A NEW WAY OF VIDEO COMPRESSION VIA FORWARD-REFERENCING USING DEEP LEARNING

S.M.A.K. Rajin*, M. Murshed*, M. Paul**, S.W. Teng*, J. Ma*

ABSTRACT

To exploit high temporal correlations in video frames of the same scene, the current frame is predicted from the already-encoded reference frames using block-based motion estimation and compensation techniques. While this approach can efficiently exploit the translation motion of the moving objects, it is susceptible to other types of affine motion and object occlusion/deocclusion. Recently, deep learning has been used to model the high-level structure of human pose in specific actions from short videos and then generate virtual frames in future time by predicting the pose using a generative adversarial network (GAN). Therefore, modelling the high-level structure of human pose is able to exploit semantic correlation by predicting human actions and determining its trajectory. Video surveillance applications will benefit as stored “big” surveillance data can be compressed by estimating human pose trajectories and generating future frames through semantic correlation. This paper explores a new way of video coding by modelling human pose from the already-encoded frames and using the generated frame at the current time as an additional forward-referencing frame. It is expected that the proposed approach can overcome the limitations of the traditional backward-referencing frames by predicting the blocks containing the moving objects with lower residuals. Experimental results show that the proposed approach can achieve on average up to 2.83 dB PSNR gain and 25.93% bitrate savings for high motion video sequences.

Index Terms— Video compression, predictive coding, forward referencing, pose estimation, generative adversarial network

1. INTRODUCTION

Video compression is the process of encoding frames so that less space (bitrate) is used while still maintaining acceptable distortion (image quality). Video compression and transmission are considered fundamental functionalities of the multimedia driven Internet with applications in many fields such as video surveillance, social media, video streaming, and broadcasting. Traditional video compression has always used already-encoded data, that are also available to the decoder, to reconstruct the current frame [1]. To achieve this, each frame has to go through three main functional units: prediction model, spatial model, and entropy encoder [1]. The prediction model attempts to reduce redundancy in the current frame by exploiting the spatiotemporal correlations from the previously encoded frames (inter-prediction) or previously encoded neighboring pixels within the same frame (intra-prediction). We term this as backward-referencing (BR) where the current frame is predicted from ‘real’ frames that have already been encoded i.e., looking backward w.r.t. the coding order of frames. The prediction model uses rate-distortion optimisation techniques to create a projection of the current frame with minimal bitrate for a fixed target image quality (variable bitrate (VBR) coder) or maximal image quality for a fixed target bitrate (constant bitrate (CBR) coder).

While backward-referencing can efficiently exploit translation motion of the moving objects, it is vulnerable to other types of affine motion e.g., rotation, scaling, and shearing. It is also useless when parts of the moving objects are occluded (hidden in the reference frame) or deoccluded (reappear in the current frame). To address these limitations, researchers have considered multiple reference frames with some success e.g., the H.264/AVC video coding standard allows up to 16 reference frames to improve compression efficiency [2]. Existing video coders are designed to compress data in a backward-referencing manner by making assumptions about next frames based on previously encoded ones. In this paper, we introduce a new way of video coding with forward-referencing where next frames are reconstructed not only from previously encoded frames but also from ‘virtual’ frames that are artificially generated at current/future time by modelling the movement of moving objects using deep learning.

The recent success of deep learning in image recognition tasks has prompted research into their use within the field of video compression. Many companies have developed dedicated Neural Processing Units (NPUs) for mobile devices, which can process many trained Deep Neural Networks (DNNs) based applications in real-time. Even though training a DNN may suffer from a long delay, testing the network can be done in real-time [3, 4]. Various methods have been proposed in the literature that focused on leveraging neural network based coding models for image and video compression. Most of the changes or improvements to traditional video compression using a deep neural network are done either by
improving certain modules of the existing codec [5, 6, 7] or by introducing pre- and post-processing [8] to the original and compressed frame sequence, respectively. A very few studies have tried to introduce pure learning-based video compression [9]. Very recently, deep learning has been used to model the high-level structure of human pose in specific actions from short videos and then generate virtual frames in future time by predicting the pose using a generative adversarial network (GAN) [10].

Levering this recent advancement in virtual frame generation, we introduce a novel forward-referencing inter-prediction model, which complements the BR models used in the state-of-the-art video coding standards. The main contributions of our work in this paper are as follows:

- We propose a forward-referencing coding path using high-level structure (human pose) and deep visual-structure analogy as an additional prediction mode to the existing video coding standard. The proposed method uses an artificially generated future frame as an additional reference frame for inter-coding.

- Our novel architectural design compares and takes the best predictive model between the traditional standard and the proposed method for encoding the predictive (P) frames. If the proposed method produces better predictions, then it will be used for encoding; otherwise the traditional standards will be employed.

- For a long Group-of-Picture (GOP), which is highly desirable to exploit temporal redundancy maximally, the two anchor (I) frames differ greatly when objects are moving fast. For video sequences with fast-moving objects, we show that the proposed model outperforms the state-of-the-art video coding approach on several human action datasets.

