Abstract—Existing compression methods typically focus on the removal of signal-level redundancies, while the potential and versatility of decomposing visual data into compact conceptual components still lack further study. To this end, we propose a novel conceptual compression framework that encodes visual data into compact structure and texture representations, then decodes in a deep synthesis fashion, aiming to achieve better visual reconstruction quality, flexible content manipulation, and potential support for various vision tasks. In particular, we propose to compress images by a dual-layered model consisting of two complementary visual features: 1) structure layer represented by structural maps and 2) texture layer characterized by low-dimensional deep representations. At the encoder side, the structural maps and texture representations are individually extracted and compressed, generating the compact, interpretable, inter-operable bitstreams. During the decoding stage, a hierarchical fusion GAN (HF-GAN) is proposed to learn the synthesis paradigm where the textures are rendered into the decoded structural maps, leading to high-quality reconstruction with remarkable visual realism. Extensive experiments on diverse images have demonstrated the superiority of our framework with lower bitrates, higher reconstruction quality, and increased versatility towards visual analysis and content manipulation tasks.

Index Terms—Conceptual compression, deep generative models, low bit-rate coding, structure and texture.

I. INTRODUCTION

The human visual system (HVS) perceives visual contents by processing and integrating manifold information into abstract high-level concepts (e.g., structure, texture, semantics), which form the basis for subsequent cognitive process. From the perspective of machine vision, high-level visual concepts also play a more important role in the practical applications than signal-level pixels. Existing compression methods, including traditional block-based (e.g., JPEG and HEVC) and deep learning based methods, mainly focus on the modeling and removal of signal-level redundancy, while the potential and versatility of accomplishing compression task through decomposing visual data into compact conceptual components still lack further exploration. Following the insight of Marr and Guo et al., visual objects usually appear as structures and textures. As two primal visual components, structure and texture not only play a deterministic role in visual content synthesis, but also are critical visual feature descriptors in various analysis-based tasks. In particular, due to the lack of explicit modeling for structure, existing compression methods often introduce severe distortions in decoded images under low bit-rate scenarios, such as ringing/blocking artifacts and blurring edges, which not only degrade human perception, but also hamper the performance of visual analysis tasks. Moreover, the encoded bitstreams are less correlated to visual concepts, resulting in the difficulty of utilizing the encoded information for subsequent manipulation tasks, such as image synthesis, shape modification and content recreation.

Deep generative models, such as variational auto-encoders (VAE) and generative adversarial networks (GANs), have offered a new approach for conceptualizing images with compact latent representations, where the decoding process is implemented in a generative fashion. However, existing researches on conceptual compression often attempt to capture image contents with a single latent vector, with different conceptual components entangled together. In consequence, the encoded conceptual representation is less interpretable and editable, limiting its potential towards downstream image processing and machine vision tasks, such as target-guided content manipulation. Apparently, it is desirable to develop visual components disentangled representations for a clearer understanding and more flexible control of image contents.

In this work, we propose a novel conceptual compression framework. In this framework, images are encoded into compact structure and texture representations and decoded in a deep synthesis fashion to achieve better visual reconstruction quality, flexible content manipulation and potential support for various analysis tasks. More specifically, we propose to process images by a dual-layered model consisting of two complementary visual features: 1) structure layer represented by edges since edges depict key structure information of images, and 2) texture layer which represents non-structural
Our contributions can be summarized as follows:

- We propose a novel compression framework which encodes by abstracting visual data into compact structure and texture representations and decodes by deep synthesis processing to produce cross-modal unification of visual features and basis data.
- We propose to realize conceptual compression via extracting sparse structural maps and deep texture representations, and an HF-GAN is proposed as decoder to reconstruct images of high visual quality from texture and structure.
- The superiority of the proposed framework in image compression and vision tasks is justified and thoroughly analyzed via extensive experiments.

The rest of the paper is organized as follows. The related work and technologies are introduced in Section III. The proposed framework and networks are presented in Section IV. Section V shows the detailed experimental results and analyses, and Section VI concludes the paper and discuss directions for future research.

II. RELATED WORKS

A. Traditional Image Compression

Traditional image compression technologies have played a fundamental role in visual communication and image processing, bringing up a series of crafted image codecs, such as JPEG [3], JPEG2000 [20] and H.265/HEVC-based BPG [21]. JPEG is the most popular and widely used compression standard, which integrates well-known technologies including block-partition, discrete cosine transform (DCT), quantization and entropy coding. JPEG2000 [20] applies discrete wavelet transform (DWT) technology instead of DCT, achieving higher compression ratio and allowing various editing or processing applications. After decades of development, a series of block-based hybrid prediction/transform coding standards (e.g., MPEG-4 AVC/H.264 [22], AVS [23], [24] and HEVC [4]), are built to significantly improve the coding efficiency by reducing pixel-level redundancy. Different from JPEG, HEVC utilizes more intra prediction modes from neighboring reconstructed blocks in spatial domain to remove redundancy.

