AIVC: ARTIFICIAL INTELLIGENCE BASED VIDEO CODEC

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ABSTRACT
This paper introduces AIVC, an end-to-end neural video codec. It is based on two conditional autoencoders MNet and CNet, for motion compensation and coding. AIVC learns to compress videos using any coding configurations through a single end-to-end rate-distortion optimization. Furthermore, it offers performance competitive with the recent video coder HEVC under several established test conditions. A comprehensive ablation study is performed to evaluate the benefits of the different modules composing AIVC. The implementation is made available at https://orange-opensource.github.io/AIVC/.

Index Terms— Video coding, Conditional autoencoder

1. INTRODUCTION & RELATED WORKS
Digital technologies are becoming an ever-growing part of our daily life. This has an important environmental impact, caused by a rising number of devices (data centers, networking equipment, user terminals). In particular, video streaming causes a significant share of this impact as it represents more than 75% of overall Internet traffic [1]. Reducing the size of the videos exchanged over the Internet thus alleviates some inconveniences of digital technologies.

Standardization organisms such as MPEG and ITU have released several video coding standards (AVC [2] in 2003, HEVC [3] in 2013 and VVC [4] in 2020), reducing the size of videos while maintaining an acceptable visual quality. Recently, neural-based coders have been studied by the compression community. In the span of a few years, they have reached image coding performance on par with VVC [5]. Yet, video coding remains a challenging task for neural coders, due to the additional temporal dimension.

Conventional and neural video coders rely on similar techniques to remove temporal redundancies in a video. First, a temporal prediction is computed at the decoder. Then, only the unpredicted part is sent from the encoder to the decoder. Many previous works have refined these two steps. For instance, temporal prediction is performed either in the spatial [6] or feature [7] domain. Similarly, the unpredicted part is computed in the spatial [8] or feature [9] domain.

Yet, these refinements are often evaluated under particular test conditions which are arguably different from the requirements of the industry. Most previous works focus on the low-delay P configuration [6, 7] (used for videoconferencing) and omit the Random Access configuration (used for streaming at large). Furthermore, most neural codecs [10, 11] are assessed using an I frame period shorter (e.g. 10 or 12 frames, regardless of the video framerate) than expected by the Common Test Conditions of modern video coders such as those defined for HEVC or VVC [12]. Consequently, neural coder performance is not accurately evaluated.

This paper introduces AIVC, an AI-based Video Codec featuring both conditional coding [9] and Skip [13] mechanisms. AIVC is designed to be a versatile codec, able to implement any desired coding configuration. It is evaluated under test conditions which strive to reconcile the learned and conventional video coding community. On the one hand, the CLIC 2021 [14] test sequences and quality metric (MS-SSIM) are used. On the other hand, the HEVC Test Model (HM) serves as anchor and 3 configurations are evaluated: Random Access (one I frame per second), Low-delay P and All Intra. Our contributions are summarized as follows:

1. We propose an easy-to-train architecture, competitive with HEVC under various test conditions;
2. We provide comprehensive experimental results justifying all components composing AIVC;
3. We publicly release the trained models [15].

2. PROPOSED SYSTEM

2.1. System overview
Let us consider a video as a sequence of frames, where each frame $x_t$ is a $3 \times H \times W$ tensor. Similarly to conventional video codecs, AIVC processes a frame while using information from up to 2 already transmitted frames, called reference frames. These two references (one past and one future) are denoted $\hat{x}_p$ and $\hat{x}_f$. If the coding of $x_t$ exploits both references, $x_t$ is called a B frame. A P frame uses a single reference ($\hat{x}_f = 0$), while an I frame uses no references ($\hat{x}_p = \hat{x}_f = 0$).

AIVC processes a frame $x_t$ following the coding pipeline shown in Fig. 1. First, motion information is computed and sent by a neural network MNet. This information comprises

1 A bilinear upsampling is used to convert YUV 420 data into YUV 444.
two pixel-wise motion fields $v_p, v_f$ (for the past and future references) and one pixel-wise prediction weighting $\beta$. Then, a bi-directional motion compensation algorithm computes a temporal prediction $\hat{x}_t$:

$$\hat{x}_t = \beta w (\hat{x}_p, v_p) + (1 - \beta) w (\hat{x}_f, v_f),$$

with $w$ a bilinear warping. Finally, the unpredicted part of $x_t$ is sent using a second neural network CNet. That is, the coding of $x_t$ is performed conditionally to its prediction $\hat{x}_t$.