2. PROPOSED FORWARD-REFERENCING MODEL

2.1. Forward referencing frame generation

The proposed forward-referencing frame generation model was developed based on [10] hierarchical approach of generating future frames. The model consists of two Neural Networks; the Hourglass Network [11] and the Variational Auto Encoder Generative Adversarial Network (VAE-GAN) [12]. The Hourglass Network estimates the high-level structure of human pose in terms of 2D pose (x,y) coordinate position of 13 joints from RGB image as shown in Fig. 1. These poses and their corresponding images are then used to make the visual-structure analogy which follows as \( p_{t} \) as \( x_{I-frame} \) is to \( x_{t} \), denoted as \( p_{I-frame} \): \( p_{t} \) :: \( x_{I-frame} \): \( x_{t} \). Therefore, given that we have any of the three elements, reconstruction of the 4th element is possible.

The main success of our framework comes from the new idea of first making high-level structure estimation which allows us to send significant object information of the current frame to the decoder with minimal bits. The estimated pose structures of the current frame \( p_{t} \), the I-frame \( x_{I-frame} \), and its corresponding estimated pose structure \( p_{I-frame} \) use visual structural analogy to synthesize the forward referencing frame. The visual-structure analogy can be performed by eq. 1

\[
\bar{x}_{t} = f_{dec}(f_{pose}(g(p_{t}))) - (f_{pose}(g(p_{I-frame}))) + f_{img}(x_{I-frame})
\]

where \( \bar{x}_{t} \) is the generated prediction image and \( p_{t} \) is its corresponding pose, and, \( x_{I-frame} \) and \( p_{I-frame} \) are the reference image and its corresponding pose, respectively. The function \( g(.) \) maps the output from the Hourglass Network into a depth-concatenated heatmap. Fig. 2 shows the network diagram of forward-referencing model.

2.2. Overview of the architecture

Our model acts as an add-on to traditional inter-predictive coding architecture. The forward-referencing model was integrated into the traditional video coder to improve its coding efficiency. Our approach utilizes the two major components
in addition to the traditional video encoder-decoder as shown in Fig. 3.

\[ \text{Fig. 3. The proposed framework shows two additional components (in orange) to the traditional inter-predective coding architecture.} \]

Let \( V = \{x_1, x_2, x_3, ..., x_t, ...\} \) denote the current video sequence, where \( x_t \) is the frame at time step \( t \). The predicted frame is denoted as \( \hat{x}_t \) and the decoded/reconstructed frame is denoted as \( \tilde{x}_t \). The residual frame, \( r_t \) is the error (difference) between the original frame \( x_t \) and the predicted frame \( \hat{x}_t \). \( \tilde{x}_t \) represents the decoded/reconstructed residual frame. Since the first frame in a Group Of Picture (GOP) is the I-frame, we can represent \( x_1 = x_{I-frame} \). Traditional approach of block-based motion compensated predicted frame is denoted as \( \tilde{x}_t^p \) and \( r_t \) represents the motion vector. The forward referencing frame is denoted as \( x_t^b \) and \( p_t \) is the estimated high-level structure (in our case 26 x y coordinates of the human pose) outputted by the Hourglass model for input images. To generate the future referencing frame, \( x_t^b \), inputs to the VAE-GAN are \( x_{I-frame} \) and its’ corresponding pose, \( p_{I-frame} \) and current frames’ corresponding pose, \( p_t \). The predicted frame, \( \tilde{x}_t \), is constructed using the rate-distortion optimization technique and the best macroblock is chosen between \( \tilde{x}_t^a \) and \( \tilde{x}_t^b \). \( \hat{y}_t \) is the transformed and quantized version of \( r_t \).

3. EXPERIMENTAL RESULTS

3.1. Dataset for training and testing

We used the Penn Action dataset [13] to train, test and validate our model. The Penn Action dataset consists of 2326 video sequences of 15 different actions with 13 human pose joints annotation for each sequence. However, in total 1101 video sequences (611 for training and 490 for testing) of 8 different actions were used due to very noisy ground truth. These are baseball pitch (BP), baseball swing (BS), clean and jerk (CJ), golf swing (GF), jumping jacks (JJ), jump rope (JR), tennis forehand (TF), and tennis serve (TS). Frames are cropped based on temporal tubes to remove as much background as possible while making sure the foreground object i.e. the human of interest is in all frames. To train our VAE-GAN, we used the compound loss from [14], which can be defined by

\[
L = L_{img} + L_{feat} + L_{Gen}
\]

where \( L_{img} \) is the loss in image space, \( L_{feat} \) is the loss in feature space and \( L_{Gen} \) is the adversarial loss that allows our model to generate realistic-looking images. Each of these loss functions can be define as follows:

\[
L_{img} = ||x_t - \hat{x}_{I-frame}||^2
\]

