Memorize, Then Recall: A Generative Framework for Low Bit-rate Surveillance Video Compression

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Abstract—Surveillance video applications grow dramatically in public safety and daily life, which often detect and recognize moving objects inside video signals. Existing surveillance video compression schemes are still based on traditional hybrid coding frameworks handling temporal redundancy by block-wise motion compensation mechanism, lacking the extraction and utilization of inherent structure information. In this paper, we alleviate this issue by decomposing surveillance video signals into the structure of a global spatio-temporal feature (memory) and skeleton for each frame (clue). The memory is abstracted by a recurrent neural network across Group of Pictures (GoP) inside one video sequence, representing appearance for elements that appeared inside GoP. While the skeleton is obtained by the specific pose estimator, it served as a clue for recalling memory. In addition, we introduce an attention mechanism to learn the relationships between appearance and skeletons. And we reconstruct each frame with an adversarial training process. Experimental results demonstrate that our approach can effectively generate realistic frames from appearance and skeleton accordingly. Compared with the latest video compression standard H.265, it shows much higher compression performance on surveillance video.

Index Terms—video compression, skeleton, attention, generative adversarial network

I. INTRODUCTION

Surveillance systems are widely applied for public safety, daily life, remote management, etc. Video sequences recorded by surveillance systems typically contain moving objects, especially human beings, and usually be used for detecting and recognizing. Considering the massive data generated by surveillance systems should be transmitted or stored, as well as being dealt with intelligent algorithms, urgent demands are imposed on an efficient and intelligent compression scheme.

In general, the goal of the compression algorithm is to achieve a compact representation (bit-stream), from which the original content can be reconstructed in a lossy or lossless manner. Such an autoencoder-like process can be formulated as a Rate-Distortion Optimization (RDO) problem, where bitrate and distortion (the original content v.s. the decompressed content) are considered in the optimization. Traditional hybrid video coding frameworks [1], [2] (such as MPEG-2 [3], H.264 [4] and H.265 [5]) typically tackle the compression problem with four basic steps: prediction, transform, quantization and entropy coding. In this kind of coding framework, the redundancy between neighboring frames is mainly correlated by block-wise motion compensation. Motion vectors are estimated by searching the best matching block from previous/subsequent frames, which is typically optimized for pixel-level fidelity (e.g., Mean Squared Error).

In the past two years, learning-based image compression has attracted wide attention [6]–[13], while a few research works pay attention to end-to-end learned video compression. Wu et al. [14] formulated the video compression as an interpolation problem, and reduced the redundancy in adjacent frames with pre-defined keyframes. Chen et al. [15] proposed a block-based compression scheme by modeling the spatio-temporal coherence. Lu et al. [16] mimicked traditional coding frameworks with learning-based components.

However, both traditional coding standards and learning-based schemes are typically optimized for pixel-level fidelity. The inherent structure information inside video signals is not well exploited during the compression process. In this paper, we want to formulate the video compression from the perspective of the semantic-level video decomposition. Our contributions can be summarized as follows.

- We firstly formulate video compression as memorizing and recalling processes. Then we propose a new end-to-end video compression framework, named Memorize-Then-Recall (MTR).
- We leverage the success of generative adversarial networks, presenting a generative decomposition scheme. To the best of our knowledge, this is the first generative end-to-end video compression framework.
- We verify our MTR framework on video sequences with someone moving around or performing various actions, and achieve superior performance compared with the latest coding standards.

II. MEMORIZE-THEN-RECALL FRAMEWORK

Different from traditional hybrid coding frameworks that heuristically optimize each component, we trained our framework with end-to-end manner. The overall pipeline of the proposed MTR is illustrated in Fig. 1.

For one video sequence, given a Group of Pictures (GoP) $X = \{x_1, x_2, \ldots, x_N\}$, where $x_t$ denotes the $t$-th frame and $N$ represents the total number of frames in the GoP, our goal is to decompose the video content into a global spatio-temporal
For each frame, we sequentially feed it into ConvLSTM, and reconstruction \( \hat{x}_t \) with two different discriminators to achieve a realistic frame feed the feature into a generator and train it in conjunction the appearance with regard to the current frame. We then clues obtained by the specific pose estimator [17], which served as by quantization and entropy coding. For skeletons, they are that appeared inside GoP, which will be further compressed

Specifically, we split a GoP into frames \( \{x_1, x_2, \ldots, x_N\} \) between pixels in a video sequence. Therefore, we leverage ConvLSTM [18] to model spatio-temporal coherence inside GoP. It represents appearance for elements that appeared inside GoP, which will be further compressed by quantization and entropy coding. For skeletons, they are obtained by the specific pose estimator [17], which served as clues. It will be compressed through predictive coding and entropy coding.

