EXTREME GENERATIVE IMAGE COMPRESSION BY LEARNING TEXT EMBEDDING FROM DIFFUSION MODELS

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ABSTRACT

Transferring large amount of high resolution images over limited bandwidth is an important but very challenging task. Compressing images using extremely low bitrates (<0.1 bpp) has been studied but it often results in low quality images of heavy artifacts due to the strong constraint in the number of bits available for the compressed data. It is often said that a picture is worth a thousand words but on the other hand, language is very powerful in capturing the essence of an image using short descriptions. With the recent success of diffusion models for text-to-image generation, we propose a generative image compression method that demonstrates the potential of saving an image as a short text embedding which in turn can be used to generate high-fidelity images which is equivalent to the original one perceptually. For a given image, its corresponding text embedding is learned using the same optimization process as the text-to-image diffusion model itself, using a learnable text embedding as input after bypassing the original transformer. The optimization is applied together with a learning compression model to achieve extreme compression of low bitrates <0.1 bpp. Based on our experiments measured by a comprehensive set of image quality metrics, our method outperforms the other state-of-the-art deep learning methods in terms of both perceptual quality and diversity.

1 Introduction

With the increasing amount of image streams available for broad range of applications, lossy image compression is a very useful technique for efficient image storage and transmission. Over the years, various engineered codes such as JPEG [30], JPEG2000 [52], and the more recent BPG [4] have been proposed to compress single images but their performance have saturated overall. More recently, deep learning based image compression methods have been studied [8][36][7]. These models are generally trained in an end-to-end fashion to minimize a rate-distortion object $R + \lambda D$. Here $R$ represents the entropy of latent representations which is estimated by an entropy model, $D$ is the difference between the original image and the compressed one, and $\lambda$ determines the desired trade-off between rate and distortion. When $\lambda$ is small, the optimization gives higher priority to compression rate so the resulted bitrate (evaluated as bits-per-pixel, bpp) is low. Consequently, the compressed image has lower quality due to higher $D$ loss term. With accuracy metrics like mean squared error (MSE) and multi-scale structural similarity (MS-SSIM) are often used for $D$, the low quality compressed images are usually blurry. For extremely low bitrates (<0.1 bpp), both engineered codecs and deep learning compression models are subject to very poor perceptual qualities.

To tackle this problem, some recent methods [61][63][29][35] aim to restore less blurry image from highly compressed latent representations at the cost of accuracy. These model adopt generative adversarial networks (GAN) [19] to fully or partially replace the accuracy metrics in $D$ with discrimination loss so they can generate sharp and realistic images even at very low bitrates. For the challenging task of extremely low bitrates, GAN is further exploited in more recent studies [2][11][25] to restore sharp images with minimized distortion and visual artifacts. However, they all inherit the drawback of unstable training from GAN, making it difficult to tune the training process for large datasets. In this paper, we propose the first generative image compression method with extremely low bitrates using denoising diffusion models. As it utilizes an existing text-to-image model which is already trained with a gigantic dataset, it is applicable to any type of image with no need of further tuning.

Similar to GAN a few years back, denoising diffusion models [53][22][54] are gaining popularity increasingly for their advantages in generating images with high qualities in both fidelity and diversity without disadvantage of unstable training like GAN. In addition to unconditional image generation, diffusion models have also empowered the breakthrough developments in diffusion-based text-to-image generation models [47][38][43][49] which are able to create
realistic images according to given text descriptions. They often use existing transformer models to encode text prompts as textual embeddings and use them as conditions in training and sampling of the diffusion model. Realising the power of these model in turning short texts into high resolution and high quality images, the generative image compression we propose here encodes an input image as a textual embedding which is quantized and compressed for storage. At inference time for decompression, the compressed textual embedding is decoded and used as the conditional input for image generation. While sampling from the diffusion model can generate high quality images, the random sampling could lead to diverse outcomes without guarantee of resembling the original input. To ensure the generation success, the original image is also compressed from an existing learning based compression model and it is used as a guidance at sampling time, on top of the classifier-free guidance. The additional bitrates for compression guidance is only $0.01 - 0.02$ bpp so the overall bitrates is still very low. Note that there are a couple of newly proposed methods which are concurrently working on lossy image compression using diffusion models. However, not like our method here, they both need ground-up training of a dedicated diffusion model and do not address the challenge of extremely low bitrates. Based on our experiments, our proposed model is capable of generating image of the highest perceptual quality while maintaining overall resemblance with the original image. As shown in Fig. 1, the other state-of-the-art methods are subject to blurry artifacts when the bitrate gets below 0.1 while our method is able to generate very sharp details. In the example of snowy mountains, our generated sample has details sharper even than the original. Although details like the number of snowy tracks are different, which results in poor measurements in terms of pixel by pixel accuracy, our sample is highly photo-realistic and look like the same image as the original overall.