B. Deep Learning-based Image Compression

Recent years have witnessed a surge of interest in learning-based image compression, which benefits from large-scale data, effective network architectures, end-to-end optimization, and other advanced techniques such as generative models and unsupervised learning. Typical deep image compression systems usually adopt end-to-end framework [25] to model the pixel distribution and jointly optimize rate-distortion performance with reconstruction tasks, outperforming popular block-based codecs, such as JPEG, JPEG2000 and HEVC. Pixel probability modeling [26] and auto-encoder [5], [6], are two main approaches in deep learning based image coding schemes, as pointed in [27]. Meanwhile, multiple deep structures, such as CNN [5], RNN [28] and GAN [12], [29], are...
II. CONCEPTUAL IMAGE COMPRESSION FRAMEWORK

Our goal is to explore the potential of performing compression via decomposing visual data into compact visual components and develop a set of feasible examplar scheme. In particular, we propose to compress images by extracting the compact representations of two primal complementary visual features, structure and texture. In the proposed framework, the images $I$ are represented with compact texture representations $I^t$ and sparse structural maps $I^s$, i.e., $I \rightarrow I^s + I^t$. As shown in Fig. 1, images are decomposed into texture layer and structure layer and compressed separately on the encoder side. We obtain the sparse structure maps $I^s$ with the edges extractor $Enc^s$ (Section III-A) and low-dimensional texture representations $I^t$ with variational texture auto-encoder $Enc^t$ (Section III-B), i.e., $I^s = Enc^s(I)$, $I^t = Enc^t(I)$. Both texture representations and sparse structural maps are further compressed to bitstreams for transmission using existing standard codec. On the decoder side, a hierarchical fusion generator $Gen$ is designed to reconstruct the high quality images $\hat{I}$ from decoded components, texture $\hat{I}^t$ and structure $\hat{I}^s$, i.e., $\hat{I} = Gen(\hat{I}^t, \hat{I}^s)$ (Section III-C). To achieve reconstruction of high visual quality and fidelity, we take advantage of both adversarial training and multi-perspective distortion measurement to supervise the reconstruction process. In particular, we also propose a latent regression loss to better learn the paradigm of texture extraction and synthesis (Section III-D).

A. Structure Layer Compression

Considering that edges are one of the most sparse and abstract image representations and can depict the key structure information of images, edge maps are extracted as the structure layer representation via widely used edge detection methods, such as holistically-nested edge detection (HED) and Canny edge detection. On account of the sparsity and binarization of structural maps, we employ the Lanczos downsampling algorithm to further reduce data volume of structure layer with 4-scale. Furthermore, screen content coding is adopted to compress the structure maps into bitstreams since this framework has strong capability of compressing images with abundant sharp edges.

At the decoder side, the process is reversed to recover the structural maps before synthesizing images. To regain the structural maps of original resolution, we upsample the decoded low resolution structure maps using one of the state-of-the-art super-resolution methods, deep back-projection networks (DBPN). The DBPN model is optimized with the mean square error (MSE) in which is not sensitive to the fluctuation of sparse binary data, leading to the significant distortion in reconstructed edges. To improve the restoration performance on the datasets which are characterized by sparse and binary edges, the binary cross entropy (BCE) is employed.

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Fig. 2. Architecture of hierarchical fusion generator networks. Generator consists of fully connected layers (FC), Residual blocks (Resblock), RGB transformation module (To RGB), upsampling and cumulatively summing module. Structural maps are resized and concatenated to feature maps as input for corresponding Resblock.

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utilized to explore efficient compression architectures. Despite the constant improvement of compression performance, most deep learning-based end-to-end compression algorithms mainly aim to model signal-level correlations, while the visual concepts are less explored.

In addition to rate-distortion optimization, subsequent analysis tasks, such as image retrieval and semantic analysis, have also been incorporated into learning-based compression frameworks to encourage analysis-friendly signal representation. However, extra task-related networks are adopted in their frameworks for joint image analysis and compression, potentially limiting the application to specific tasks.

C. Conceptual Compression

Conceptual compression aims to encode images into compact, high-level interpretable representations for reconstruction, allowing a more efficient and analysis-friendly compression architecture. Gregor et al. introduced convolutional Deep Recurrent Attentive Writer (DRAW), which extends VAE by using RNNs as encoder and decoder, to transform an image into a series of increasingly detailed representations. However, the models in are only verified on datasets of small resolutions. Hu et al. compress images into compact structure and color representations with generative models, where the representations are characterized with edge maps and reference sample pixels near edges specifically. Despite that the structure representation can be well analyzed, the support for vision tasks, such as image synthesis and modification, are limited by pixel-level color representations. The semantic guidance is used to assist in reconstructing images from compact compressed visual data in, where the main data stream is still signal-oriented though.

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III. CONCEPTUAL IMAGE COMPRESSION FRAMEWORK

Our goal is to explore the potential of performing compression via decomposing visual data into compact visual components and develop a set of feasible examplar scheme. In particular, we propose to compress images by extracting the compact representations of two primal complementary visual features, structure and texture. In the proposed framework, the images $I$ are represented with compact texture representations $I^t$ and sparse structural maps $I^s$, i.e., $I \rightarrow I^s + I^t$. As shown in Fig. 1, images are decomposed into texture layer and structure layer and compressed separately on the encoder side. We obtain the sparse structure maps $I^s$ with the edges extractor $Enc^s$ (Section III-A) and low-dimensional texture representations $I^t$ with variational texture auto-encoder $Enc^t$ (Section III-B), i.e., $I^s = Enc^s(I)$, $I^t = Enc^t(I)$. Both texture representations and sparse structural maps are further compressed to bitstreams for transmission using existing standard codec. On the decoder side, a hierarchical fusion generator $Gen$ is designed to reconstruct the high quality images $\hat{I}$ from decoded components, texture $\hat{I}^t$ and structure $\hat{I}^s$, i.e., $\hat{I} = Gen(\hat{I}^t, \hat{I}^s)$ (Section III-C). To achieve reconstruction of high visual quality and fidelity, we take advantage of both adversarial training and multi-perspective distortion measurement to supervise the reconstruction process. In particular, we also propose a latent regression loss to better learn the paradigm of texture extraction and synthesis (Section III-D).
to replace the MSE loss for the super resolution model training,
\[
\mathcal{L}_{BCE} = - \sum_{u,v} \sum_{I^s(u,v)} \log(\hat{I}^s_{(u,v)}) + (1 - \hat{I}^s_{(u,v)}) \log(1 - \hat{I}^s_{(u,v)}],
\]
where \(I^s_{(u,v)}\) represents the true pixel value of structural map \(I^s\) at position \((u,v)\), while \(\hat{I}^s_{(u,v)}\) represents the predicted value of upsampled structural map \(\hat{I}^s\) at position \((u,v)\). We adopt the pre-trained DBPN model for high efficiency.