In the decoder, the reconstructed spatio-temporal feature \( \hat{M} \) and reconstructed skeletons \( \hat{S} \) can be obtained by corresponding inverse operations in the decompression phase. After that, we introduce a Recalling Attention mechanism to implement the recalling process, from which we can attain a feature that combines the information from the \( \hat{M} \) and \( \hat{s}_t \), describing the appearance with regard to the current frame. We then feed the feature into a generator and train it in conjunction with two different discriminators to achieve a realistic frame reconstruction \( \hat{x}_t \).

We give a detailed description of each component in the following subsections.

A. Memorize over Sequence

Typically, there exist high spatio-temporal correlations between pixels in a video sequence. Therefore, we leverage ConvLSTM [18] to model spatio-temporal coherence inside GoP. Specifically, we split a GoP into frames \( \{x_1, x_2, \ldots, x_N\} \). For each frame, we sequentially feed it into ConvLSTM, and finally generate a spatio-temporal feature for the whole GoP, which is leveraged as memory in our framework.

B. Memory Compression & Decompression

We utilize the spatio-temporal feature \( M \) as memory to represent appearance for elements that appeared inside GoP. To compress the spatio-temporal feature \( M \), we firstly apply a quantization operation. Then, the quantized spatio-temporal feature \( \hat{M} \) is fed into an entropy coder to reduce the redundancy further. The details are stated as follows:

a) Quantization: We utilize round operation as our quantization in the end-to-end MTR framework. However, the round operation is non-differentiable, which places an obstacle for end-to-end training. Inspired by [19], we substitute round with an additive uniform noise during training. Formally, let \( U(a, b) \) denote the uniform distribution on the interval \((a, b)\), the quantized spatio-temporal feature \( \hat{M} \) in the training process can be approximated by:

\[
\hat{M} = M + U(-\frac{1}{2}, \frac{1}{2}).
\]  

b) Entropy Coding with Hyperprior Modeling: Context-based entropy coding is a general lossless compression method and commonly used after quantization in traditional coding frameworks. Following Ballé et al. [20], we utilize the hyperprior network to predict the probability distribution \( p_M \) of \( M \), which is illustrated in Fig. 2. The hyperprior network takes the quantized spatio-temporal feature \( \hat{M} \) as input to obtain hyperprior \( z \), which will be utilized to predict a probability distribution \( p_M \). Based on \( p_M \), we can utilize entropy coding to compress \( M \). Since the \( p_M \) is needed in the entropy decoding process, hyperprior \( z \) is encoded by quantization and entropy coding and transmitted along with the quantized memory.

Therefore, the bit-stream from the memory compression includes two parts, \( \hat{M} \) and \( z \). We can estimate the bits by the following function:

\[
R_M = \underbrace{\mathbb{E}_{\hat{M} \sim p_M}[-\log_2 p_M(\hat{M})]}_{\text{rate}(\hat{M})} + \underbrace{\mathbb{E}_{z \sim p_M}[-\log_2 p_z(z)]}_{\text{rate}(z)},
\]  

Fig. 2. Our memory compression & decompression. Convolution parameters are denoted as: number of filters \( \times \) kernel height \( \times \) kernel width / stride.
The significance of the above formula is to introduce the rate constraint in the end-to-end model, which will be utilized as a part of the loss function in section III-B. In the memory decomposition phase, the reconstructed spatio-temporal feature $\hat{M}$ can be obtained by the corresponding inverse operations.

C. Clue Compression & Decompression

In this part, we design a lossless compression method to compress the skeleton. The skeleton $s_i$ is represented by 18 body nodes and extracted by a pose estimator [17]. For each body node, the coordinates are used to represent the position.

