TOWARDS IMAGE COMPRESSION WITH PERFECT REALISM AT ULTRA-LOW BITRATES

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ABSTRACT

Image codecs are typically optimized to trade-off bitrate *vs*. distortion metrics. At low bitrates, this leads to compression artefacts which are easily perceptible, even when training with perceptual or adversarial losses. To improve image quality and remove dependency on the bitrate we propose to decode with iterative diffusion models. We condition the decoding process on a vector-quantized image representation, as well as a global image description to provide additional context. We dub our model "PerCo" for "perceptual compression", and compare it to state-of-the-art codecs at rates from 0.1 down to 0.003 bits per pixel. The latter rate is more than an order of magnitude smaller than those considered in most prior work, compressing a 512×768 Kodak image with less than 153 bytes. Despite this ultra-low bitrate, our approach maintains the ability to reconstruct realistic images. We find that our model leads to reconstructions with state-of-the-art visual quality as measured by FID and KID. As predicted by rate-distortion-perception theory, visual quality is less dependent on the bitrate than previous methods.

1 INTRODUCTION

Traditional image and video codecs are optimized for the rate-distortion function (Shannon, 1948), which minimizes the expected size of the data under a distortion constraint such as mean-squared error. Recent research has developed neural image compression methods that surpass handcrafted image compression codecs in terms of rate-distortion performance (Ballé et al., 2017; Ballé et al., 2018; Cheng et al., 2020; He et al., 2022a). However, optimization for the rate-distortion function comes at a cost of "realism", where realism is mathematically related to the statistical fidelity or f-divergence between the compressed image distribution and the true image distribution (Blau & Michaeli, 2018; 2019). The typical qualitative manifestation of unrealistic images is blurring.

Generative modeling compensates for artefacts such as blurring by introducing a divergence term (Agustsson et al., 2019; Mentzer et al., 2020; Muckley et al., 2023), typically in the form of an adversarial discriminator loss, which improves human-perceptual performance (Mentzer et al., 2020). Such codecs are called "generative compression" codecs, and are evaluated in terms of the rate-distortion-realism tradeoff (Blau & Michaeli, 2019). A further result of rate-distortion-realism theory is the theoretical possibility of a perfect realism codec, *i.e.*, a codec with no f-divergence, and zero FID across all rates, with no more than twofold increase in mean-squared error from the rate-distortion optimal codec. This result motivates research on perfect realism codecs, where original and reconstruction are different from each other, but it is not possible to tell which is which. Such codecs are particularly interesting for extremely low bitrate settings, where existing codecs introduce severe artefacts that are easily perceptible, see Fig. 1. So far, the primary effort towards building such a codec was the work of Theis et al. (2022), who demonstrated lower FID scores than HiFiC (Mentzer et al., 2020) via a combination of a pretrained variational diffusion model and reverse channel coding. However, computational constraints prohibited application to images larger than 64×64 pixels.

In this paper we make further progress towards perfect-realism codecs. Similar to Theis et al. (2022), we leverage a pretrained text-to-image diffusion model; however, rather than using the diffusion

Figure 1: Kodak images compressed with the diffusion-based Text-Sketch approach PICS (Lei et al., 2023), the hand-crafted codec VTM (vtm), MS-ILLM (Muckley et al., 2023) which leverages an adversarial loss, and with PerCo (ours). Taking the lowest available bitrate for each method.

model for compression directly, we use it as a decoder in a VQ-VAE-like autoencoder. The (approximate) log-likelihood loss of diffusion models offers an alternative to the use of distortions such as MSE or LPIPS used to train most neural compression models that make strong assumptions on the conditonal distribution on images given the latents which are inappropriate at low bitrates, and lead to compression artefacts. For decoding, we sample from the conditional diffusion model, which allows us to obtain a set of reconstructions that reflect the uncertainty about the original source image. We augment the quantized image representation with a global image description that captures the high-level semantic information of the image. To this end, we use an automatically generated textual image description, *e.g.* using BLIP (Li et al., 2023). Alternatively, this can take the form of a global image feature extracted from a pre-trained image backbone. We demonstrate that this high-level information is helpful for compression performance at extremely low rates. Our work is closely related to that of Lei et al. (2023), who explored text-conditioned diffusion decoders for image compression, and the only prior work that we are aware of that considers the same ultra-low bitrates as we do. In contrast, their work uses (automatically generated) binary contour maps as a spatial conditioning signal which carry little detail on colors and textures, and leads to reconstructions that are not faithful to the original. Experimentally we observe significantly improved FID and KID scores compared to competing methods. Moreover, we find that FID and KID are much more stable across bitrates than other methods, which aligns with our goal of image compression with perfect realism.

In sum, our contributions are as follows:

- We develop a novel diffusion model called PerCo for image compression that is conditioned on both a vector-quantized latent image representation and a textual image description.
- We obtain realistic reconstructions at bitrates as low as 0.003 bits per pixel, significantly improving over previous work, see Figure 1.
- We obtain state-of-the-art FID and KID performance on the MS-COCO 30k dataset; and observe no significant degradation of FID when reducing the bitrate.