\[
L_{feat} = ||C_1(x_t) - C_1(\hat{x}_{I-frame})||^2 + ||C_2(x_t) - C_2(\hat{x}_{I-frame})||^2
\]

\[
L_{Gen} = -\log D([p_t, \hat{x}_{I-frame}])
\]

where, \( x_t \) and \( \hat{x}_t \) are the target and predicted frames, respectively. \( C_1(.) \) and \( C_2(.) \) are functions that extracts features representing mostly image appearance and image structure, respectively. \( p_t \) is the pose corresponding to \( x_t \) and \( D(.) \) is the discriminator network [10]. During the optimization of \( D(.) \), we use the mismatch term defined in [15], which allows \( D(.) \) to become sensitive to mismatch between the condition and the generation. The discriminator loss can be defined as

\[
L_{Gen} = -\log D([p_t, x_{I-frame}]) -0.5 \log(1 - D([p_t, \hat{x}_{I-frame}])) -0.5 \log(1 - D([p_t, x_t]))
\]

To illustrate our result, we chose five video sequences from the dataset corresponding to 3 different translation motion of moving object, which are fast moving (JJ & TF), moderately moving (BP & BS) and slow moving (GS) objects. We used H.264 video coding standard initially to compare the relative performance against our forward referencing model. Due to the nature of the coding. We denote the H.264 standard as the BR model.

3.2. Comparison with traditional BR video coding

The first frame (I-frame) in a GOP is always intra-coded using the conventional approach and is the reference frame for the corresponding P-frame. To measure the effectiveness of our model, we encoded a sequence of P-frames, starting from frame \( t=2 \) up to \( t=32 \). Fig. 4 shows the visual illustration of the mode selection process of the BR model compared to the mode selection when including our forward referencing
model. The results shows the P-frames at t where the difference between the reference frame and its current frame is most significant. When the correlation between the two frames differ greatly, BR coding standards show some vulnerability, especially in the case of object occlusion/deocclusion. An example can be seen in Fig. 4 (d), where the back of the golfer was not fully exposed in the reference I-frame. We calculate the sum of absolute difference (SAD) for each mac-
roblock and sub macroblock of both reference frames, and the lowest SAD is used to reconstruct the current P frame. A subjective quality analysis on JJ can be seen in Fig. 5. Our proposed method (Q=31) only consumes 0.5935 bpp while achieving the best perceptual quality which can be clearly observed between the legs where the texture is coarse for the BR model (Q=34). We have kept the bitrate of BR method higher in order to take no undue advantages.

![Fig. 5](image)

**Fig. 5.** Visual quality of the reconstructed frames from different models. (a) is the original P-frame showing the region of interest (ROI) in green box. (b)-(d) are the original frame, reconstructed frame using our method and BR method.

Fig. 6 shows the RD performance graph of three video sequence (JJ, BP, & GF) using BR coding standards and our proposed method at QP = 24, 28, 34, and 38. Fig. 6 reports the highest object motion difference between the I-frame and the predicted P-frame which occurs at times t=9, t=21, and t=30, respectively. Here the P-frame is encoded referencing both I-frame (traditional approach) and VAE-GAN generated frame. We calculate the average PSNR gains and bitrate saving using Bjontegaard metrics.

Fig. 7 shows the PSNR gain from our proposed model with respect to traditional video coding standards for 32 frames. It shows that the PSNR gain is dependent on the object movement and is at most when the pose of the object differs the most from the initial pose at t=1. It can be noted that among the three datasets, JJ-1124 has the highest PSNR gain of 2.83dB and bitrate saving of 25.93% since the object in this video sequence has rapid movement. Subsequently, GS-0942 has the lowest PSNR gain of 0.41 and bitrate saving of 5.26% due to less motion of the object. Table 1 reflects the average PSNR gain and bitrate saving of the 32 frames for the three datasets compared to a traditional video coding standard.

| Dataset   | Avg PSNR gain | Avg bitrate savings |
|-----------|---------------|---------------------|
| JJ-1124   | 1.3887        | 14.36%              |
| BP-0106   | 0.8498        | 9.00%               |
| GS-0942   | 0.1656        | 2.19%               |
| TS-2288   | 0.1646        | 2.13%               |

4. CONCLUSIONS AND DISCUSSION

In this paper, we present a new forward-referencing framework as an additional component to the SOTA video coding standards. Leveraging the advancement of deep generative models, we propose a new solution for video coding. In our experiment, we implement our framework on H.264 and compare the performance. One of the key features of our architecture is that the performance evaluation of encoding video sequences will not be less than the SOTA, rather in certain cases it will only improve the codec. As a future direction, we would like to explore more advanced deep neural network models and improve them to produce better quality forward-referencing frames. We will also implement our concept on HEVC and VCC codec in the future with higher resolution video sequences.

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Fig. 6. Rate-distortion (RD) performance comparison of the proposed technique with the traditional approach.

Fig. 7. PSNR gain of each frame in GOP = 32

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