Towards Photorealistic Colorization by Imagination

Chenyang Lei∗ Yue Wu∗ Qifeng Chen
The Hong Kong University of Science and Technology

Abstract

We present a novel approach to automatic image colorization by imitating the imagination process of human experts. Our imagination module is designed to generate color images that are context-correlated with black-and-white photos. Given a black-and-white image, our imagination module firstly extracts the context information, which is then used to synthesize colorful and diverse images using a conditional image synthesis network (e.g., semantic image synthesis model). We then design a colorization module to colorize the black-and-white images with the guidance of imagination for photorealistic colorization. Experimental results show that our work produces more colorful and diverse results than state-of-the-art image colorization methods. Our source codes will be publicly available.

1 Introduction

There exist numerous black-and-white photos captured decades ago, and there is a need for skilled artists to perform image colorization. However, such a manual process is labor-intensive and may take a long time to obtain photorealistic colorization results. In this work, we are interested in automatic image colorization that aims to produce a colored photorealistic image from a grayscale one by a computer program without any user guidance or reference. However, existing state-of-the-art methods have various weaknesses compared with human experts. The results by existing methods are often grayish or have color-bleeding artifacts, although many dedicated designs [47, 34] are proposed. Besides, most methods [47, 34, 18, 13, 5] can only provide one colorization result.

Why can human experts colorize black-and-white photos so well? This question is connected to diverse colors for the same kind of object. Intuitively, when we judge whether the color is reasonable, we have to understand the concept of objects. Similarly, when experts colorize a black-and-white photo, they understand what it is and imagine different colorful objects with the same concept. Also, experts can colorize black-and-white images by finding correspondences between the two objects (of the same concept). As a comparison, although direct colorization models are also designed to understand the contexts of an image, they only predict a color with the highest possibility for each pixel [47, 13]. Hence, the automatic colorization performance varies a lot among different objects. When the color is closely related to the object category (e.g., green trees, blue sky), the performance is often satisfactory; for the other objects, the performance can be poor as there are multiple plausible colors, and the model often outputs the average color among all possible colors.

By imitating the imagination of human experts, our approach can achieve photorealistic colorization for legacy black-and-white photos, as shown in Figure 1 and Figure 2. We design an imagination module for understanding the contexts of images and imagining relevant visual content, similar to human imagination. The distribution of diverse and realistic colors can be embedded in the imagination module. Specifically, given a black-and-white image, we first predict the semantic layout or class of objects explicitly. Then we use an off-the-shelf generative model to synthesize images with the same semantic context, as shown in Figure 2. The synthesized images are then used as the

*Joint first authors

2bit.ly/color_history_photos

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reference for colorization. Although the structures of synthesized images are not perfect, we notice that generative models can generate images with diverse and colorful colors.

Instead of using a single image as the reference, we propose to compose a novel image through multiple images for better colorization results. This strategy is designed to solve a problem: even though the synthesized object and the input object share the same context/concept, the luminance of the synthesis object can be different from the input object. For example, given a black-red T-shirt, the synthesized T-shirt can be white.

Extensive experimental results demonstrate that images colorized by our approach are more colorful and photorealistic than state-of-the-art methods. Besides, our results are quite diverse. We hope our imagination module can inspire tasks beyond colorization.

2 Related Work

User-guided colorization. Most classical approaches rely on user guidance for colorization, including scribble-based colorization and example-based colorization. Scribble-based colorization aims to propagate the color provided by users. Most methods achieve this goal based on optimization with some assumption. For example, Levin et al. assume pixels with similar intensity should have similar colors and design an optimization approach based on this objective. In addition to optimization based approach, Zhang et al. propose a learning-based model for scribble-based colorization. Compared with previous work, fewer scribbles are required in their method.

Example-based colorization further reduces the difficulty of colorizing a black-and-white photo for normal users. Only an additional reference image is required to colorize images automatically. Since the reference image is usually closely related to grayscale images, these methods can find the correspondence between two images. However, it is non-trivial to find a good reference image since the reference image should be semantically similar to the input grayscale image. User needs to search the image on the Internet or provide semantic text labels and segmentation cues to an image retrieval system, which is not user-friendly. He et al. introduce deep learning to example-based colorization and adopt an image retrieval algorithm to search an image from a large dataset. While the performance of colorization is improved a lot, searching for a good reference is still time-consuming for them. In this work, our imagination module avoids the efforts to find a reference image.