2 Related work

Neural image compression codecs. Ballé et al. (2017) demonstrated that an end-to-end neural image compression codec could outperform the classical JPEG codec in terms of rate-distortion performance. Ballé et al. (2018) enhance this approach by conditioning the latent on a "hyperprior" that encodes high-level information in the image, greatly improving performance. Follow-up works improved the latent conditioning mechanism (Minnen et al., 2018; Minnen & Singh, 2020; Cheng et al., 2020; He et al., 2022a). Optimization for rate-distortion alone leads to distributional mismatch between the compressed image distribution and the natural image distribution (Blau & Michaeli, 2018;

2019). Agustsson et al. (2019) and Mentzer et al. (2020) added an adversarial loss term and demonstrated its usefulness for human perception. Similarly He et al. (2022b) builds upon ELIC (He et al., 2022a) by adding perceptual losses including adversarial ones. Follow-up works have improved the discriminator architecture (Muckley et al., 2023), decode-time realism guidance (Agustsson et al., 2023), or investigated alternative autoencoders with discrete entropy models (El-Nouby et al., 2023). Xu et al. (2023) introduce the notion of conditional perceptual quality, where perceptual quality is dependent on side information. Our work is related to this, as the global textual or visual representation on which we condition the decoder can be seen as a form of side information.

Diffusion models. Ho et al. (2020) improved the original diffusion probabilistic model (Sohl-Dickstein et al., 2015) that gave it impressive performance on image generation benchmarks. Dhariwal & Nichol (2021) demonstrated superior performance to GANs for image generation with classifier guidance, while Kingma et al. (2021) improved diffusion model likelihood estimation. Conditioning diffusion models on large text-encoder networks enables these models to generate realistic images from natural language prompts (Nichol et al., 2022; Saharia et al., 2022), and defining the diffusion process in an autoencoder latent space reduces the computational cost of the diffusion process. In our work we build upon large-scale pretrained text-conditioned diffusion models to benefit from the image generation capabilities embedded in them.

Diffusion generative compressors. Ho et al. (2020) considered compression with diffusion models and reverse channel coding and the corresponding rate-distortion performance, but reported only experiments on 32×32 CIFAR-10 images and MSE distortion. Theis et al. (2022) demonstrated that the reverse channel coding approach gave FID numbers superior to HiFiC for 64×64 ImageNet images. Saharia et al. (2022) introduced a super-resolution diffusion model that removed artefacts from JPEG images. Ghouse et al. (2023) developed a complete version of a residual diffusion codec with images of high quality for a suite of codecs. Hoogeboom et al. (2023) showed similar results using a neural autoencoder baseline codec, and using a separate diffusion model that does not require any additional bits to refine the reconstruction. Yang & Mandt (2023) developed an alternative approach, where a hyperprior-based neural encoder was trained jointly with a diffusion decoder, also showing improved performance to HiFiC. In Pan et al. (2022), they optimize a textual embedding on top of a pretrained text-to-image diffusion model. They also design a compression guidance method used at each denoising step to better reconstruct images. Lei et al. (2023) leverage text-conditioned diffusion models for image compression at very low bitrates, using prompt inversion to encode the image into text, and adding spatial detail via compressed binary contour maps. Our work is similar, but we replace computationally costly prompt inversion (Wen et al., 2023) with fast feed-forward image captioning (Li et al., 2023), and replace binary contour maps which carry little appearance information with end-to-end learned vector-quantized image features.

3 Perceptual compression with a diffusion decoder

3.1 Overall framework

The foundation of most lossy compression lies in rate-distortion theory (Shannon, 1948), which quantifies the balance between the bitrate needed to transmit a signal *vs*. the distortion of the signal. Let us assume an input signal $\boldsymbol{x}$, with its corresponding quantized representation $\boldsymbol{z}$ and reconstruction $\hat{\boldsymbol{x}}(\boldsymbol{z})$. Neural compression is commonly achieved via the minimization of a training objective formulated as a linear combination of a rate and a distortion term:

$$\mathcal{L}_{\text{RD}} = \mathbb{E}_{P_{\boldsymbol{x}}}[\mathbb{E}_{P_{\boldsymbol{z}|\boldsymbol{x}}}\mathcal{L}_{\text{R}}(\boldsymbol{z}) + \lambda\mathcal{L}_{\text{D}}(\hat{\boldsymbol{x}}(\boldsymbol{z}), \boldsymbol{x})], \tag{1}$$

where $P_{\boldsymbol{x}}$ is the data distribution and $P_{\boldsymbol{z}|\boldsymbol{x}}$ is the posterior distribution of the quantized codes. The rate term $\mathcal{L}_{\text{R}}(\boldsymbol{z})$ estimates the bitrate either by means of scalar quantization and a continuous entropy model (Ballé et al., 2017), or using vector-quantization in combination with discrete entropy models (El-Nouby et al., 2023). For simplicity, in PerCo, we employ vector-quantization combined with a uniform entropy model leading to a constant rate controlled through two hyper-parameters: the number of elements that are quantized, and the codebook size. Therefore, the rate $\mathcal{L}_{\text{R}}$ can be considered fixed when training our models and can be dropped from the optimization formulation. Next, we introduce a new formulation of the distortion term, $\mathcal{L}_{\text{D}}$, enabling the integration of a pre-trained diffusion model, thereby achieving a higher level of perceptual quality. Our aim with this formulation is to leverage a large pre-trained diffusion model as a robust image prior, enabling realistic image reconstruction even at extremely low bitrates.

