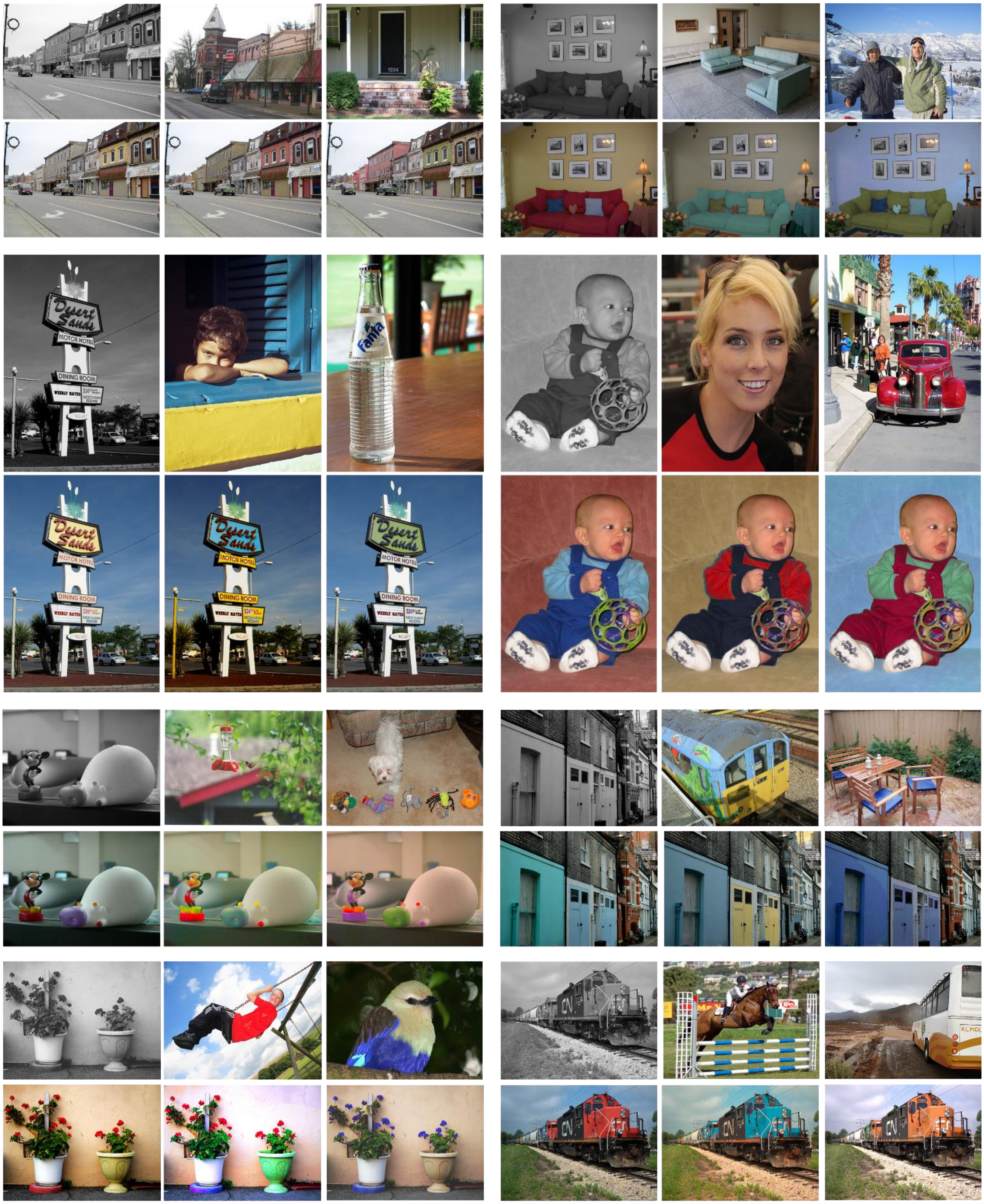
Globally and Locally Semantic Colorization via Exemplar-Based Broad-GAN



(a) (b) (c) (d) (e) (f)

Fig. 1: Colorization results of our approach with different reference images. These images belong to different types of images and contain different objects. (a) and (d) Target grayscale images and ground truths. (b), (c), (e) and (f) Difference reference images and corresponding colorized images.