B. Texture Layer Compression

As shown in Fig. 1, the compact texture representations are extracted with a neural network-based encoder and integrated with the reconstructed structural maps to synthesize target images by an elaborator generator. The encoder \(Enc\) and generator \(Gen\) are jointly trained in an end-to-end manner. In this section, we will introduce the process of texture extraction and compression.

The image texture extractor is designed based on variational auto-encoder for conceptual level information extraction \([11]\). In particular, the encoder \(Enc\) is constructed with several residual blocks \([40]\) and convolutional layers to model the input image \(I\) into a posterior multivariate Gaussian distribution \(q_\phi(I|\bar{I})\). Then the representation \(I^t\) is generated by sampling from the posterior distribution \(q_\phi(I^t|\bar{I})\) using reparameterization \([9]\) method, i.e., \(I^t \sim q_\phi(I^t|\bar{I})\).

Subsequently, the extracted texture discrete representation \(I^t\) is further compressed through scalar quantization and entropy coding. We follow the quantization method defined in HEVC \([4]\), where the quantization step \(Q_{step}\) is determined by the quantization parameter \((QP)\) and we take the factor \(s = 2^10\) empirically:
\[
Q_{step} = \frac{2^{QP-4}}{s} = 2^{QP-4-10}.
\]
The quantization is performed by,
\[
I^{qt} = floor\left(\frac{I^t}{Q_{step}}\right),
\]
where representation \(I^t\) is quantized to \(I^{qt}\) and \(floor(\cdot)\) represents the truncation operation for designated binary digit precision. Finally the quantized texture representations are encoded with Arithmetic codec \([41]\) for transmission. The decoded texture representations for image synthesis can be denoted by \(\hat{I}^t\), where \(\hat{I}^t = I^{qt} \times Q_{step}\).

C. Image Synthesis

Motivated by the strong capability of the instance normalization in style transfer \([42]\), we adopt the adaptive instance normalization \([43]\) to integrate texture layer and structure layer. Specifically, a group of modulation parameters, including mean and variance, are learned from texture representations. The feature statistics of the feature maps are transferred with learned modulation parameters during adaptive affine transformations, where feature maps contain both structure information and previously generated texture information in forward propagation as shown in Fig. 3. The particular channel-wise modulation parameters are learned corresponding to each intermediate feature map. In this manner, the structure and texture are fused and integrated gradually through convolutional operation and affine transformation. Additionally, inspired by impressive generation capability of progressive growing GAN \([19]\), we devise a generator which progressively increases the resolution of synthesized feature maps as shown in Fig. 2. The generator consists of a pile of residual blocks as basic units and takes advantage of skip connections and hierarchical fusion. Each residual block includes three fully convolutional layers followed by adaptive instance normalization operation. The structural maps are concatenated to the feature maps as new input for each residual block. Finally, the target images are obtained by upsampling and summing the contributions of RGB outputs corresponding to different resolutions as \([42]\). The formulation of the hierarchical fusion process is presented as follows.

Given the input image \(I \in \mathbb{R}^{H \times W \times 3}\), we can obtain the structure map \(I^s \in \mathbb{R}^{H \times W \times 3}\) and the texture representation \(I^t \in \mathbb{R}^{d \times 1}\), where \(H, W\) represent the size of input image and \(d\) denotes the dimension of texture representation. Let the initial block of the generator function \(G_0\) be defined as \(G_0 : I^s \mapsto A_0\) such that \(A_0 \subseteq \mathbb{R}^{2 \times 2 \times c_0}\) and \(c_0\) denotes the number of feature channels. We define the intermediate output of the \(i\)-th residual block as \(A_i\), and \(i \in \mathbb{N}\). The structure map \(I^s\) is resized to \(I^t_i\) which has the same size as \(A_i\). Thus, the input of each residual block is defined as:
\[
\hat{A}_i = [A_i; I^t_i],
\]
where \([\cdot]; [\cdot]\) is a channel-wise concatenation operation. Let \(G_i\) be a generic function where \(G_0\) acts as the initial convolutional layer and \(G_i\) acts as the basic Resblock: \(G_i : A_{i-1} \mapsto A_i\), where \(A_i \in \mathbb{R}^{2^{i+1} \times 2^{i+1} \times c_i}\) and \(c_i\) is the number of channels in the intermediate activations of the \(i\)-th generator block. Then \(A_k\) can be obtained by the general formula composed with a sequence of \(G\) functions, where \(k \in \mathbb{N}\):
\[
A_k = G_k(\cdot, I^t_k) \circ G_{k-1}(\cdot, I^t_{k-1}) \circ \cdots \circ G_1(\cdot, I^t_1) \circ G_0(I^s).
\]
The symbol $\circ$ in Eq (5) is defined as the function composition operation. In particular, $A_k$ can be unfolded with composition function as following:

$$A_k = g_k(g_{k-1}(\cdots g_1(g_0(I^s), I_1^s), \cdots, I_{k-1}^s)), I_k^s)$$

We employ skip connections and multi-scale fusion to improve reconstruction quality of the generator. $u_p^{(2)}$ is defined as the upsampling function by 2-scale and $conv_p^{3(3)}$ simply serves as a 3 x 3 convolution function which converts the output feature map $A_i$ of each block into RGB images: $conv_p^{3(3)}: A_i \rightarrow B_i$, where $B_i \subseteq \mathbb{R}^{2^{i+1} \times 2^{i+1} \times 3}$. Hence, the RGB output of initial convolutional layer $x_0$ is:

$$x_0 = conv_0^{3(3)}(A_0) = conv_0^{3(3)}(G_0(I^s)).$$

The RGB output of the $i$-th intermediate block can be computed with the recurrence formula as following:

$$x_i = conv_i^{3(3)}(A_i) + u_p^{(2)}(x_{i-1}), i \geq 1.$$

The network starts incremental reconstruction process from the resolution of $4 \times 4$ at the first Resblock, conducts 2x upsampling and fusion affine transformation in each Resblock, and obtains the target resolution output at the final Resblock. The selection of the number of Resblocks in hierarchical fusion generator network depends on the target image resolution of the dataset. For the target synthetic resolution $n \times n$, the number of Resblocks is set to $\lceil \log_2 n - 1 \rceil$. Therefore, the proposed generator consists of seven Resblocks for the target resolution $256 \times 256$.

In the basic residual block of the generator shown in Fig. 3, there are three convolutional layers whose scale and bias are modulated by three groups of parameters learned from texture representations by three fully connected layers respectively. The feature maps at the $j$-th convolutional layer of $i$-th basic block is denoted by $A_{ij}$. Receiving the texture representation $I^t$, a fully connected function $f_{ij}: I^t \rightarrow \alpha_{ij}, \beta_{ij}$ first maps $I^t$ into affine parameters, where $\alpha_{ij}, \beta_{ij} \subseteq \mathbb{R}^{1 \times 1 \times c_i}$.

Thus, we adaptively normalize the previous activations $A_{ij}$ with the learnable texture affine parameters:

$$AdaIN(A_{ij}, t^s) = \alpha_{ij} A_{ij} - \mu(A_{ij}) + \beta_{ij},$$

where the normalized feature maps are scaled with $\alpha_{ij}$, and shifted with $\beta_{ij}$ in the channel-wise manner, and $\mu(A_{ij})$ and $\sigma(A_{ij})$ are the means and standard deviations of the activations in $A_{ij}$. By transferring the feature statistics from texture representations and concatenating the structural maps with intermediate generated content, structure and texture are effectively integrated to reconstruct images of which texture are progressively enriched. Moreover, during the training of reconstruction task, the mapping and synthesis paradigm between deep latent space and spatially-aware texture content are jointly well learned and stored as deep prior in the designed generative model, allowing the flexible examplar-based image content manipulation in the compressed domain.

\subsection*{D. Loss Objectives}

The proposed texture encoder and the image generator are jointly trained in an end-to-end manner with a multi-scale discriminator. The image compression and reconstruction tasks are mainly optimized on three type of losses as shown in Fig. 4: reconstruction loss which aims to improve reconstruction visual quality and fidelity, prior divergence which provides a prior distribution instruction for deep texture representation, and the proposed latent regression loss which constrains the mapping between deep latent space and synthesized texture content.

Compared to typical learned lossy compression methods [5], [6] which only optimize image reconstruction quality with pixel-wise similarity metric, we introduce diverse distortion metrics to supervise reconstruction task from low level pixel-wise loss to high level perceptual loss and adversarial loss. The reconstruction loss is introduced as follows:
- Self-reconstruction loss: the pixel-wise loss $L_1^{rec}$ is imposed to force the visual components to complete reconstruct the original images:
  $$L_1^{rec} = E_{I \sim p(I), I' \sim p(I')} \| I - \text{Gen}(I, I') \|_1.$$  

- Structure similarity loss: the SSIM [44] loss is incorporated to supervise the optimization process of improving structural fidelity:
  $$L_{SSIM} = \text{SSIM}(I, \text{Gen}(I, I')).$$  

- Perceptual loss: we use the perceptual loss $L_{vgg}$ in [45] to encourage the perceptual fidelity through deep feature matching from pre-trained VGG-16 networks [46].
- Adversarial loss: we apply the discriminator $D_{Is}$ and follow the variant of conditional adversarial training scheme [47] to encourage the visual realism of reconstructed images:
  $$L_G^{GAN} = \frac{1}{2} \mathbb{E}_{I \sim p(I)} \| 1 - D_{Is}(I, I') \|_2$$  
  $$+ \frac{1}{2} \mathbb{E}_{I \sim p(I), I' \sim p(I')} \| D_{Is}(\text{Gen}(I, I'), I') \|_2,$$  

$$L_D^{GAN} = -\mathbb{E}_{I \sim p(I), I' \sim p(I')} \| D_{Is}(\text{Gen}(I, I'), I') \|_2.$$  