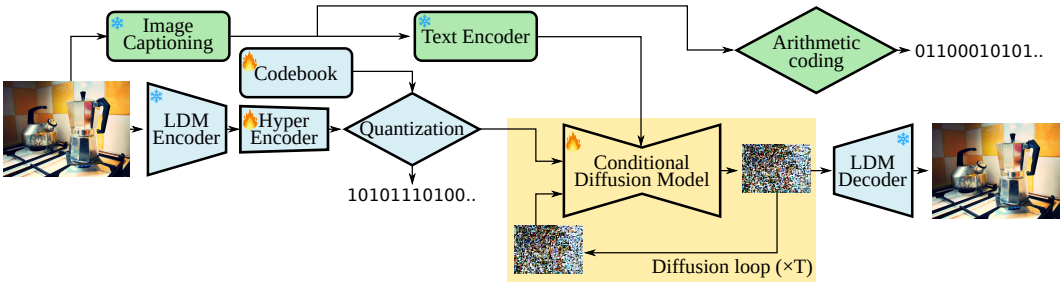

Figure 2: Overview of PerCo. The LDM encoder maps an RGB image into the latent space of the diffusion model. The "hyper encoder" then maps the image to a hyper-latent with smaller spatial resolution, which is then vector-quantized and represented as a bitstream using uniform coding. The image captioning model generates a textual description of the input image, which is losslessly compressed, and processed by a text encoder to condition the diffusion model. The diffusion model reconstructs the input image in its latent space conditioned on the output of the text encoder and the hyper encoder. Finally, the LDM decoder maps the latent reconstruction back to RGB pixel space.

Diffusion models (Sohl-Dickstein et al., 2015; Ho et al., 2020) approximate a data distribution by gradually denoising a unit Gaussian random variable. This is achieved by training a denoising function to reverse a diffusion process that takes an initial sample, denoted as $\boldsymbol{x}_0$, from the data distribution and adds small Gaussian noise over a large number of steps. In practice, a noise estimator $\epsilon_\theta(\boldsymbol{x}_t, t, \boldsymbol{z})$ implemented as a neural network is trained to denoise input data points at timesteps $t \in [0, T]$, where $\boldsymbol{x}_t = \sqrt{\alpha_t}\boldsymbol{x}_0 + \sqrt{1-\alpha_t}\epsilon$ is a corrupted version of the original data point $\boldsymbol{x}_0$ with Gaussian noise ϵ. The scalar α_t fixes the noise strength, varying from $\alpha_0 \simeq 1$ for no noise to $\alpha_T \simeq 0$ for pure Gaussian noise. Finally, $\boldsymbol{z}$ is an optional condition, such as a text-prompt in text-to-image models. In our case, $\boldsymbol{z}$ is the quantized representation of the input image. Once the noise estimator is trained, the model can generate samples by drawing $\boldsymbol{x}_T \sim \mathcal{N}(0, I)$, and applying iterative denoising for $t = T, \ldots, 1$. To reduce the computational cost, we use a latent diffusion model (LDM) where the variables $\boldsymbol{x}_t$ are defined in the latent space of an autoencoder.

We formulate our distortion loss within the probabilistic diffusion framework. For every the diffusion step t, we compute an estimation $\hat{\boldsymbol{x}}_{t-1}$ of $\boldsymbol{x}_{t-1}$ from $\boldsymbol{z}$ and $\boldsymbol{x}_t$ and minimize its error:

$$\mathcal{L}^t_{\text{Diff}} = \mathbb{E}_{P_{\boldsymbol{x}}} \mathbb{E}_{P_{\boldsymbol{z},\boldsymbol{x}_t|\boldsymbol{x}}} \left\| \boldsymbol{x}_{t-1} - \hat{\boldsymbol{x}}_{t-1}(\boldsymbol{x}_t, \boldsymbol{z}) \right\|_2^2. \tag{2}$$

Up to a multiplicative constant, this loss can be rewritten as

$$\mathcal{L}^t_{\text{Diff}} \propto \mathbb{E}_{P_{\boldsymbol{x}}} \mathbb{E}_{P_{\boldsymbol{z},\boldsymbol{x}_t|\boldsymbol{x}}} \mathop{\mathbb{E}}_{\epsilon \sim \mathcal{N}(0,1)} \|\boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\boldsymbol{x}_t, \boldsymbol{z}, t)\|_2^2. \tag{3}$$

We obtain the final loss by taking the expectation of Eq. (3) w.r.t. the steps t, and use $\boldsymbol{v}$ prediction objective of Salimans & Ho (2022), which is more stable during training. The loss can be augmented with any image-level loss such as LPIPS (Zhang et al., 2018) to improve perceptual image similarity.

