

L-CAD: Language-based Colorization with Any-level Descriptions using Diffusion Priors

Zheng Chang^{1#} Shuchen Weng^{2,3#} Peixuan Zhang¹ Yu Li⁴ Si Li^{*1} Boxin Shi^{2,3}

¹School of Artificial Intelligence, Beijing University of Posts and Telecommunications ²National Key Laboratory for Multimedia Information Processing, School of Computer Science, Peking University ³National Engineering Research Center of Visual Technology, School of Computer Science, Peking University ⁴International Digital Economy Academy

Outline

Introduction

- Background
- Motivation
- Method
 - Pipeline
 - Luminance-guided image compression
 - Semantic-aligned latent representation
 - Instance-aware sampling strategy
- Result
 - Comparison with Automatic Colorization
 - Comparison with Language-based Colorization
 - Ablation
 - Application

Background

- A person wearing a spacesuit is mowing grass on the lawn.
- 2. A rabbit with sunglasses and a hat.
- 3. An astronaut piled up a pyramid with sand.
- 4. The robot is pouring coffee.....



Motivation

The wine on the far left is purple, the middle two glasses are blue, and the wine on the far right is orange.





Outline

- Introduction
 - Background
 - Motivation
- Method
 - Pipeline
 - Luminance-guided image compression
 - Semantic-aligned latent representation
 - Instance-aware sampling strategy
- Result
 - Comparison with Automatic Colorization
 - Comparison with Language-based Colorization
 - Ablation
 - Application

Pipeline



Luminance-guided image compression



Training loss:

 $\mathcal{L}_{pix} = \mathcal{L}_{rec} + \alpha \mathcal{L}_{dis} + \beta \mathcal{L}_{per}$

New reconstruction loss:

 $\mathcal{L}_{\rm rec} = \|M^{\rm art} \odot (x - \tilde{x})\|_1.$

Artifacts map:

$$M_{h,w}^{\text{art}} = \sum_{p \in \Omega_{(h,w)}} \left(\frac{\delta_p - \mu_p}{N_{\text{win}}}\right)^2, \qquad \mu_p = \sum_{p \in \Omega_{(h,w)}} \frac{\delta_p}{N_{\text{win}}^2},$$



Semantic-aligned latent representation



Formula for extended convolution:

$$f'_{h,w} = \sum_{i=0}^{N_{k}-1} \sum_{j=0}^{N_{k}-1} \Big(\sum_{k=1}^{N_{\text{fix}}} \omega_{i,j,k}^{\text{fix}} f_{p,q,k} + \sum_{k=1}^{N_{\text{ext}}} \omega_{i,j,N_{\text{fix}}+k}^{\text{ext}} \bar{y}_{p,q,k}^{\text{lum}} \Big),$$

Training loss:

$$\mathcal{L}_{\text{lat}} = \mathbb{E}_{t, z_0, \epsilon \sim \mathcal{N}(0, 1)} \big[\|\epsilon_t - \epsilon_\theta(z_t, t, y^{\text{tex}}, y^{\text{lum}})\|^2 \big],$$

Instance-aware sampling strategy

Algorithm 1: Instance-aware sampling strategy **input** :Roughly estimated object contour M^{est} **output**: Colorized latent representation z_0 for t = T ... 1 do _, $M_*^{\text{att}} = \epsilon_{\theta}(z_t, t, y^{\text{lum}}, y^{\text{tex}})$ for $l = 1 \cdots L$ do $\hat{M}_l^{\text{est}} \leftarrow \text{Downsampling}(M^{\text{est}}, l)$ $\mathcal{M} \leftarrow \text{Sigmoid}(M_I^{\text{att}})$ $\hat{M}_{l}^{\text{att}} \leftarrow M_{l}^{\text{att}} - \lambda \nabla_{M_{l}^{\text{att}}} \mathcal{L}_{\text{BCE}}(\mathcal{M}, \hat{M}_{l}^{\text{est}})$ end $\hat{\epsilon}_t, _ = \epsilon_\theta(z_t, t, y^{\text{lum}}, y^{\text{tex}}) \{ M_*^{\text{att}} \leftarrow \hat{M}_*^{\text{att}} \}$ $z_{t-1} = \text{DDIM}(z_t, \hat{\epsilon}_t, t)$ end



Ground-truth



M^{est} for

M^{est} for "left orange car" "right yellow car"

Outline

- Introduction
 - Background
 - Problems
- Method
 - Pipeline
 - Luminance-guided image compression
 - Semantic-aligned latent representation
 - Instance-aware sampling strategy
- Result
 - Comparison with Automatic Colorization
 - Comparison with Language-based Colorization
 - Ablation
 - Application

Comparison with Automatic Colorization



Grayscale

CIC

BigColor

DISCO

Comparison with Language-based Colorization



Description

Grayscale

Ground Truth

ML2018

L-CoDe

L-Colns

Ablation



Application