In summary, we propose an innovative generative image compression method with the following main contributions:

- Using existing text-to-image diffusion models, our method can compress an input image as a textual embedding of extremely low bitrates and later generate diverse diverse sharp images which resemble the input perceptually.
- A hybrid guidance method is studied to combine classifier-free guidance from pre-trained text-to-image models and newly introduced compression guidance for optimal generation results.
- The number of bits needed to compress the textual embedding is largely independent of image content and resolution, so the bitrate is relatively constant for a fixed resolution and decrease when the image resolution increases.

2 Related Works

2.1 Image Compression

Shannon’s theory of communication has provided the fundamental basis for the coding theory used in classical image compression methods. Using explicit probabilistic modeling and feature extractions, various codes, like JPEG, BPG and WebP, have been effectively engineered for the task of image compression. The earliest learning based image compression methods relied on RNNs. Ballé et al. were the first to introduce an end-to-end autoencoder and entropy model that jointly optimizes rate and distortion, which was then enhanced with a scale hyperprior to capture spatial dependencies in the latent representation. Later various autoregressive and hierarchical priors were introduced to further improve the compression performance. Cheng et al. added attention modules and used a Gaussian Mixture Model (GMM) to estimate the latent representation distribution for further improvements.
Figure 2: Overview of the sampling process of proposed generative image compression using two inputs of extremely low bitrates, where $\hat{e}_x$, a highly compressed textual embedding, is used as the conditional input for a pre-trained latent diffusion model, and $\hat{x}_g$, a highly compressed image from original image $x$, is used a constraint to guide the intermediate latent image $z_0^t$ at each time step $t$. These two are saved after the initial compression process and are the only two needed to reconstruct a high quality image $x_0$.

Since their introduction in [19], GANs have progressed greatly in unconditional and conditional image generation of high resolution photo-realistic images [14, 62, 27, 26]. The adversarial loss function was first introduced in an end-to-end framework [46] for improved perceptual quality, and has been continuously improved in following studies [50, 61]. While these methods are capable of reconstructing photo-realistic image with very low bitrate, generative image compression with extremely low bitrates (<0.1 bpp) was first studied in [2] and further improved in following studies [11, 25]. Comparing to these GAN based extreme generative compression models, ours is the first to utilize diffusion models to tackle this challenging task.

2.2 Denoising Diffusion Models

Inspired by non-equilibrium thermodynamics [53], the denoise diffusion models define a Markov chain of diffusion steps to slowly add random noise to data so the intractable real data distribution is transformed to a tractable one like Gaussian. Then the models learn to reverse the diffusion process to construct desired data samples from randomly sample Gaussian noise. Ho et al. [22] proposed a denoising diffusion probabilistic model (DDPM) to interpret the reverse diffusion process as a large amount of consecutive denoising steps following conditional Gaussian distribution. Alternatively, Song et al. [55, 56] used stochastic differential equations to model the reverse diffusion process and developed a score-based generative model to produce samples via Langevin dynamics using estimated gradients of the data distribution. Later numerous methods [39, 54, 33] have been proposed to use much fewer denoising steps without significant degradation in image quality. To improve image quality, Dhariwal et al. [12] proposed a classifier guidance method to iteratively modify the denoised step using a gradient calculated from a retrained noisy classifier. Later Ho et al. [23] invented a classifier-free guidance method that trains a conditional model using randomly masked class labels and treat the difference between conditional and unconditional sampling at inference time as a proxy classifier. The compression guidance proposed here is applied similarly as the classifier guidance.