3.2 Encoding local and global context

We encode the input image as $\boldsymbol{z} = (\boldsymbol{z}_l, \boldsymbol{z}_g)$, where $\boldsymbol{z}_l$ and $\boldsymbol{z}_g$ carry complementary local and global context, respectively. The overall structure of our compression scheme is illustrated in Figure 2.

Local spatial encoding. We encode the input image into a quantized tensor proceeding in three stages. First, we employ the LDM encoder $E(\cdot)$ to achieve a first dimension reduction. Assuming an input image of resolution 512×512, we obtain a feature map of dimension $4 \times 64 \times 64$. Second, we add a lightweight "hyper encoder" H composed of several convolutional layers to project the LDM features to a lower spatial resolution tensor $\boldsymbol{H}_s$. The spatial resolution, $h \times w$, of $\boldsymbol{H}_s$ is chosen according to the target bitrate. Third, we proceed to quantization of $\boldsymbol{H}_s$ to obtain $\boldsymbol{z}_l$ via vector-quantization. As in VQ-VAE (van den Oord et al., 2017; Razavi et al., 2019), each of the $h \times w$ vectors $\boldsymbol{h}_s$ in $\boldsymbol{H}_s$ is mapped to an element in a codebook learned using the vector quantization loss:

$$\mathcal{L}_{\text{VQ}} = \mathbb{E}_{\boldsymbol{h}_s} \left[\|sg(\boldsymbol{h}_s) - \boldsymbol{z}_q\|_2^2 + \|sg(\boldsymbol{z}_q) - \boldsymbol{h}_s\|_2^2 \right], \tag{4}$$

where $sg(.)$ is the stop-gradient operation, and $\boldsymbol{z}_q$ is the mapping of $\boldsymbol{h}_s$ to its closest codebook entry. For better codebook usage, we follow Yu et al. (2022) and set the output of the hyper encoder to be relatively low dimensional: 32 in our case. We also found it beneficial to replace the codebook loss by exponential moving average on the codebooks and thus the first term in Eq. (4) is no longer used. The quantized encoder output is then upsampled to 64×64 resolution, to be channel-wise concatenated to the input of the noise estimation network of the diffusion model. The hyper-network is trained end-to-end while finetuning the diffusion model. For simplicity, we opt for uniform coding to map the quantized latents to a bitstream. Using $\log_2 V$ bits to encode each element in the $h \times w$ sized hyper latent encoding, where V is the codebook size, results in a total of $hw \log_2 V$ bits.

Global encoding with image captioning. While $\boldsymbol{z}_l$ can accurately encode local information, our experiments show that relying on $\boldsymbol{z}_l$ alone leads to unsatisfying realism. Therefore, we add a global encoding of the image $\boldsymbol{z}_g$ which provides additional context. For this purpose, we use an off-the-shelf state-of-the-art image captioning model, such as BLIP-2 (Li et al., 2023) or IDEFICS (Laurançon et al., 2023), which we keep fixed when training our model. Note that user-generated captions can also be used, as explored in our experiments. Similar to Lei et al. (2023), we losslessly compress the caption using Lempel-Ziv coding as implemented in the zlib library (zli) to obtain $\boldsymbol{z}_g$. Alternatively, we also explore the use of global image features extracted using an image backbone network.

Decoding with a diffusion model. The quantized local image features in $\boldsymbol{z}_l$ are fed to the denoising U-Net of the diffusion model via concatenation with the latent features $\boldsymbol{x}_t$ of the current time step. To adapt to this change of dimension, we extend the kernel of the first convolutional layer of the U-Net by adding a number of channels that corresponds to the channel dimension of $\boldsymbol{z}_l$ which is randomly initialized. The global encoding $\boldsymbol{z}_g$ is losslessly decoded and passed to the diffusion model through cross-attention layers of the pre-trained diffusion model.

Furthermore, we found it beneficial to use classifier-free guidance (Ho & Salimans, 2021), which we apply at inference time for the text conditioning $\boldsymbol{z}_g$, *i.e.* we contrast conditioning on local featues $\boldsymbol{z}_l$ alone *vs.* conditioning on both $\boldsymbol{z}_l$ and $\boldsymbol{z}_g$. This leads to the noise estimate:

$$\hat{\epsilon}_\theta = \epsilon_\theta(\boldsymbol{x}_t, (\boldsymbol{z}_l, \emptyset), t) + \lambda_s \left(\epsilon_\theta(\boldsymbol{x}_t, (\boldsymbol{z}_l, \boldsymbol{z}_g), t) - \epsilon_\theta(\boldsymbol{x}_t, (\boldsymbol{z}_l, \emptyset), t)\right), \tag{5}$$

where λ_s is the guidance scale. We empirically found $\lambda_s = 3$ to work well. To enable classifier-free guidance, we train PerCo by dropping the text-conditioning in 10% of the training iterations. When dropping the text-conditioning we use a constant learned text-embedding instead.