Automatic colorization. Deep learning methods achieve fully automatic colorization by learning the relationship between semantic and color on a large dataset. For automatic colorization, the performance is usually good when the color of the object (e.g., a green tree) is closely related to the semantic. However, for the other objects that can have diverse colors (e.g., T-shirt), the colorization results are usually grayish. While treating the colorization as a classification problem can improve the colorfulness, these cases are
still not rare. Compared with them, our model can generate diverse and colorful results with the help of our imagination module.

**Conditional image generation.** The generative models are classified into two categories: unconditional and conditional. From the aspect of unconditional generative models, the most recent work is StyleGAN [15] and StyleGAN2 [16], which are based on style transfer literature and achieve state-of-the-art performance for high-resolution image synthesis. From the aspect of conditional image synthesis, BigGAN [2] use object class and a random noise as input, and can synthesis high-quality images. Another source of conditional GANs takes more concrete conditions, such as layout [35, 36], semantic map [21, 37] et al. These generative models capture the distribution of a dataset and can be utilized to help solve colorization problem.

### 3 Overview

Given a grayscale image $X \in \mathbb{R}^{H \times W \times 1}$ as input, our goal is to automatically predict its color channels $Y \in \mathbb{R}^{H \times W \times 2}$. $X$ and $Y$ are the lightness and $ab$ channel in the CIE $Lab$ color space. The key difference between our approach and existing automatic colorization methods is that: we propose to synthesize color images based on the context of the input image as a reference for colorization.

Figure 3 shows the architecture of our approach. From the imagination module, we obtain a colorful reference image $R \in \mathbb{R}^{H \times W \times 3}$ with coarsely aligned context information for a grayscale image $X$. In our imagination module, we first extract the context and location information through off-the-shelf methods (e.g., semantic segmentation, detection, classification). Then, we can synthesize images based on the extracted information using a generative model. The details of the imagination module is described in Section 4.

As shown in Figure 3, the grayscale image $X$ and synthesized reference image $R$ are then used as input to our colorization network $f$ to predict the color channels $\hat{Y}$. The colorization network $f$ aligns reference color and grayscale images. It keeps the original correct color and removes undesirable artifacts simultaneously. The training strategy and details of network $f$ are presented in Section 5.

### 4 Imagination Module

#### 4.1 Objective

Given a grayscale image $X$, our imagination module aims to generate images $R$ as references for photorealistic colorization. The motivation is to imitate human imagination: experts can produce photorealistic colorized results since they know diverse and colorful examples for the black-and-white
Figure 3: The overall framework of our approach. In our imagination module, we firstly synthesize a reference image $R$ that has the similar context with the input grayscale image $X$. In our colorization network, $X$ is colorized with the guidance of reference image $R$.

objects. Hence, the images $R$ generated by our imagination module must be diverse, colorful, and realistic since the color of the final colorized image is mainly decided by our imagination $R$.

Specifically, we need to understand the context of the grayscale image $X$ first. Then we generate images $R$ using the extracted context $S$, as described in Section 4.2. Take Figure 2 as an example; our model first understands that there is a car in the grayscale image $X$. Then, our model can ‘imagine’ cars with diverse colors. Since the color of synthesized images is closely related to the contexts, the color is usually reasonable, and we can colorize the grayscale images with guidance.

Comparison to image retrieval. He et al. [12] propose a novel image retrieval algorithm that automatically recommends good references to the user. Compared with them, our approach is more efficient in memory and time. Firstly, we do not need a large-scale dataset (e.g., ImageNet has more than 1 million images) in the inference time. Secondly, we do not need to spend time searching for the most similar reference.

Comparison to GAN inversion. Another possible solution for synthesizing a reference image is GAN-inversion, as demonstrated by Pan et al. [26]. However, we notice that images obtained by GAN inversion are not satisfying: the contents are wrong in many cases (and hence, colors are wrong). We believe it is because only structure information is utilized in the optimization process, and the degradation operation (color to gray) makes this problem even more difficult. Some examples can be found in the supplementary material.