Additionally, to obtain meaningful texture representations by stochastic sampling and benefit entropy coding process, we introduce the prior divergence to enforce the distribution of extracted texture representation to be close to the prior Gaussian distribution, i.e., $p_0(I') \sim \mathcal{N}(0, I)$ and $I$ denotes the identity matrix:
  $$L_{KL} = E_{I \sim p(I)} [D_{KL}(q_\theta(I'|I)||p_0(I'))].$$  

Furthermore, we propose a latent regression loss to further constrain the bidirectional mapping between the learned texture representation $I'$ and the synthesis texture content $\hat{I}$. More specifically, the texture encoder $\text{Enc}_t$ is utilized to analyze and extract the texture representation $\hat{I}_{ext}^{t}$ of the generated image $\hat{I}$. Given the fact that the reconstructed images $\hat{I}$ are trained to maintain texture fidelity, the texture representations which are extracted from original images and reconstructed images should be encouraged to be consistent, i.e., $I' = \text{Enc}_t(I) \approx \hat{I}_{ext}^{t} = \text{Enc}_t(\hat{I})$. Thus, the latent regression loss $L_{1}^{latent}$ is proposed to minimize the $L_1$ distance between two texture representations as follows:
  $$L_1^{latent} = E_{I' \sim p(I'), \hat{I}_{ext} \sim p(\hat{I}_{ext})} \| I' - \hat{I}_{ext} \|_1.$$  

The unique association between specific representation and corresponding texture are further reinforced by the latent regression loss, which not only helps learn a continuous latent space for texture expression in the data-driven manner, but also benefits the learning of synthesis paradigm. Above all, the final training objective is shown as following:
  $$L_{G,D,E} = \lambda_{GAN}L_{G}^{GAN} + \lambda_{rec}L_{1}^{rec} + \lambda_{vgg}L_{vgg}$$  
  $$+ \lambda_{SSIM}L_{SSIM} + \lambda_{KL}L_{KL} + \lambda_{latent}L_1^{latent},$$  

where the hyper-parameters $\lambda_{name}$ weights each loss respectively.

### IV. Experiments

#### A. Implementation details

We implement the proposed model using PyTorch and trained on two NVIDIA Tesla V100 GPUs. For training, we use the Adam optimizer with exponential decay rates $(\beta_1, \beta_2) = (0.5, 0.999)$. The batch size is set to 16 and the learning rate is set to 0.0002. The training procedure follows the Least Squares GANs (LSGANs) [47]. We adopt the following hyper-parameters in all experiments for the training: $\lambda_{GAN} = 1.0, \lambda_{rec} = 10.0, \lambda_{SSIM} = 0.25, \lambda_{vgg} = 0.2, \lambda_{latent} = 1.0, \lambda_{KL} = 0.01$. As for the size of texture representations, we find that the capacity and capability of texture representations are growing as size increases. Thus, factored by texture complexity of specific datasets, the best sizes vary for different datasets. In our experiments, the dimension of texture representations is empirically set to $d = 64$ across all datasets for comparison.

#### B. Datasets

We conduct experiments on several datasets including edges2shoes [17], edges2handbags [18], CelebA-HQ [19], and the multiple seasons dataset. All images are resized to $256 \times 256$ in the experiments.

**Edges2shoes and edges2handbags.** We combine these two datasets for training due to their high content similarity. It contains 188,392 paired training images and 400 images for testing. The images of edges are utilized for providing structural information.

**CelebA-HQ.** It includes 30000 high-quality face images [19]. We split 29800 as training set and 200 as testing set. For structural maps, we employ facial landmark detection to obtain contours in the facial region, and the Canny edge detector [37] to obtain structural edges in the background region.

**Multiple seasons dataset.** We collect 8000 images from the Yosemite dataset [48] and the alps seasons dataset [49]. The dataset contains four seasons of images, and 400 images are split for testing. We use the Canny edge detector incorporated with the Gaussian blur algorithm to acquire the corresponding structural maps.

#### C. Compression Performance Comparison

In this subsection, we conduct extensive qualitative and quantitative experiments to compare the compression performance with traditional and learning-based approaches. To compress structure and texture representation into bitstreams with high efficiency, we adopt different strategies for structure layer and texture layer compression. In particular, the reference software of screen content coding [38] is employed to compress the structural maps. Moreover, texture representations are quantized with $QP = 51$ (Eq. 2) and truncated with 16 bits range (Eq. 3). Then, the quantized results are encoded with lossless Arithmetic codec [41]. Texture representations take less than 10% of the total bits cost and most of the bits originate from edge maps coding. Thus, we adjust the QP of the codec of edge maps to obtain bitrate coding results at different bitrates for the proposed method.
1) Baselines: We compare the proposed method with traditional compression standards and learning-based compression methods on the test datasets. For the traditional compression codecs, the widely-used compression standards JPEG and JPEG2000, HEVC-based image compression codec BPG, and the latest standard Versatile Video Coding (VVC) [50] are applied for comparisons. Moreover, some prior works aim to optimize conventional codecs using perceptual metrics to improve the perceptual quality [51–53]. We also provide a comparison with a perceptually optimized method based on VVC using quantization parameter adaptation (VVC+QPA) [52]. For deep learning-based image compression approaches, we compare with Minnen et al. [6] which adopts end-to-end optimization, previous generative compression Agustsson et al. [29], and an existing conceptual compression method (LCIC) [33]. LCIC employs basic VAE-GAN architecture for encoder and decoder, where the generator applies the U-Net structure and combines edge maps and latent codes by direct concatenation as input. The specific settings are detailed as follows:

- JPEG: we use JPEG Encoder of Matlab with quality factor $QF = 1$, which obtains maximum compression ratio of JPEG.
- JPEG2000: the images are compressed by OpenJPEG
platform with quality parameter aligned with the compression ratio of proposed method, ranging from 200 to 500.