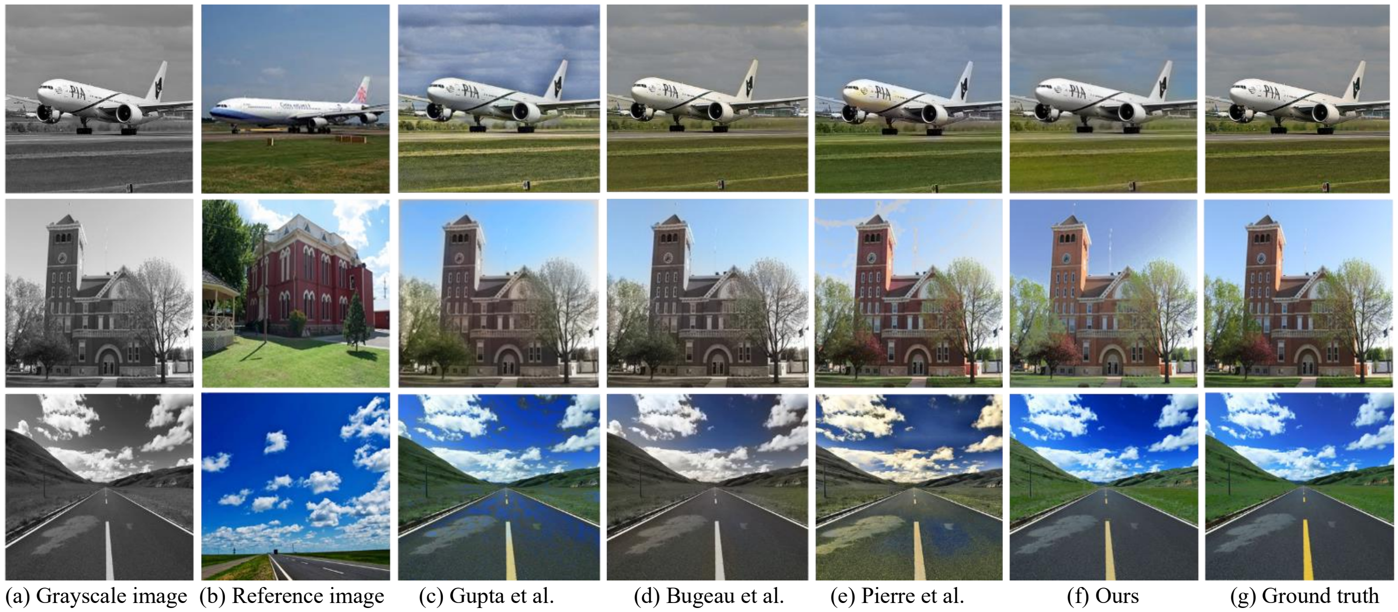


Fig. 2: Comparison of our colorization results with exemplar-based methods, i.e., Gupta et al. [1], Bugeau et al. [2], and Pierre et al. [3].

Fig. 3: Comparison of our colorization results with learning-based methods, i.e., Iizuka et al. [4], Zhang et al. [5], and Larsson et al. [6].

Fig. 1 demonstrates some colorization results of the proposed method. Fig. 2 and Fig. 3 demonstrate more comparative results with some alternative state-of-the-art colorization methods. In pre-processing, we transform the color space of the target images and reference image and extract their features for implementation. Since all images in the dataset are RGB color images which present a rich information of colors, the relationship between grayscale and color cannot be expressed correctly. Therefore, we adopt the CIE Lab color space. In our experiments, all target images only preserve luminance channel L and all reference images have a luminance channel L and two chrominance channels a and b. We reconstruct the target grayscale image by sparse representation of the features extracted from the reference image. To make it comparable, features from both the target images and reference images are extracted only from luminance channel L. We use the pre-trained VGG network to extract features of the target image and the reference image. And these features will be used as inputs to the match sub-net. Our network is trained using the Places Database dataset and Pascal VOC data sets. Note that the GAN model is non-linear, and it can be easily trapped at suboptimal local minimum during the process of optimization. Therefore, the generator only needs to learn correctly propagate colors of the reference image. In the initialization phase, we train the generator G with adversarial loss and chrominance loss. In this phase, the generator only reconstructs the colors of input images and is irrespective of visual pleasure. Experiments show that this initialization phase can effectively improve the convergence of our proposed approach.

References

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