4.2 Context extraction and image generation

Given a grayscale image $X$, the pipeline to imagine a reference image $R$ can be described as follows:

$$R = g(c(X), z),$$

(1)

where $c$ is the context extraction model, $g$ is the image generation model, and $z$ is the latent code for the image generation model $g$.

Representation of context. The representation of context can be quite diverse in computer vision. The key is that the model needs to know what the object is. In addition, it would be better if there is an existing image synthesis model $g$ based on that representation. Generating an image with context can be achieved by various methods, including semantic image synthesis [27, 37], layout to image generation [49], text to image synthesis [29], etc. In this paper, we mainly choose semantic segmentation as the representation of context.

Implementation. Since we use the semantic segmentation to represent the context, the context extraction model $c$ is a semantic segmentation method, and the image generation model $g$ is the semantic image synthesis method.

As shown in Figure 4, given a grayscale image $X$, we implement semantic segmentation to obtain the segmentation $S$ using an off-the-shelf model by $S = c(X)$. The number of segments is different in each image, and we denote each segmentation as $S^j$. Given the segmentation $S$, we can synthesize a
Figure 4: The imagination module of our approach. First, we extract the segmentation of the grayscale image $X$ with a segmentation network $c$. Secondly, we synthesize diverse images $\{R_i\}_{i=0}^n$ by using the semantic segmentation $S$ and latent codes $\{z_i\}_{i=0}^n$. At last, our composition module composes a reference $R$ from all images $\{R_i\}_{i=0}^n$ for each segmentation based on the luminance of input $X$.

reference image $R_i$ through a semantic image synthesis model $g$ by:

$$R_i = g(S, z_i),$$

where the diversity of reference image $R_i$ is controlled by the latent code $z_i$. Note that we can sample an arbitrary number of reference images $R_i$ using various $z_i$. We denote $R_j^i$ as the area of the reference image $R_i$ in each segmentation $S_j$.

Diversity of imaginations. While mode collapse [33] is still an open problem, we observe that image synthesized by generative models without structure-regularization is colorful and diverse. As shown in Figure 2, although the structures of objects look poor, the color is relatively realistic and colorful.

4.3 Composition module

Although a single reference image $R_i$ is is enough in many cases, we improve the performance further using multiple references to solve a problem: while $R_i$ has a similar architecture with $X$, there might be some incompatible segmentations where $R_j^i$ mismatches with $X_j$ in terms of luminance. For example, a desk within high luminance tends to be bright color, while the image generation model may provide a dark color desk.

We address this problem by composing a new image through sampling multiple reference images $\{R_j^i\}_{i=0}^n$, where $n$ is the number of samples images. For each segmentation $S^j$, we aim to find the best reference segmentation from all candidates $\{R_j^i\}_{i=0}^n$. Specifically, for each segmentation $S^j$, we select the nearest neighbor among all references in terms of the average difference in luminance:

$$\beta(j) = \arg \min_i \sum_p \left\| R_j^i(p) - X^j(p) \right\|_1,$$

where $p$ is the pixel and $\beta(j)$ denotes the best index for segmentation $S^j$. At last, a final reference image $R$ can be obtained through the set $\{R_j^i_{\beta(j)}\}_{j}$.

Interactive composition. So far, all the steps can be implemented automatically. Here we describe how to allow interactive colorization. When the user is unsatisfied about an object $X_j$ in the image, we can directly remove $R_j^i_{\beta(j)}$ from the current $\{R_j^i_{\beta(j)}\}_{j}$. We can also replace a segmentation with another one. For example, in Figure 2 we can replace the blue car with the green car and preserve the colors in the other area.