- **BPG**: we use standard bpg codec with $QP$ ranging from 40 to 51 for compression ratio alignment.

- **VVC**: We adopt the intra mode in VVC reference software VTM 11.4 and present reconstruction results at a similar bitrate to ours for comparison.

- **VVC+QPA**: Perceptually optimized method \(^\text{[52]}\) has been adopted in the reference software of VVC. Thus, we conduct testings on VTM with QPA macro turned on.

- **Agustsson et al. \(^\text{[29]}\)**: We provide the experimental results of Agustsson et al. using a reproduced implementation \(^\text{[56]}\). For fair comparisons, we have trained the models of generative compression without adding noise on the same datasets as ours with 120 epochs.

- **LCIC**: We trained the model of LCIC \(^\text{[6]}\) on the same datasets as ours for fair comparisons. The dimensionality of texture latent codes is set to 64 to compare reconstruction quality at equal bitrate.

- **Minnen et al. \(^\text{[6]}\)**: The deep compression network is trained exactly following the procedure in \(^\text{[6]}\) with hyper prior. We set $\lambda = 0.0025$ for obtaining average 0.16 bits per pixel (bpp), and $\lambda = 0.005$ for average 0.2 bpp.

2) **Qualitative Evaluations**: For the evaluation of visual reconstruction quality, we mainly focus on the global structural fidelity and aesthetic sensibility. Making comparisons at the same bitrate is difficult since most compression methods cannot generate a specified bitrate. As such, we select comparison images with sizes that are as close as possible to our encoding bpp. We present qualitative comparisons in Fig. 5. In particular, the decoded images of JPEG and JPEG 2000 show serious structure and color distortion and blocking artifacts under extreme low bit-rate scenarios resulting from the limitation of block-wise processing. The results of BPG show more distortion and degradation in visual quality than that of ours, e.g., the face skin looks unnatural and partial key edges are missing in the second row. Meanwhile, the structure and texture are over smoothed and blurred in VVC and Minnen et al. \(^\text{[6]}\), hence losing significant structural details and reducing visual reality compared to our method, e.g., the teeth and jawline in the third row of Fig. 5. The perceptually optimized VVC scheme does not improve visual quality compared to VVC but with a slightly higher bitrate, indicating that such methods cannot improve perceptual quality of traditional codec well under extreme low-bitrate setting. The reproduced results of Agustsson et al. exhibits severe distortion and degraded image quality compared to ours. Regarding the existing conceptual compression method, LCIC achieves visually pleasing reconstruction on edge2shoes and edge2handbags datasets. Nonetheless, the synthesis images appear apparent visual distortion and artifacts on complex scenarios, e.g., the checkerboards artifacts on the decoded natural scene images. Overall, the results demonstrate that our method can produce reconstructed images of high visual quality under extremely low compression bitrate and outperform the baselines in regard to visual fidelity and aesthetic sensibility.

3) **Quantitative Evaluations**: Due to the ultimate arbiter of lossy compression remaining human evaluation, we choose LPIPS \(^\text{[54]}\), DISTS \(^\text{[55]}\) and user preference as perceptual quality metrics to evaluate the fidelity quantitatively, which prove to be highly correlate with human quality judgments \(^\text{[56]}\) instead of only assessing signal fidelity. Lower score of LPIPS and DISTS indicates higher visual fidelity of reconstructed images. The average results of LPIPS and DISTS, and corresponding average bitrate over three datasets from different methods are shown in Table I. It should be noted that we provide the available lowest bitrate of BPG on the edge2shoes and edge2handbags datasets, though still higher than which of our method. It can be clearly seen that the proposed method almost excels all other comparison methods on DISTS and LPIPS under similar bitrate (except for BPG obtains better score of LPIPS and DISTS on edges2shoes and edges2handbags testing set, and Minnen et al. obtains better DISTS score on multiple seasons testing set, while both of them take more bits for coding).
A user study of pairwise comparison is conducted to evaluate fidelity and aesthetics. Given image pairs, users are asked to choose the one matching original image better (fidelity) in the first part of the survey, and the one of better visual quality (aesthetic) in the second part. 16 cases from test data of three datasets are selected to show for comparison. A total of 46 subjects participate in the user study and a total of 2944 selections are tallied. User preference results are shown in Fig. 6. The proposed conceptual compression method obtains the best preference ratio in each comparison pair for both fidelity and aesthetics. The quantitative results fully verify the superiority of our method in obtaining better visual quality and maintaining higher structure and texture fidelity.

D. Graceful Quality Degradation

To have a better understanding of the performance comparison, we evaluate graceful quality degradation by varying bitrate for both the proposed method and conventional image codecs BPG and VVC. We adjust the compression level of edge maps to obtain variable bitrate coding results for the proposed method and present the similar bitrates of BPG and VVC, shown in the rate-distortion curves of Fig. 8. Moving the quantizer from lossless to coarse, the bitrate of the proposed is mainly varied at the range of $(0, 0.3)$ bpp. As shown in Fig. 8, the proposed method achieves a better LPIPS score than both BPG and VVC under an extremely low bitrate range ($<0.07$ bpp). However, the increase of the bitrate brings constant quality improvement of conventional codecs BPG and VVC, while no significant improvement for the proposed method. It validates that the proposed method aims to achieve better reconstruction quality at extremely low bitrate ($<0.1$ bpp) than conventional codecs.