Since there exists continuity between video frames, we first de-correlate them by predicting the coordinate $s_{ti}$ of the $i$-th node at the current frame with the node in the previous frame $s_{t-1,i}$. Thereby we can calculate the residual by:

$$res_{ti} = s_{ti} - s_{t-1,i}.$$  (3)

After that, we use the arithmetic entropy coding to compress the residual information $res_{ti}$, which can obtain the bit-stream of the clues. In the decompression phase, the reconstructed skeletons $\hat{S}$ can be computed by the corresponding inverse operations.

D. Recall from Skeleton

a) Recalling Attention: Inspired by the success of the attention mechanism [21], [22], we here present Recalling Attention, which mimics the typical recalling process existed in human behaviors.

Our Recalling Attention allows clues to attend over memory and generate a joint representation that combines the information from both sides. Formally, we define a query matrix $Q$, a key matrix $K$ and a value matrix $V$. The Recalling Attention $R(Q, K, V)$ can be formulated as:

$$R(Q, K, V) = [WV^T + Q, V],$$  (4)

where "+" represents a residual connection, $[,]$ indicates concatenation, and $W$ is a weight matrix can be calculated as:

$$W = QR^T.$$  (5)

Adapting to our system, as Fig. 3 illustrated, the reconstructed spatio-temporal feature $\hat{M}$ is regarded as key and value, and the reconstructed skeleton $\hat{s}_i$ is regarded as the query. Intuitively, our Recalling Attention is computed as a weighted sum over memory, where the weight assigned to each part of memory is computed by the clue with the corresponding part of memory.

b) Adversarial Generation: We treat the process of frame reconstruction as a kind of conditional generation [23], where the generation is conditioned on the output of Recalling Attention. We base our network of the generator on the objective presented in pix2pixHD [24]. The goal of the generator is to yield reconstructed frames that cannot be distinguished by two discriminators:

- **Spatial Discriminator** ($D_s$) takes the skeleton ($s_i$) and the generated or real frame ($x_t$) as input to judge whether the input data is real or fake. The insight of Spatial Discriminator is to facilitate the generator to yield realistic images conditioned on certain input skeleton.

- **Temporal Discriminator** ($D_t$) takes the skeleton and frames that come from the current frame ($s_t, x_t$) and the previous frame ($s_{t-1}, x_{t-1}$) as input to judge whether frames are from real video. The goal of the Temporal Discriminator is to ensure the continuity between adjacent frames.

The target of the generator is to make the two discriminators unable to distinguish the frame generated by the generator. Therefore, we can utilize the adversarial function to evaluate the performance of the generator:

$$\ell_{adv} = \mathbb{E}_{(s_t, x_t)} [\log D_t(s_t, x_t)] + \mathbb{E}_{x_t} [\log(1 − D_t(s_t, G(s_t)))] + \mathbb{E}_{s_t} [\log D_s(s_{t-1}, s_t, x_{t-1}, x_t)] + \mathbb{E}_{x_{t-1}} [\log(1 − D_s(s_{t-1}, s_t, G(s_{t-1}), G(s_t)))]$$  (6)

E. Loss Function for End-to-end Training

From the perspective of compression, the objective of our MTR model is to maximize the quality of the reconstruction while compressing the bit as lower as possible. Therefore, the full loss function of our model can be formulated as follows:

$$\ell = \lambda_{rate} \ell_{rate} + \ell_{adv} + \lambda_{VGG} \ell_{VGG} + \lambda_{fm} \ell_{fm}.$$  (7)

where the rate part has already defined in (2). In the distortion part, we utilize perceptual loss, which is more similar to the human visual system compared with the pixel-level fidelity. The perceptual loss contains $\ell_{adv}$ and $\ell_{VGG}$. $\ell_{adv}$ is defined in (6). $\ell_{VGG}$ is a common VGG perceptual loss [25]. In addition, following Ledig et al. [26], we introduce the feature matching loss $\ell_{fm}$ to improve the training process of our generative model. In our experiments, we heuristically set $\lambda_{rate} = 1$, $\lambda_{fm} = 10$ and $\lambda_{VGG} = 10$ to train our MTR network.