4 Experiments

4.1 Experimental setup

Implementation details. We base our model off a text-conditioned latent diffusion model, with latent space provided by a convolutional autoencoder and diffusion model with an architecture similar to GLIDE (Nichol et al., 2022). The model is pre-trained on a proprietary dataset consisting of around 300M image-caption pairs. We also experiment with an image-conditioned model. We use BLIP-2 (Li et al., 2023) to obtain image captions for conditioning the decoder, and limit the maximum caption length to 32 tokens. The hyper encoder consists of nine residual convolutional blocks, and includes a number of downsampling layers depending on the spatial map resolution selected for the target bitrate. In total, the hyper encoder contains between 4M and 8M parameters. During all our experiments, the autoencoder weights are frozen. We train the hyper encoder and finetune the diffusion model on OpenImages (Kuznetsova et al., 2020), similar to Lei et al. (2023) and Muckley et al. (2023). We use random 512×512 crops, and instead of finetuning the full U-Net we found it beneficial to only finetune the linear layers present of the diffusion model, representing around 15% of all weights.

Datasets. For evaluation, we use the **Kodak** dataset (Franzen, 1999) as well as **MS-COCO 30k**. On COCO we evaluate at resolution 256×256 by selecting the same images from the 2014 validation set (Lin et al., 2014) as Hoogeboom et al. (2023) and Agustsson et al. (2023). We evaluate at resolution 512×512 on the 2017 training set (Caesar et al., 2018), which is the same resolution used for evaluation by Lei et al. (2023), and use captions and label maps for some metrics.

Metrics. To quantify image quality we use **FID** (Heusel et al., 2017) and **KID** (Bińkowski et al., 2018), which match feature distributions between sets of original images and their reconstructions.

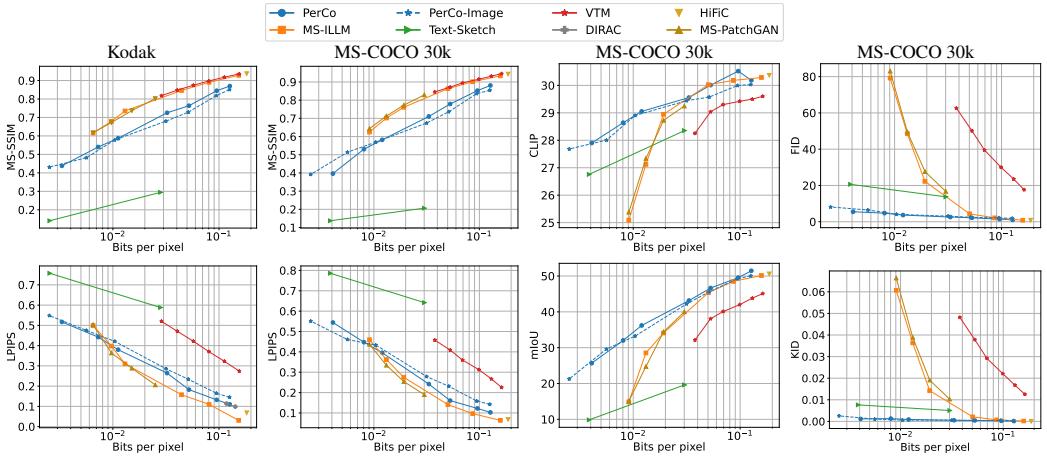

Figure 3: Evaluation of PerCo and other image compression codecs on Kodak and MS-COCO 30k.

We measure distortion using **MS-SSIM** (Wang et al., 2003) and **LPIPS** (Zhang et al., 2018). In **??** we also report **PSNR**, but find these low-level distortion metrics to be less meaningful for low rates, see **??**. Therefore we include other more semantic-level metrics. We compute the **CLIP score** to measure global alignment of reconstructed samples with ground truth captions (Hessel et al., 2021). Unless otherwise specified, we condition our model on captions generated by BLIP2, which are different from the ground-truth captions used to compute the CLIP score. Second, we adopt the mean Intersection over Union (**mIoU**) metric to measure the local semantic preservation, see *e.g.* Sushko et al. (2022). In this case, we pass reconstructed images through a pre-trained semantic segmentation model, and compare the predicted semantic maps to the ground truth ones. We take the pretrained ViT-Adapter segmentation network (Chen et al., 2023), which was trained on the COCO train split. For Kodak we only report LPIPS and MS-SSIM, as the dataset is too small (24 images) to reliably compute FID and KID, and does not come with semantic annotations.

Baselines. We include representative codecs from several families. VTM is a state-of-the-art hand-crafted codec used in the VVC video codec (vtm). Among neural compressors using adversarial losses, we include MS-ILLM (Muckley et al., 2023) which improves over HiFiC (Mentzer et al., 2020) using an adversarial loss based on multi-class classification. For HiFiC we include their model with the lowest available bitrate, and add MS-PatchGAN, which is a close reproduction of HiFiC by Muckley et al. (2023). We compare to multi-realism approach of Agustsson et al. (2023), at their lowest bitrate with the best realism. Text-Sketch (Lei et al., 2023) is the only prior work we are aware of that evaluates image compression at bitrates below 0.01, it is based on text-conditioned diffusion models. We include two other recent diffusion-based approaches: DIRAC (Ghouse et al., 2023) and HFD/DDPM (Hoogeboom et al., 2023).