While some previous works [6] require a separate I frame network, AIVC compresses all frame types (I, P & B) identically, simply zeroing the unavailable references.

2.2. Content adaptation with Skip mode

Conventional video coders (e.g. HEVC, VVC) are characterized by the important number of available coding modes i.e. different ways of processing a set of pixels. This allows performing operations adapted to different video content and leads to compelling performance. Following this idea, AIVC features an additional coding mode called Skip mode [13].

Skip mode offers the possibility to shortcut CNet, by directly using areas of the prediction $\hat{x}_t$ as the decoded frame. This coding mode is particularly convenient for well-predicted areas. The choice between CNet and Skip is arbitrated pixel-wise through a multiplication by $\alpha$, the mode selection (see Fig. 1). As $\alpha$ must be known at the decoder, it is computed and conveyed by MNet, alongside the motion information. Adding Skip mode improves the performance of AIVC as it can better adapt to the video to be compressed. Furthermore, Skip mode eases the training convergence since it fosters the learning of a relevant prediction and accurate motion information.

2.3. Conditional coding for MNet & CNet

Despite different roles, CNet and MNet share the same architecture called conditional coding (CC) [9, 16], to exploit decoder-side information as much as possible. To this effect, CC adds a conditioning transform to the usual analysis-synthesis convolutional autoencoder [17]. At the decoder, the conditioning transform computes a conditioning latent variable representing the available decoder-side information. At the encoder, the analysis transform identifies the information missing at the decoder. It is fed with the encoder-side and decoder-side data to compute an analysis latent variable, which is then sent to the decoder. Consequently, the encoder (subject to a rate constraint) transmits only the unpredicted part of $x_t$. Finally the synthesis transform processes both latent variables to obtain the desired output.

CC is used as a generic architecture to exploit decoder-side information regardless of the information nature. For instance, MNet leverages CC by using the image-domain data (reference frames) to retrieve information about the motion information and the coding mode selection. Compared to residual coding, CC offers a richer non-linear mixture in the latent domain which results in better compression performance.

2.4. Variable quantization gains

The importance of the analysis latent variable (both for MNet and CNet) depends on the availability of the reference frames. When no reference is available, the conditioning transform cannot extract relevant decoder-side information. Consequently, all the required information is conveyed through the analysis transform. To better adapt to the importance of the analysis latent variable, AIVC features different quantization gains based on the frame type.

Quantization gains are derived from the multi-rate codec proposed in [18]. For each frame type $f \in \{I, P, B\}$, a
feature-wise pair of gains \((\Gamma^\text{enc}_f, \Gamma^\text{dec}_f)\) is learned. Each gain \(\Gamma \in \mathbb{R}^F\), with \(F\) the number of channels of the analysis latent variable. Gains multiply the analysis latent variable before and after an unitary quantizer.

2.5. Architecture details

MNet and CNet analysis and synthesis transforms are implemented using the convolutional autoencoder architecture proposed in [5]. They feature attention modules, residual blocks and the hyperprior mechanism. The conditioning transform of MNet and CNet replicates the architecture of the analysis transform. As a result, AIVC has 50 million parameters.

3. EXPERIMENTAL RESULTS

3.1. Training

AIVC is designed to code any configuration composed of I, P and B frames. As such, a configuration featuring all 3 frame types is used for training (Fig. 3a). For each training iteration, the 3 frames are coded and gradient descent is used to minimize the loss function:

\[
L_{\lambda} = \sum_t D(x_t, \hat{x}_t) + \lambda (R_{m} + R_{c}).
\]  

(2)

The distortion \(D\) is based on MS-SSIM to comply with the CLIC 2021 test conditions [14]. The rate constraint \(\lambda\) balances \(D\) with MNet rate \(R_m\) and CNet rate \(R_c\). During training, the entropy of the analysis latent variables acts as a proxy for the rate [17]. Different \(\lambda\) are used to obtain systems with different rate targets. Training examples are extracted from several datasets: KoNVid_1k [19], YouTube-NT [20], YUV_4K [21] and CLIC [14].