III. Experiments

a) Datasets: We train the proposed video compression framework using KTH dataset [27] and APE dataset [28]. We randomly divide the KTH dataset into training (130 sequences), validation (12 sequences) and test set (8 sequences) and evaluate the performance on the test set. Similarly, APE dataset is also randomly divided into training (230 sequences), validation (8 sequences) and test set (7 sequences).
b) Implementation Details: We utilize the weight of the well-trained model \([17]\) as the initial weight of the pose estimator. The output of the pose estimator is directly fed into the recalling attention module during the training phase. We utilize random crops and random horizontal/vertical flips to realize the data augmentation. The mini-batch size is 4. We use Adam optimizer \([29]\) to update network parameters, in which \(\beta_1\) is set as 0.5 and \(\beta_2\) is 0.999. The initial learning rate is 0.0002. Two discriminators are initialized with the pre-trained VGG19. The whole system is implemented based on PyTorch, and it takes about one day to train the model using one NVIDIA GTX 1080Ti GPU.

A. Comparison with Traditional Codecs

In this subsection, we compare the compression quality of our method with the traditional video codecs, including H.264\(^1\) and H.265\(^2\). For fairness, all codecs use the same GoP size as 10.

Fig. 4 visualizes the experimental results on the test set of KTH dataset (top two rows) and APE dataset (bottom two rows), in which the fourth column is generated by our scheme. Note that H.264 and H.265 cannot compress the sequence to a bit-rate lower than about 3 Kbps.

Subjectively, MTR successfully generates video frames with rich details such as grassland and the colorful background. It gets rid of blocking artifacts, and preserve the reality while adapting to the specific pose. We also provide a quantitative evaluation of our framework in Table I, from which we can see that for APE dataset, our scheme significantly outperforms the strong baselines up to 3.61dB with only 56.70% bit-rate. Moreover, our model can be generalized to KTH dataset, which has more complex scenarios (e.g., camera movement), also showing comparable results with the latest video codecs.

B. Ablation Experiments

a) Ablation on memorizing and recalling mechanisms: We verify the effectiveness of memorizing and recalling mechanisms by building the framework without memorizing or without recalling respectively. Specifically, the model without memorizing is implemented as directly adopting the first frame as memory, instead of memorizing over the whole sequence. While the model without recalling is implemented as directly concatenating the reconstructed spatio-temporal feature \(\hat{M}\) and skeletons \(\hat{S}\), rather than performing Recalling Attention. The experimental results are demonstrated in Table II, from which we can see that the model combined with both techniques (MTR) significantly outperforms two individual baselines.

b) Variants of attention mechanism: We conduct different Recalling Attention mechanisms in this part. Specifically, there are two possible attention directions for our Recalling Attention. The first one is “Clues Attend on Memory” (ConM, a.k.a MTR), which is employed in our scheme. As a counterpart, the second one is “Memory Attend on Clues” (MonC). Different with ConM, MonC utilize \(\hat{s}_t\) as the key and value, and \(\hat{M}\) is regarded as query. We illustrate the experimental

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\(^1\)https://www.itu.int/rec/T-REC-H.264  
\(^2\)https://www.itu.int/rec/T-REC-H.265

![Fig. 4. Comparison between our proposed method and traditional codecs on the test set of KTH and APE dataset respectively.](image-url)

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**TABLE I**

| Method | Rate (Kbps) | MS-SSIM | PSNR (dB) |
|--------|-------------|---------|-----------|
| KTH    |             |         |           |
| JM (H.264) | 3.96 | 0.84   | 25.78     |
| HM (H.265) | 3.54 | 0.86   | 26.92     |
| MTR (Ours) | 2.10 | 0.82   | 25.68     |
| APE    |             |         |           |
| JM (H.264) | 3.27 | 0.84   | 23.43     |
| HM (H.265) | 3.21 | 0.87   | 24.04     |
| MTR (Ours) | 1.82 | 0.97   | 27.65     |

**TABLE II**

| Rate (Kbps) | MS-SSIM | PSNR (dB) |
|-------------|---------|-----------|
| w/o recalling | 2.13 | 0.78   | 23.47     |
| w/o memorizing | 3.41 | 0.78   | 23.48     |
| MonC       | 2.16 | 0.82   | 25.53     |
| MTR (Ours) | 2.10 | 0.82   | 25.69     |
results in Table II. The result shows that MTR achieves better performance than MonC.

IV. CONCLUSION

In this paper, we propose a Memorize-Then-Recall framework for low bit-rate surveillance video compression by leveraging the inherent structure between frames. With the assistance of the adversarial training technique, the proposed framework significantly surpasses the latest coding standards. In the future, we plan to extend our framework to more complex surveillance scenarios such as traffic intersections.

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