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Compression artifacts reduction by improved generative adversarial networks

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Abstract

In this paper, we propose an improved generative adversarial network (GAN) for image compression artifacts reduction task (artifacts reduction by GANs, ARGAN). The lossy compression leads to quite complicated compression artifacts, especially blocking artifacts and ringing effects. To handle this problem, we choose generative adversarial networks as an effective solution to reduce diverse compression artifacts. The structure of "U-NET" style is adopted as the generative network in the GAN. A discriminator network is designed in a convolutional manner to differentiate the restored images from the ground truth distribution. This approach can help improve the performance because the adversarial loss aggressively encourages the output image to be close to the distribution of the ground truth. Our method not only learns an end-to-end mapping from input degraded image to corresponding restored image, but also learns a loss function to train this mapping. Benefit from the improved GANs, we can achieve desired results without hand-engineering the loss functions. The experiments show that our method achieves better performance than the state-of-the-art methods.

Keywords

GANs CNN, Compression artifacts, JPEG compression.

1. Introduction

Image restoration technology has become one of the most important applications in computer vision and computer graphics and attracted increasing attention in the field of digital image processing, such as image haze removal [1], image super-resolution [2, 3, 4], image deblur [5, 6], and image understanding [7]. Image compression artifacts reduction aims at recovering a sharp image from the degraded image which is formed by JPEG compression or other causes. JPEG compression is a kind of lossy compression method that uses inaccurate approximations for representing the encoded content. Although JPEG compression is very common in our daily life, it may lead to quite complicated compression artifacts, especially blocking artifacts and ringing effects which not only decrease the perceptual visual quality, but also introduce obstruction to other low-level image processing routines.

In this paper, we use a deep learning-based approach for image compression artifacts reduction. More specifically, we propose a principled and efficient generative adversarial network (GAN) for this task. We denote the proposed networks as artifacts reduction by GANs (ARGAN) which was inspired from the GANs [8]. Similar to the standard GANs, ARGAN also consists of two feed-forward convolutional neural networks (CNNs), the generative network *G* and the discriminative network *D*. The purpose of the generative network *G* is to generate reasonable results from the input degraded images. The goal of the discriminative network *D* is to discover the discrepancy between the generated image and the corresponding ground-truth image. Our proposed method differs from the existing traditional [9] or other deep learning-based approaches [10]. The traditional approaches need to extract the features of the images manually. The deep learning-based approaches are usually based on CNN. We are the first to use (GANs) for image compression artifacts reduction.

There are two main contributions in our work:
We are the first to use an end-to-end generative adversarial network (GAN) for image compression artifacts reduction. The experiments show that our method achieves better performance than the state-of-the-art methods [9, 10, 11]. In this paper, we focus on the restoration of the luminance channel (in YCrCb space) as in [10], and the network is specially designed for this task

We demonstrate that generative adversarial networks are useful in the image compression artifacts reduction task and can achieve better quality than the traditional or other deep learning-based methods. Our method directly learns an end-to-end mapping which can effectively estimate the reasonable results from input degraded images and make the restored image more real.

2. Background

For convenience of explanation, this paper describes the proposed algorithm of the camera path planning under simple video stabilization with a 2D translational motion model as depicted in Fig. 1. However, the proposed method can be modified to plan the camera path for other stabilization using a different motion model such as homography.

The original camera path of videos shot by a hand-held camera is usually shaky, as depicted in Fig. 2. To provide steady output videos, it is necessary to predict a smooth camera path from the original camera path. The simplest method for estimating a smooth camera path is to apply a low-pass filter to the original camera path as follows.

Here, $P_O(t)$ and $P_N(t)$ denote the original and new camera positions, respectively. $w(k)$ is the kth coefficient of the low-pass filter. Since the above ideal filter requires an infinite number of signals, it is impossible to realize. In practice, the low-pass filter should consider a finite number of signals. Specifically, a casual filter that depends on camera positions of past and present frames is considered in real-time applications as follows.

3. Method

Simple tests were performed to observe how camera paths affect visual perception. People who did not have related knowledge were selected as participants. Ten participants evaluated the visual perception of synthetic videos with different types of camera paths. Each video has one type of camera path among various types including static view, horizontally moving views with zero acceleration, and randomly moving views. If the synthetic video includes local motion, it will disturb the evaluation of the visual perception caused only by the camera path. In order to exclude the local motion, the test videos are synthesized by shifting a single image along the camera path. The participants were asked to sort the videos in a high-quality order according to their visual perception. Table 1 shows the results. Interestingly, the scores made by the participants were in the same order. Obviously, the static camera path obtained a high score. Hence, the constant path is the first property to consider when planning a camera path. The next property is the linearity of a camera path. Consistency in camera movements is an important feature. Even a small random motion gives a poor visual impression. A camera path with a 4 pixel horizontal movement is better than a camera path with a ± 1 random camera movement. The amount of slope of the linear camera path also affects the visual quality. A linear camera path with a gentle slope gives better visual quality than that with a steep slope.

4. Conclusion

This paper presents a novel camera path planning algorithm for real-time video stabilization by cross-optimizing two terms related to steady camera path and the amount of image margin. Hence, the proposed algorithm attempts to provide a steady camera path while maintaining a sufficient image margin to compensate for dynamic or sudden camera motions.

While all the frames can be used for to plan the new camera path in post-processing video stabilization, only a limited number of frames can be used in real-time video stabilization. Moreover, the real-time camera path planning algorithm should predict the new camera path on-the-fly. Once the new camera path is planned, it cannot be updated or modified to improve the quality, unlike post-processing video stabilization. Hence, camera path planning is a challenging issue in real-time video stabilization. If the quality of a planned camera path is not acceptable, although accurate camera motions are predicted, the quality of stabilized videos will be degraded. Hence, camera path planning is an essential feature in real-time video stabilization, and our work is thus meaningful.

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