5 Colorization by Imagination

Our colorization module takes the original grayscale image $X$ and a reference image $R$ as input. The overall goal of this module is similar to reference-based colorization: we need to extract the color
Comparison | CIC [47] | Iizuka [13] | Larsson [18] | Deoldify [1] | Lei [19] | Zhang [48] | Su [34] | Ours
--- | --- | --- | --- | --- | --- | --- | --- | ---
Colorfulness $\uparrow$ | 0.158 | 0.116 | 0.079 | 0.087 | 0.057 | 0.114 | 0.116 | **0.184**
Diversity | × | × | × | × | ✓ | × | × | ✓

Table 1: Comparisons to existing automatic colorization methods.

from the reference image $R$. However, our reference $R$ is different from natural images. Our $R$ has the advantage that objects are coarsely aligned, but the detailed structures of synthesized images are inconsistent with grayscale images $X$. Some artifacts might also appear in the reference image $R$. Briefly speaking, it is impossible to have a perfect reference image since models in the imagination modules cannot be perfect (e.g., semantic segmentation and semantic image synthesis). Hence, we design a strategy to train a dedicated network that produces photorealistic results.

5.1 Training
We need to generate simulated reference images $R'$ that mimic artifacts of synthesized images $R$ at test time. The details for simulating $R'$ is introduced at the end of this section. In the training time, we predict color channels $\hat{Y}$ directly given the grayscale image $X$ and simulated reference $R'$:

$$\hat{Y} = f(X, w(R'); \theta_f),$$

where $\theta_f$ is the parameters of the colorization network, $w$ is the warp function to align $R'$ and $X$, following Zhang et al. [44]. The network $f$ is trained with a perceptual loss:

$$L(\theta_f) = \sum_{l} \lambda_l \|\Phi_l(r(X, \hat{Y})) - \Phi_l(r(X, Y))\|_1,$$

where $\Phi_l$ is the feature maps for $l$-th layer of a pretrained VGG-19 network [32] and $\lambda_l$ is the weights for each layer. We adopt 5 layers ‘conv1_2’, ‘conv2_2’, ‘conv3_2’, ‘conv4_2’, and ‘conv5_2’ in practice. $r$ is the function to convert image from Lab space to RGB space. We adopt the U-Net [30] as the architecture of the colorization network $f$.

Our training strategy is different from previous reference-based colorization methods [12, 44]. The comparison is presented in the experiments.

Data simulation. Our key idea is to ensure the simulated image $R'$ has the similar color with ground truth. Otherwise, while the reference image $R$ has reasonable color, it might be different from the ground truth. In this case, we observe the training process is unstable and results tend to reduce the colorfulness like previous work [12].

Given a grayscale image $X$ and its corresponding color channels $Y$, we randomly sample the location and area to obtain a mask $M \in \{0, 1\}^{H \times W \times 1}$. Then we synthesize a new image $Y'$:

$$Y' = Y \odot (1 - M) + Y^{fake} \odot M,$$

where $Y^{fake}$ is the color channels from an irrelevant image. The simulated reference image $R'$ is then obtained by $R' = r(X, Y')$. Our motivation is to preserve the original color of reference $R$ if the color is reasonable and remove the artifacts if the color is wrong.

6 Experiments
6.1 Experimental setting
Dataset. Our experiments are mainly conducted on COCO-stuff dataset [22]. The images in COCO-stuff contain complex objects and scenes. The training set and validation set of COCO-stuff contain 118K and 5K images, respectively. All networks used in our approach are trained on the COCO-stuff dataset. We adopt the original split in our experiments. We also demonstrate qualitative results on ImageNet [7].

Baselines. We adopt the most recent and related automatic colorization methods as baselines, including CIC [47], Zhang et al. [48], Lei et al. [19], Deoldify [1], Su et al. [34]. All of them can be used for automatic image colorization. Zhang et al. [48] and Su et al. [34] are trained or finetuned on the COCO-stuff dataset. We directly use the released results by Su et al. [34] in our experiments.
6.2 Comparisons to baselines

**Quantitative comparison.** We compute the colorfulness through the metric proposed by Hasler et al. [11] to compare with existing methods quantitatively. As shown in Table 1, our approach generates the most colorful results. We do not adopt the PSNR metric since it cannot represent the colorization quality for diverse colorization, as reported by Lei et al. [19]. The analysis of PSNR is presented in supplement for reference.