In recent years, GAN based deep learning models have been successful used for various generative tasks [14, 62, 27], including text-to-image generations [45, 66, 64, 41, 57, 17]. More recently, autoregressive (AR) models have also shown promising results in image generation [40, 6, 15]. For text-to-image generations, various frameworks, including DALL-E [44], CogView [13] and M6 [31], have been proposed to use large transformer structure to model the joint distribution of text and image tokens. Diffusion models have progressed rapidly to set state-of-the-art for many generative tasks, including text-to-image generations. Previously, text-to-image generation are dominated by GANs [45, 66, 64, 41, 57, 17] and autoregressive (AR) models [44, 13, 31]. Most recently, diffusion-based text-to-image generation has been a red hot research topic in both the academia and industry. Initially, an unconditional diffusion model [9] was demonstrated highly capable of text-to-image generation using sampling guidance to match the CLIP scores [42] of the text input and generated image. More recent models all use transformer based text embedding to train the conditional diffusion model, generating either a low-resolution image [38, 49] or an image embedding [49] before generating the full resolution output. Alternatively, Rombach et al. [47] proposed to conduct the conditional text-to-image diffusion in a latent space of reduced resolution for faster training and sampling. Based on that, a large text-to-image model, Stable Diffusion [10], is trained with a huge dataset and released for open research. Our proposed image compression method is validated using the released version v1-4.
As shown in DDPM [22], a re-weighted variational lower-bound (VLB) is used as an effective surrogate objective for
where
\( \hat{z} \). The resulting new perturbed mean
\( z \) to perturb the estimated mean by adding the gradient of the log-probability
\( \nabla \log p_{\theta}(z_t|y) \) of the target class \( y \) predicted by a classifier to be decoded as an image \( x_t \), denoted as \( x_t = d(z_t) \) where \( d \) stands for the decoding process, before feeding to classifier in the case of latent diffusion. The resulting new perturbed mean \( \hat{z} \) is given by
\[
\hat{z} = z + \nabla \log p_{\theta}(z_t|y)
\]
In order to improve image sampling quality at inference time, Dhariwal et al. [12] proposed a classifier guidance method to perturb the estimated mean by adding the gradient of the log-probability
\( \log p_{\theta}(y|z_t) \) of a target class \( y \) predicted by a classifier to be decoded as an image \( x_t \), denoted as \( x_t = d(z_t) \) where \( d \) stands for the decoding process, before feeding to classifier in the case of latent diffusion. The resulting new perturbed mean \( \hat{z} \) is given by
\[
\hat{z} = z + \nabla \log p_{\theta}(y|z_t)
\]
where coefficient \( s \) is called the guidance scale. A larger \( s \) leads to higher sample quality but less diversity. \( \phi \) represents the classifier parameters which can be further refined with noisy images and conditional to \( t \) as \( x_t \) is normally noisy.

For our proposed compression guidance, the reference to use in place of \( y \) is an extremely low bitrate image \( \hat{x}_g \), which is compress from \( x \) as \( \hat{x}_g = c(x) \). Similar to classifier guidance, the estimated mean during the reverse denoising process is perturbed by the gradient of the difference between \( \hat{x}_g \) and compressed \( x_t \):

\[
\hat{\mu}_\theta(z_t, t) = \mu_\theta(z_t, t) - s \Sigma_\theta(z_t, t) \nabla_{z_t} |\hat{x}_g - \hat{x}_t| \tag{4}
\]

where \( \hat{x}_t = d(c(z_t)) \). However, unlike classifier guidance where \( \phi \) can be optimized for noisy images, there is no learnable variable to optimize in the case of our compression guidance. To mitigate the impact of noise present in \( \hat{x}_t \), here we propose an alternative guidance method to calculate the perturbing gradient by comparing the "noise-free" \( \hat{x}_0 \) and reference \( \hat{x}_g \) instead