4.2 Main results

Comparison to state-of-the-art methods. In Fig. 3 we compare our results to state-of-the-art codecs. We observe that PerCo (ours) yields significantly lower (better) FID and KID compared to other approaches at lower bitrates (<0.04 bpp), and that our FID and KID curves are much flatter, indicating a decoupling of realism and bitrate that is not seen for other methods. For the semantics-related CLIP and mIoU metrics we also obtain consistent improvements over all other methods, in particular at low rates. For LPIPS, PerCo is better than Text-Sketch and VTM, but somewhat worse than other approaches for rates >0.01 bpp. Similarly, for MS-SSIM we improve over Text-Sketch, but are worse than other methods. However, as we illustrate in **????** in **??**, such similarity metrics are not necessarily meaningful at low bitrates, as they do not capture realism.

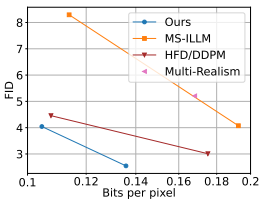

Figure 4: Evaluation on COCO at 256×256 res.

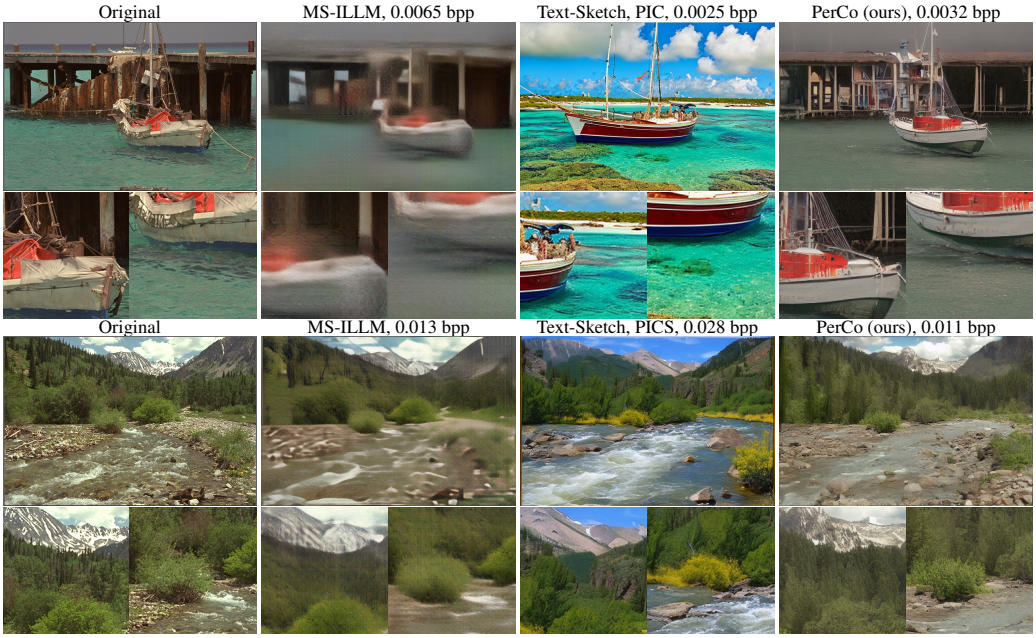

Figure 5: Comparing PerCo on images from the Kodak dataset to MS-ILLM (Muckley et al., 2023) which leverages an adversarial loss, and the diffusion-based Text-sketch approach (Lei et al., 2023) conditioned on a text only (top, PIC, 0.0025 bpp) and text + sketch (bottom, PICS, 0.028 bpp).

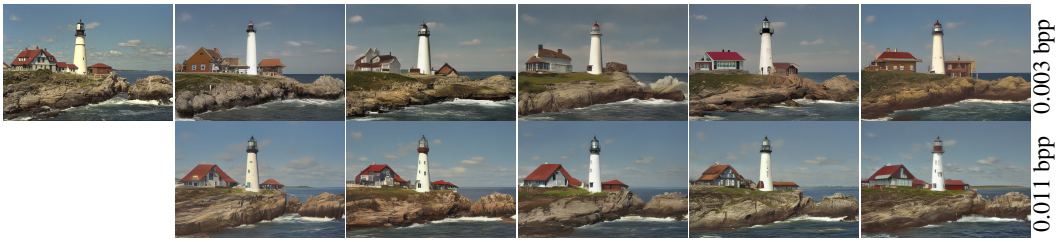

Figure 6: Reconstruction sampled of a Kodak image at 0.003 and 0.011 bpp. Best viewed zoomed.

In Fig. 4 we compare to HFD/DDPM (using their lowest bitrates: 0.107 and 0.175 bpp) on FID on MS-COCO 30k at 256×256 resolution, as used in their paper. We also include MS-ILLM and the multi-realism approach of Agustsson et al. (2023). We find that PerCo yields best FID for both rates.

