific algorithms
   b. Balancing the trade-off between photorealism and style faithfulness

Novel solutions:

1. **Photorealism regularization using locally affine color transforms**
   a. Introduce a custom fully differentiable energy term based on the Matting Laplacian
   b. Constrain the transformation to be locally affine in colorspace, preventing spatial distortions
2. **Semantic segmentation guidance for context-aware style transfer**
   a. Use DilatedNet to generate semantic masks for both input and style images
   b. Augment the style loss function to consider semantic labels, preventing spillover effects
3. **Two-stage optimization process**
   a. First stage: Initialize with neural style transfer using the augmented style loss
   b. Second stage: Apply photorealism regularization to refine the result
4. **Merged semantic classes to improve stability and cleaner segmentations**

(a) Input and Style (b) $\lambda = 1$ (c) $\lambda = 10^2$ (d) $\lambda = 10^4$, our result (e) $\lambda = 10^6$ (f) $\lambda = 10^8$

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(a) Input image (b) Reference style image (c) Neural Style (d) CNNMRF (e) Our result

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