\[
x_0 = c(d((z_t - \sqrt{1 - \alpha_t} \epsilon_\theta(z_t, t))/\sqrt{\alpha_t})) \tag{5}
\]

\[
\hat{\mu}_\theta(z_t, t) = \mu_\theta(z_t, t) - s_c \Sigma_\theta(z_t, t) \nabla_{z_t} |\hat{x}_g - \hat{x}_t|
\]

where \( \alpha_t \) is set from pre-determined noise schedule, and \( s_c \) is the compression guidance scale, to differentiate from the classifier-free guidance \[23\] which is adopted in the diffusion model used for our experiments. The scale used in classifier-free guidance is denoted as \( s_f \). As both guidance methods are used together, we empirically studied the optimal settings for both \( s_c \) and \( s_f \) for best effects of this hybrid guidance.

### 3.3 Textual Inversion

For the adopted textual inversion, the goal is to find an optimal textual embedding \( e_x \) backwards from a given image \( x \). This process is a learning process to minimize the following expected error:

\[
E_{t,\epsilon}||\epsilon - \epsilon_\theta(z_t, t, e_x)||^2 \tag{6}
\]

where \( \epsilon_\theta \) is the diffusion model pre-trained with the loss term defined in Equation\[2\] with fixed weights \( \theta \) and \( x \) is fixed too. By optimizing iteratively using varying \( \epsilon \) and \( t \), the target textual embedding \( e_x \) can be learned effectively. For any image \( x \), the embedding \( e_x \) has a fixed number of \( T \) tokens and each token is embedded as a \( N \)-dimensional vector. To effectively compress the \( T \times N \) real numbers to meet needs of our extreme compression application, \( e_x \) is quantized and compressed with an existing compression model \[3\], denoted as \( \hat{e}_x \). To further optimize the whole process, the quantization and compression process are included in the learning process of textual inversion by minimizing the following error instead

\[
E_{t,\epsilon}||\epsilon - \epsilon_\theta(z_t, t, \hat{e}_x)||^2 \tag{7}
\]

### 4 Experiments

All experiments in this study are conducted using pre-trained Stable Diffusion \[10\] model. For \( \hat{x}_g \) used in compression guidance, the original image \( x \) is first downsampled with a scale of \( x \times 4 \) before compressed using an existing compression model \[7\] with GMM and attention. For textual inversion, we use 64 embedded vectors, each has 768 elements. For compression of said textual embedding using the same existing compression model \[7\], it is reshaped as a RGB color image of \( 64 \times 256 \) pixels.

To assess the effectiveness of our proposed method, we use the photo-realistic images from the Kodak dataset \[10\] to conduct the compression experiments. For each image, the optimal compressed textual embedding is determined using 4000 iterative learning steps before tested for image generation. To generate high quality image at inference time, we use 100 DDIM \[54\] sampling steps \((\eta = 1)\) for the diffusion model. To assess the image quality quantitatively, a comprehensive set of metrics are used. The first set of metrics use the original image as the ground-truth (GT) reference. In addition to the standard PSNR metric, FSIM \[67\] is chosen as a measure relying on low-level features the human visual systems often use. and LPIPS \[68\] is also used for its effectiveness as a perceptual metric. For blind metrics without GT reference, NIQE \[37\] is the one comparing image statistics with those of undistorted images. FID \[21\] and KID \[5\] are also no-reference metrics, calculated from statistics of learned features. The are both chosen for their popular application on generative models and KID is known to be more robust as an unbiased one.

#### 4.1 Hybrid Guidance

For the classifier-free guidance included in the diffusion model, it is generally known that higher guidance scale improves generated image quality. However, with the introduction of compression guidance in our method, it is useful to validate the effects of different compression guidance scales by themselves, as well as in combination of...
Table 1: Quantitative image quality comparison of generative compression methods using Kodak dataset (best of three marked in red).