We also conduct subjective testing for evaluating image quality at various bitrate. The double stimulus image quality assessment method is adopted to collect the subjective image quality scores from 25 participants. The testing consists of four typical bitrates (0.037 bpp, 0.074 bpp, 0.112 bpp, 0.3 bpp) considering the bitrate range of the proposed method is $(0, 0.3)$ bpp as shown in Fig. 8, where each test contains nine images selected randomly from the testing set from the testing set of CelebA-HQ dataset. The test images are presented by pairs, containing one uncompressed reference image and one random decoded image over all testing images. The test is conducted on the screen with resolution of $1920 \times 1080$ or higher and a HiDPI/Retina mode is not enabled. The recommended score consists of value $\{1, 2, 3, 4, 5\}$ corresponding to the subjective
quality level of Bad, Poor, Fair, Good and Excellent. The mean opinion scores (MOS) are calculated for assessing the image quality of each method at each bitrate as following:

\[
MOS_i = \frac{1}{MN} \sum_{n=1}^{N} \sum_{m=1}^{M} s_{imn},
\]

where \( N \) is the number of valid subjects and \( M \) is the number of testing images at the bitrate \( i \). The experimental results are shown in the rate-distortion curve of Fig. 9. It can be seen that the proposed method obtains higher MOS than VVC at low bitrate testing (0.037 bpp, 0.074 bpp, 0.112 bpp), but a slightly lower score at high bitrate (0.3 bpp). The subjective results validate the proposed method can achieve better visual reconstruction quality at an extremely low bitrate than traditional coding standard, consistent with the quantitative results of Fig. 8.

![Rate-Distortion Curve (MOS)](image)

Fig. 9. The mean opinion scores (MOS) of the proposed method and VVC at multi-level bitrate. Higher score demonstrates better subjective reconstruction quality.

### E. Application in Image Manipulation

In our conceptual compression framework, images are explicitly disentangled to structure domain and texture domain, and reconstructed through integrating texture and structure with generator. The structure and texture representations act as both raw frame data and inter-operable and manipulable visual features. During the data-driven training, a continuous bidirectional mapping between deep latent representations and spatially-aware texture is well learned, allowing generator to synthesize corresponding content from any representation in texture latent space. Benefited from the disentanglement of visual components and learned synthesis paradigm, the generator is able to progressively render the texture following the instruction of any given structural maps. Thus, besides high efficiency compression, the proposed framework can be also applied in image manipulation tasks via editing structure and texture representations.

In particular, we can synthesize new texture in the way of changing the texture representations while constraining specific structural maps as image content. On the other hand, we can also modify the structural maps while maintaining the image texture to satisfy particular needs for image manipulation. The powerful capability of manipulating images flexibly in compression domain demonstrates the versatility of our conceptual compression framework in supporting both compression tasks and efficient content manipulation in the compressed domain compared to normal compression methods.

1) **Texture Synthesis:** The results of the texture synthesis results are shown in Fig. 7. Attribution to analyzing and compressing images into compact disentangled structure and texture representations, the proposed method is able to process images in two independent layer before decoding. Due to the unique association between specific representation and global texture of image instance, the implication of texture representation can be confirmed and reflected in the source images and synthesized images. Thus, with all accessible images serving as a texture source library, the proposed method can synthesize different texture by replacing the texture representation with ones encoded from images of desired texture styles, and construct creative and attractive images. The texture synthesis results in Fig. 7 show that our model has strong capacity of effectively capturing image global texture distribution, integrating representation layers without relying on encoder, and synthesizing pleasing target images, which suggest a great potential of proposed method in support of joint image compression and vision tasks.

2) **Structure Modification:** We also demonstrate example results of applying the proposed method to structure modification in Fig. 10. Under the layered framework, the shape of images can be modified through editing the structural maps in optional ways, e.g., user interactive edition, image morphing algorithms. The texture layer can be flexibly rendered fitting...
the layout and shape of updated structural maps and the results show that original texture can perfectly fit new shapes in synthesized images. Structure modification is very useful in visual communication and image-based retrieval applications. Moreover, operating machine vision tasks in the compressed domain is shown to be more efficient than operating it after decoding under low bit-rate scenarios [16]. Our experimental results also prove the potential advantage of the proposed method in performing high efficiency coding and machine vision tasks jointly.

F. Advantage in Image Analysis

To further verify the advantage of our framework in image analysis task, we also perform the facial landmark detection task on the decoded images. Facial landmark detection [57] is carried out on the original images in CelebA-HQ testset and the detection results are served as ground truth. For comparison, we perform landmark detection on the decoded images from JPEG and the proposed method respectively. Then the normalized root mean squared error (NRMSE) between the detection results on compressed images and original images is calculated as quantitative metric. Fig. 11 illustrates the cumulative error distribution of our method and JPEG with quality factor $2, 3, 4$, where about 97% of the test images reconstructed by proposed method have minor errors less than 0.4. It should be noted that the average bit-rate of our method and JPEG under $QF = 1$ are 0.099 bpp and 0.237 bpp respectively. Our method can achieve 58.1% bits saving and 56.5% accuracy improving of landmark detection task compared to JPEG under $QF = 1$. Above all, the face landmark detection results demonstrate robustness and accuracy of the proposed image compression method in image analysis tasks.