Training AIVC does not require auxiliary losses [22] or pre-trained motion components [23]. Instead, Skip mode fosters the learning of relevant motion information \((v_p, v_f\) and \(\beta)\) and coding mode selection \(\alpha\). However, during the first training iterations CNet is not yet ready to compete with Skip. As such, \(\alpha\) is forced to zero (Skip) and one (CNet) on some areas of the frame (Fig. 3b).

3.2. Visual examples

Figure 2 illustrates the processing of a B frame \(x_t\) (Fig. 2a). First, MNet computes and transmits two motion fields (Fig. 2b and 2c) allowing a temporal prediction \(\hat{x}_t\) to be computed, leveraged by two coding modes: Skip and CNet. These modes are arbitrated by \(\alpha\) (Fig. 2d). Skip mode (Fig. 2e) is a direct copy of \(\hat{x}_t\) which is mostly used for the well-predicted areas e.g. slow moving objects. Areas which do not rely on Skip are conveyed by CNet. Finally, both coding mode contributions are added to obtain the decoded frame (Fig. 2f).

Although the optimization process is driven only by the rate-distortion objective, MNet learns relevant motion fields and coding mode selection. They present accurate values and
edges as well as smooth low-frequency areas suited for low-rate transmission. Supplementary animated illustrations are provided alongside the models [15].

### 3.3. Rate-distortion performance

AIVC performance is evaluated against the HEVC test Model (HM) 16.22 under 3 configurations: Random Access (RA) which features I, P and B frames, Low-delay P (LDP) with one initial I frame followed by P frames and All Intra (AI) consisting only of I frames. Test sequences are from the CLIC 2021 validation set and the quality metric is MS-SSIM.

Figure 4a presents the results. AIVC is competitive with HEVC for RA and LDP at higher rates, while it is slightly worse at lower rates. Moreover, AIVC significantly outperforms HEVC for AI coding. These results validate the design choices made for AIVC. Yet, further work should focus on enhancing the motion-related components of AIVC to outperform HEVC RA results.

### 3.4. Ablation results

This section illustrates the benefits brought by different components of AIVC. Figure 4b shows the rate-distortion performance of the different configurations presented in Table 1. Residual is the most basic configuration. It does not feature motion compensation nor Skip (\(v_p = v_f = \alpha = 0\)) and the prediction \(\hat{x}_t\) is the average of the reference frames. CNet is implemented as a normal autoencoder (i.e. no conditioning transform) conveying the prediction error \(x_t - \hat{x}_t\).

Conditional simply modifies CNet, replacing residual coding by conditional coding and adding frame type adapted quantization gains (no motion compensation is present). The significant increase in performance highlights the benefits of replacing residual coding with conditional coding.

Motion adds MNet and motion compensation yielding a more accurate prediction. MNet is a normal autoencoder (i.e. no conditioning transform) and Skip mode is not used. The introduction of motion information improves high-rate results but does not enhance performance at lower rates. AIVC shows the relevance of Skip mode and conditional coding for MNet which yields better results for lower rates.

| Name     | CNet | MNet | Motion comp. | Skip |
|----------|------|------|--------------|------|
| AIVC     | CC   | CC   | ✓            | ✓    |
| Motion   | CC   | AE   | ✓            |      |
| Conditional | CC   |      |              |      |
| Residual |      | Residual |                |      |

### 4. CONCLUSION

This paper presents AIVC, a learned video coder able to compress videos using any coding configuration composed of I, P and B frames. AIVC is shown to be competitive with the best implementation of HEVC under several test conditions. Finally an ablation study highlights the benefits of each component e.g. conditional coding and Skip mode.

Although AIVC offers compelling performance, it remains challenging for neural codecs to outperform modern conventional codecs (HEVC and VVC) especially at lower rates. We believe that the introduction of additional coding modes (similar to Skip mode) would improve neural codec results. Moreover the experimental results provided highlight the relative weakness of the motion component, which needs to be refined to obtain better performance.
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