**User preference comparison.** We conduct a perceptual experiment by user study to evaluate which approach is preferred by human observers. Specifically, we compare our method with two strong baselines: Zhang et al. [48] and Su et al. [34]. A user is presented with a pair of colorized images (our approach and a baseline) simultaneously in each comparison. The positions of our result (i.e., left image or right image) are random in each comparison. We let the user choose the one that is more realistic and

| Comparison          | Preference rate |
|---------------------|-----------------|
| Ours > Su et al. [34] | 76.9% 23.1%     |
| Ours > Zhang et al. [48] | 77.4% 22.6%     |

Table 2: The results of our user study. Our results are preferred by human observers.

Figure 5: Perceptual comparisons to the state-of-the-art methods. Our method predicts visually pleasing colors where other methods cannot. More comparisons are presented in the supplementary material.
Figure 6: Qualitative comparisons to AVC (Lei et al. [19]). AVC is an automatic colorization that considers the diverse possible colorized results. Our results are more diverse and colorful.

Figure 7: The qualitative comparison between our model and Zhang et al. [44]. Our colorization network can preserve the original color better.

colorful. We randomly sample 100 images from the COCO-Stuff validation dataset, and 29 volunteers participated in this user study.

Table 2 shows the results of our user study. Our approach is significantly preferred than Zhang et al. [48] and Su et al. [34]. Interestingly, we observe that there is no much difference between the preference of Zhang et al. [48] and Su et al. [34]. We believe it is because Su et al. [34] is based on the model of Zhang et al. [48]. Their qualitative results are also similar, as shown in Figure 6.

**Qualitative comparisons.** Figure 5 shows qualitative comparisons among our approach and baselines. Our results are more colorful than baselines.

**Comparison to reference-based colorization.** While our imagination module can be combined with an existing reference-based image colorization method [12], we notice existing reference-based methods tend to reduce the colorfulness or change the color of reference image. Figure 7 shows an example for this phenomenon. As mentioned in Section 5, our designed colorization module can preserve the original color better.

**Multiple references.** We implement another version by replacing the multiple references with a single synthesized image for comparison. Figure 8 shows examples of qualitative comparison. If we
Input Single imagination Result Multi-imagination Result

Figure 8: Ablation study on multiple references fusion. If we use a single reference as guidance, the synthesized image may mismatch the input, producing undesirable results. Fusion multiple references based on the luminance can significantly improve the quality of reference and produce better results.

Input Result Input Result

Figure 9: Qualitative results on the ImageNet dataset \cite{7}. The reference images are generated by another imagination module introduced in the main text.

only use a single reference image, sometimes the color of the synthesized image does not match the input, leading to unsatisfying colorization results. Using multiple reference images to compose a new image improves the robustness of our approach.

**Other imagination modules.** As discussed in Section 4, the representation of context in an image can be quite diverse. We try another type of imagination module on ImageNet \cite{7}. Specifically, the context extraction network $c$ is an image detection network, which helps us obtain the class and location. Secondly, given a label of class, we use BigGAN \cite{2} as the synthesis model $g$ to synthesize images. We then compose the objects to a new reference image $R$ through the locations. The qualitative results are presented in Figure \ref{fig:9}. Details of this implementation are presented in the supplementary material.

**Limitations.** The colorized results heavily depend on the images from our imagination modules. When the imaginations are bad, our colorized results can also be bad. More analysis is presented in the supplementary material due to limited space.

### 6.4 Colorizing legacy photographs

We present qualitative results for colorizing legacy photographs in Figure \ref{fig:1}. While these photos were captured tens of years or one hundred years ago, our approach can still generate photorealistic colorized results. More results are presented in the supplementary material.

### 7 Discussion

We have presented a novel approach to automatic image colorization by imitating the imagination process of human experts. We propose an imagination module that can synthesize diverse and colorful reference images with similar contexts of input images. Then a dedicated colorization module is designed to colorize the black-and-white images with the guidance of imagination. Our results can be diverse and realistic with the imagination module. We believe that the concept of imagination can also be applied to various computer vision tasks.
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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [No]
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2. If you are including theoretical results...
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   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [N/A]
   (c) Did you include any new assets either in the supplemental material or as a URL? [No]
   (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]

5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [Yes]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [Yes]