In essence, in the proposed implementation scheme, the structural maps already contain key facial edges which act like dense landmarks, allowing straightforward content analysis without decoding. Moreover, the concrete form of the structure representation can be further adjusted towards specific vision applications, leading to a unified framework for connecting machine vision and human perception through inter-operable conceptual representations.

V. DISCUSSION

A. Analysis of Incremental Reconstruction

The design of incremental reconstruction is motivated by previous works [19], [58] with the common observation that high-resolution images is easier to learn in the coarse-to-fine manner in GANs. Fig. 12 illustrates the visualization of the output feature at each resolution stage in the proposed HF-GAN. The step-by-step synthesis process focuses on rough architecture and boundaries first, and replenish finer details incrementally when the resolution raises up, validating that the incremental reconstruction strategy facilitates better quality of high-resolution image generation.

Fig. 11. Cumulative error distribution of facial landmark detection with JPEG under quality factor 2, 3, 4 and proposed method. It can be seen from the figure that the decoded test images from the proposed method (97%), JPEG with quality factor 4 (88%), JPEG with quality factor 3 (65%), JPEG with quality factor 2 (49%) achieve errors of less than 0.4 respectively.

Fig. 12. Visualization of the generative mechanism of HF-GAN. We add the RGB feature (from toRGB) of the current Resblock to the upsampled RGB feature of the last Resblock as the incremental learning output for the current stage. The output of each stage from $4 \times 4$ to $256 \times 256$ in the hierarchical fusion generator network is visualized for illustrating the step-by-step synthesis process from rough structure to finer details.

B. Visual Quality and Signal Fidelity

The difference and relationship between visual quality and signal fidelity have been studied theoretically in various research works [59], [60]. Signal fidelity is defined to evaluate how similar is the restored signal to the original signal [60]. The representative assessment metrics include well-known mean-squared error (MSE) and its counterpart peak signal-to-noise ratio (PSNR), structural similarity (SSIM), and so on. The quality of the image, which could be defined from a natural scene statistics perspective, is rooted in the widely accepted view that the vision system has adapted and evolved to the extent that a reconstructed image looks like a valid natural image [59], and the perceptual quality refers to the extent that a reconstructed image looks like a valid natural image [59], [60] rather than the signal similarity to the input. The traditional codecs such as BPG mainly focus on signal fidelity. By contrast, GANs employ the discriminator to implicitly characterize the natural scene statistics, such that the reconstructed images of the proposed conceptual compression scheme are closer to the natural image distribution. This could inevitably damage the signal fidelity, which has been evidenced by a series of image restoration works [61], [62].
The nature of the proposed method also limits the application scopes. However, with the accelerated proliferation of digital devices, the vision-centered services that require high quality rendering have been growing exponentially. Moreover, in our future work, an engineering solution can be provided by adaptively adding a residual enhancement layer to satisfy the fidelity demand in practical application.

C. Generalization

Different from the traditional engineering codecs based on linear transform and recently end-to-end learned codecs based on nonlinear transform [63], the proposed framework lies in the deep generative models and learns a texture representation in a data-driven manner to capture the texture distribution of the training data domain. Thus, the texture representation can be generalized on images with similar distribution to the training domain. Fig. [13] shows the experimental results on testing images from the FFHQ dataset and ADE20K dataset with models trained on CelebA-HQ and collected multiple seasons training set respectively, demonstrating that the model can generalize to the dataset with similar semantic object. However, when applying to the dataset with a large semantic gap as shown in Fig. [14], the model could not generate the texture as expected, and artifacts originating from the trained datasets (e.g., eyes alike facial semantic artifacts), are perceived when generating handbag images.

While this approach has this merit, it is of considerable interest to improve the generalization capability of the proposed approach. There remains much work to be done in this direction. On one hand, we can improve the generalization capability based on domain generalization algorithms, such that data from different target domains can be efficiently compressed. Alternatively, we could also ensemble models from different domains as a more generalized codec. The images to be compressed are firstly classified into the specific domain, and the corresponding model is subsequently chosen for compression. The bitstream is composed of the representation of the images as well as the codec index, such that the images could be effectively decoded. It is worth mentioning that such an ensemble manner could well support myriad applications such as online shopping and video surveillance. It is our great desire to see that these emerging techniques could be used, especially in applications where the image content is loosely or strictly constrained.

VI. CONCLUSIONS AND FUTURE WORKS

This paper proposes a novel conceptual compression framework for efficient, interpretable and versatile visual data representation, leading to high efficiency compression, better visual reconstruction quality, increased flexibility in content manipulation and potential support for various vision tasks. In particular, the proposed framework decomposes the image contents into structural and textural layers, and performs compression in two layers respectively. To reconstruct the original image from the compressed layered features, a hierarchical fusion GAN is proposed to integrate texture layer and structure layer in a disentangled fashion. Qualitative and quantitative results show that the proposed method can reconstruct high visual quality images with better structural fidelity and aesthetic sensibility. The advantages of our conceptual compression framework are also verified in compression, content manipulation and analysis tasks through extensive experiments.

Despite the current achievements, the conceptual compression will further benefit from the enhanced rate-distortion optimization schemes and better layered decomposition of image contents. Furthermore, extending the proposed conceptual image compression framework to video domain is another promising direction, where effective spatio-temporal representation learning plays a crucial part in a wide range of video analysis tasks, such as action recognition, tracking, summarization, and editing.

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