Qualitative comparisons. We provide qualitative comparisons of PerCo to baselines in Fig. 1 and Fig. 5. PerCo yields reconstructions of higher quality with less artefacts, more faithful colors, and realistic details. VTM and MS-ILLM reconstructions are blurry and/or blocky, while Text-Sketch strongly deviates from the originals in color. When using text-only conditioning for Text-Sketch (PIC, 0.0025 bpp), it is not able to achieve spatial alignment, by lack of local image encoding.

4.3 Ablations

Diversity in reconstructions. With our model, reconstructions are sampled from a conditional diffusion model. Ideally, the conditional distribution concentrates all mass perfectly on the original input image. In practice, this does not happen due to limited model capacity, training data, and bitrate. In particular, we expect that at lower bitrates —where there is less information about the original sample— the conditional distribution would have more variance, and we expect to observe more diversity among the samples. The reconstruction at two bitrates in Fig. 6 confirm this.

Conditioning modalities. In Fig. 7, we evaluate PerCo using each conditioning modality separately (textual or spatial), to analyze the contribution of each. We compare BLIP-2 (Li et al., 2023) to generate captions (default) to using IDEFICS (Laurançon et al., 2023) which produces more detailed descriptions, and ground-truth (GT) captions. When not using descriptive captions, we consider

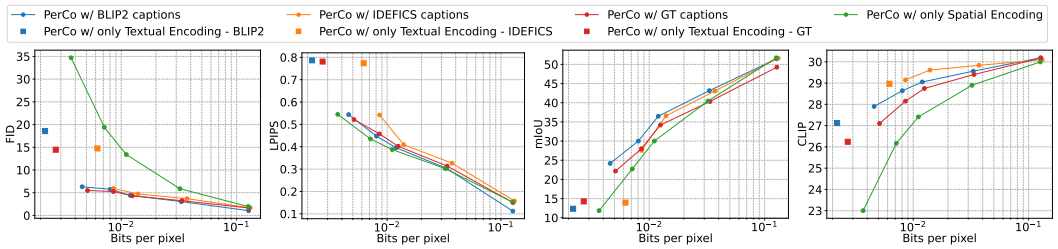

Figure 7: Ablation of conditioning on local features and/or different captions. See text for detail.

Table 1: Ablations of classifier-free guidance forms (left), and impact of conditional diffusion model and quantization on reconstruction abilities (right). All models at 0.0112 bpp, except for LDM autoencoder and PerCo w/o quantization which use single precision for non-quantized latents.

Guidance type	**↓FID**	**↓LPIPS**	**↑SSIM**	**↑mIoU**	**↑CLIP**
None	7.89	0.40	0.58	30.84	28.36
Text and spatial	13.84	0.41	0.58	32.26	28.87
PerCo: Text only	4.42	0.39	0.58	46.64	29.05

Method	**↓FID**	**↓LPIPS**	**↑SSIM**	**↑mIoU**	**↑CLIP**
LDM autoencoder	0.67	0.07	0.92	51.04	30.19
PerCo w/o quant.	0.68	0.07	0.92	51.03	30.18
PerCo (0.012 bpp)	4.42	0.39	0.58	46.64	29.05

conditioning on a learned textual embedding that is constant across images. We also tried using an empty text or on a fixed generic text —*"A high quality photograph."*— for all images, and observed similar or slightly worse performance as the learned text embedding setting.

The model using the constant text embedding (PerCo w/ only Spatial Encoding) performs significantly worse than the other models in terms of FID and CLIP score. For the LPIPS and mIoU metrics, which rely on the alignment of the original and reconstructed images, the results are comparable to other models. This can be attributed to the fact that accurate alignment is primarily achieved through local feature conditioning, which remains unchanged in this model. Consistently, we also notice that when using textual condition only (blue, orange, and red square), the performance in terms of LPIPS and mIoU is worse than for the models that use spatial conditioning, while the CLIP scores are in line with the models using both textual and spatial conditioning. Both types of conditioning contribute to improving FID, and the text-only conditioned models perform in between the models with only spatial conditioning and those with both types of conditioning.

Between models using captions from BLIP (blue curves) and IDEFICS (orange curves) in combination with spatial conditioning, we observe similar FID scores and somewhat better CLIP scores for the more detailed IDEFICS captions. In terms of LPIPS and mIoU we find that the models with BLIP captions perform better, which is largely due to bitrate required to encode the longer captions: leaving out the textual encoding cost, both models perform very similarly. Overall, using ground-truth captions (GT, red curves) yields similar results as using BLIP, while BLIP and IDEFICS yield slightly better mIoU and CLIP scores. As COCO contains five GT captions per image, we ensure that when conditioning on a GT caption, a different one is used to compute the CLIP score.

Classifier-free guidance. In Tab. 1 (left), we compare three options regarding classifier-free guidance (CFG) in our model (i) not using CFG, (ii) applying CFG on the text and spatial feature maps, *i.e.* contrasting full conditioning to no conditioning (we use an constant learned text embedding, and fixed all-zeros feature maps for local conditioning), and (iii) applying CFG to text-conditioning only, *i.e.* always conditioning on the spatial feature map. We find that best results are obtained when CFG is applied to textual conditioning only, which yields significantly better FID and mIoU metrics.