| Method          | bpp | PSNR↑ | FSIM↑ | LPIPS↓ | NIQE↓ | FID↓ | KID↓ |
|-----------------|-----|-------|-------|--------|-------|------|------|
| Original        | 0.063 ± 0.028 | 24.39 | 0.8794 | 0.3054 | 3.566 | 269.1 | 5.379 |
| Iwai et al. [25] | 0.075 ± 0.021 | 24.93 | 0.8906 | 0.2037 | 3.563 | 264.2 | 5.471 |
| Mentzer et al. [35] | 0.070 ± 0.008 | 20.61 | 0.7486 | 0.3611 | 3.731 | 258.6 | 3.960 |

Figure 4: Visual examples of generated images after extreme compression. Our model has the average bitrate for better performance while two competitive models are subject to severe artifacts due to abnormally low bitrates, a common disadvantage of prior works where models are only trained for a target average bitrate over a large training set.

4.2 Image Quality Assessment

As shown in Fig. 3, we have selected four different image metrics to cover both image reconstruction accuracy and perceptual quality, where PSNR is used to measure reconstruction accuracy, FSIM and LPIPS are chosen for both accuracy and perceptual quality and NIQE is for perceptual quality only. All experiments are conducted on the Kodak dataset. In general, higher compression guidance scale $s_c$ is preferred for reconstruction accuracy and lower for perceptual quality. While for classifier-free guidance scale $s_f$, it does not have a significant impact on accuracy for the range we tested on while it shows an optimal value slightly less than 1 for all perceptual quality related metrics. As a larger value like 5 is often recommended for the classifier-free guidance scale $s_f$ when used for its original generation applications, this is the first observation that a smaller values less than 1, probably caused by introduction of compression guidance. For final experiments, $s_c$ and $s_f$ are set empirically as 215 and 0.95 for the best trade-off between reconstruction accuracy and perceptual quality.

As shown in Table 1, our method is the best in perceptual image quality metrics when no ground-truth reference is available, including NIQE, FID and KID. For these three metrics without references, the original uncompressed Kodak
images are also assessed to compare with the compressed results. It shows that the original image indeed have higher perceptual quality compared to compressed ones. For accuracy related metrics, especially PSNR which is the least related to perceptual quality, our method is not as impressive as the peers. In addition to superior perceptual quality, our method has another advantage of near-constant bitrate. As included in Table 1, it has a much smaller standard deviation of 0.008 while the other two are 0.021 and 0.028. This is useful in applications where transmission bandwidth is very limited and an accurate estimation of bits needed for storage of image(s) is important before compression. While the average bitrate for the full Kodak dataset is similar for all three models, the bitrates for the image shown in Fig. 4 are significantly below average for the two model other than ours. As a result, generated images from both models are subject to severe blurry artifacts. In the case of [25] which has a 0.04 bpp bitrate, it has additional false color artifacts where the full face turns reddish. In contrast, our method has a sufficient 0.07 bpp bitrate and is able to generate sharp details.

4.3 Generation Diversity

While the two competitive models are generative models based on GAN, they are not able to generate high quality images with large and realistic variations. In comparison, our model is able to generate photo-realistic images with large diversity in details while maintaining overall consistency. As shown by the three sample from our model in Fig. 5, there are large variations in both foreground and background areas. For the foreground example, the red line patterns
are consistent overall but vary greatly in details like line sizes and locations, and all three have highly focused sharpness. In the other example, our samples all have smooth out-of-focus background yet are quite different from each other.

5 Conclusions

In this paper, we present a generative image compression model capable of encoding high resolution image with extremely low bitrates of 0.07 bpp. It is the first such model built on top of pre-trained text-to-image diffusion models. Comparing to similar works using GAN, it has some distinctive advantages: first, it is able to generates diverse images from one compressed source, all with higher perceptual quality and overall resemblance with the source image; secondly, it does not need training on a dedicated dataset; lastly, it has a relatively fixed bitrate for different images, while others models suffer from a large variation in bitrates.

In terms of computational efficiency, both compression and decompression steps of our proposed method are more time consuming in general. For compression, an iterative learning process is needed to find the optimal compressed textual embedding, while for decompression a large number of denoising steps are needed for high quality outputs. Beside pure research interest, findings in this study are relevant for some real world applications where it is not limited by computational resources at both server and client sides but extremely limited in communication bandwidth.

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