Impact of autoencoder and quantization. To assess to which extent performance is bounded by the LDM autoencoder or the use of limited bitrate, we compare PerCo to the LDM encoder/decoder reconstruction and to PerCo trained without quantization in Tab. 1 (right). We observe that the LDM autoencoder significantly improves all metrics, and that PerCo trained without quantization obtains roughly the same performance as the autoencoder. This shows that PerCo is a strong conditional model, and that its performance is mainly bounded by the quantization module which throttles the bitrate of the image encoding, but could also lead to suboptimal training through noisy gradients.

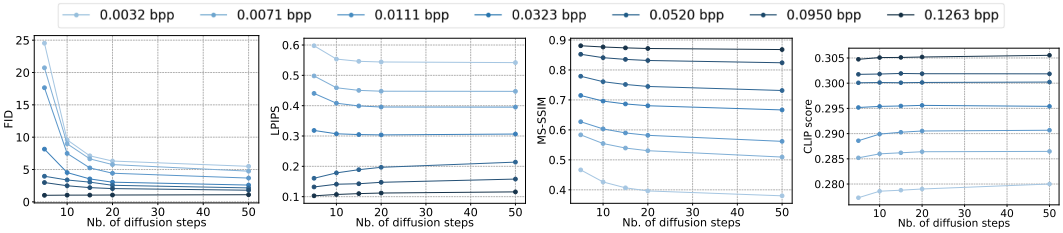

Figure 8: Evolution of FID, LPIPS, MS-SSIM and CLIP scores depending on the number of denoising steps for different bitrates. In all cases the model has been trained using 50 denoising steps.

Number of timesteps as a tradeoff between perception and distortion. In Figure 8, we show how FID, LPIPS, MS-SSIM and CLIP scores vary when we change the number of denoising steps. We do the evaluation for seven different bitrates, ranging from 0.0032 to 0.1263 bpp. First, we notice that for higher bitrates, the metrics are quite constant across the number of timesteps, which means that the model has less uncertainty about the image to reconstruct and obtains optimal performance after only few denoising steps. Secondly, we observe a tradeoff between distortion and realism for lower bitrates. Indeed, when the number of timesteps is small, FID is worse, but MS-SSIM is optimal, while this phenomenon reverses when increasing the number of denoising steps.

Conditioning on global image features. Besides the text-conditioned model described above and used in most experiments (PerCo), we also experimented with a model conditioned on image embeddings extracted from an image backbone network (PerCo-Image). While we use lossless Lempel-Ziv coding to compress the captions for the text-conditioned model, we use product quantization (Jégou et al., 2011) for lossy compression of the image embeddings. We divide the embeddings into M subvectors and quantize each subvector using a separate codebook with V elements. We empirically found that we achieve similar performance compared to training with non-quantized image embeddings with $M = 16$ and $V = 1024$. For 512×512 images, the bitrate obtained for the image embeddings is 0.00061 bpp, which is $3.5\times$ lower than the bitrate of 0.00219 bpp for BLIP image captions. From the results in Fig. 3, we observe that the model with global image embeddings obtains competitive results, but has slightly worse pairwise image reconstruction metrics at high bitrates in terms of LPIPS and MS-SSIM on Kodak and MS-COCO 30k.

5 Conclusion

We proposed PerCo, an image compression model that combines a VQ-VAE-like encoder with a diffusion-based decoder, and includes an second conditioning stream based on textual image descriptions. The iterative diffusion decoder allows for more realistic reconstructions, in particular at very low bitrates, as compared to feed-forward decoders used in previous work, even when trained with perceptual and adversarial losses. With our work we make step towards perfect realism codecs: we observe realistic reconstructions at bitrates as low as 0.003 bits per pixel, a bitrate regime that to our knowledge is explored in only one prior work (Lei et al., 2023). We find that semantics-driven metrics such as CLIP score and mIoU are improved overall and in particular for low rates, and FID and KID are dramatically improved at low bitrates and much more stable across different bitrates.

Limitations. In this study we focused on medium sized images up to 768×512 resolution, similar to prior work on diffusion-based methods (Theis et al., 2022; Lei et al., 2023) that evaluated on 64×64 and 512×512 images, respectively. Extension to higher resolutions can possibly be achieved using a patch-based approach, see *e.g.* Hoogeboom et al. (2023). PerCo exhibits somewhat poorer reconstruction performance in terms MS-SSIM, PSNR and LPIPS (the latter for rates >0.01), than existing approaches. This seems at least in part to be due to limitations of the LDM autoencoder, see **??**. It is also probably explained by the tradeoff existing between distortion and perception (Blau & Michaeli, 2019). We leave detailed study of these two points to future work.

Ethics statement

The use of machine learning models, in general and for image compression in particular, can lead to biases in the model related to the training data, and potentially work better on data similar to those

used to train the models. Therefore the models as described in this paper should be used for research purposes only, and not deployed in practice without extensive analysis of their potential biases.

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