Abstract

Creating realistic human videos introduces the challenge of being able to simultaneously generate both appearance, as well as motion. To tackle this challenge, we propose the novel spatio-temporal GAN-architecture \( G^3AN \), which seeks to capture the distribution of high dimensional video data and to model appearance and motion in disentangled manner. The latter is achieved by decomposing appearance and motion in a three-stream Generator, where the main stream aims to model spatio-temporal consistency, whereas the two auxiliary streams augment the main stream with multi-scale appearance and motion features, respectively. An extensive quantitative and qualitative analysis shows that our model systematically and significantly outperforms state-of-the-art methods on the facial expression datasets MUG and UvA-NEMO, as well as the Weizmann and UCF101 datasets on human action. Additional analysis on the learned latent representations confirms the successful decomposition of appearance and motion.

1. Introduction

Generative Adversarial Networks (GANs) [9] have witnessed increased attention due to their ability to model complex data distributions, which allows them to generate realistic images [5, 16, 17, 20, 23, 24, 38, 40], as well as to translate images [2, 14, 27, 30]. While realistic video generation is the natural sequel, it is substantially more challenging w.r.t. complexity and computation related to the simultaneous modeling of appearance, as well as motion.

Specifically, in inferring and modeling the distribution of human videos, generative models face three main challenges: (a) generating uncertain motion, (b) retaining of human appearance throughout the generated video, as well as (c) modeling spatio-temporal consistency. Such challenges have been alleviated by conditioning the generation on potential priors such as input images [39], human keypoints [6] and optical flow [22]. This relates to learning to sample from conditional distributions, assuming access to the marginal distributions instead of learning the joint distributions [26].

Deviating from such approaches, in this work we focus on the highly intricate problem of video generation without prior knowledge w.r.t. either appearance or motion. Specifically, based on noise variables, we generate an appearance, e.g. human face and body, which we concurrently animate, by a facial expression or human action.

\( G^3AN \), our new generative model, is streamlined to learn a disentangled representation of the video generative factors appearance and motion, allowing for manipulation of both. A disentangled representation has been defined as one, where single latent units are sensitive to changes in single generative factors, while being relatively invariant to changes in other factors [4]. In this context, our \( G^3AN \) is endowed with a three-stream Generator-architecture, where the main stream encodes spatio-temporal video representation, augmented by two auxiliary streams, representing the independent generative factors appearance and motion. A self-attention mechanism targeted towards high level feature maps ensures video quality.

\( G^3AN \) is hence able to generate realistic videos (tackling challenges (a) and (c)) by following a training distribution and without additional input, as well as able to manipulate the appearance and motion disjointly, while placing emphasis on preserving appearance (challenge (b)).

The main contributions of our work are the following:

- We propose a new spatio-temporal approach, which seeks to learn disentangled representations of the generative factors appearance and motion. This is achieved by a Generator-architecture, incorporating hierarchical \( G^3 \)-modules. Each module contains three streams, where two auxiliary streams augment the main spatio-temporal stream.
- The learned disentangled representation allows for individual manipulation of appearance and motion.
- We propose a novel spatio-temporal fusion scheme, which fuses the feature maps in each \( G^3 \)-module. The fusion scheme ensures that the output from each auxiliary stream represents appearance and motion, individually.
• We propose a factorized spatio-temporal self-attention, which improves the quality of generated videos.

• We demonstrate qualitatively and quantitatively that $G^3\text{AN}$ systematically and significantly outperforms state-of-the-art baselines on a set of datasets.

2. Related Work

Despite the dynamic progress in image generation, the extension to video generation is surprisingly challenging. While videos constitute sequences of temporally coherent images, video generation encompasses a majority of challenges that have to do with generation of plausible and realistic appearance, coherent and realistic motion, as well as spatio-temporal consistency. A further challenge, namely the generation of uncertain local or global motion, associated to future uncertainty, allows for multiple correct, equally probable next frames [35]. Finding suitable representation learning methods, which are able to address these challenges is critical. Existing methods include approaches based on Variational Autoencoders (VAEs) [19], auto-regressive models, as well as most prominently GANs [9].

While video generation tasks aim at generating realistic temporal dynamics, such tasks vary with the level of conditioning. We have video generation based on additional priors related to motion or appearance, as well as contrarily, video generation following merely the training distribution. We note that the latter is more challenging from a modeling perspective, due to lack of additional input concerning e.g. structure of the generated video and therefore the majority of approaches include a conditioning of some kind.

Video generation with additional input. Due to difficulty of modeling high dimensional video data, additional information such as semantic maps [25, 37], human key points [15, 39, 36, 6], 3D face mesh [41] and optical flow [22] can be instrumental as guidance for appearance and motion generation. This additional information is either pre-computed throughout the generated video [15, 41, 6] or predicted based on an initial input image [39]. The additional information guides conditional image translation, which though results in lack of modeling of spatio-temporal correlations.

Video generation from noise. Directly generating videos from noise requires the capturing and modeling of a dataset distribution. Existing works usually reduce the complexity of this task by decomposing either the output [34] or latent representation [28, 33]. VGAN [34] was equipped with a two-stream spatio-temporal Generator, generating foreground and background separately. TGAN [28] decomposed the latent representation of each frame into motion and content, aiming at controlling both. However, there are two crucial differences between MoCoGAN and $G^3\text{AN}$. Firstly, instead of only sampling two noise vectors for each video, MoCoGAN samples a sequence of noise vectors as motion and a fixed noise as content. However, involving random noise for each frame to represent motion increases the learning difficulty, since the model has to map these noise vectors to a consecutive human movement in the generated videos. As a result, MoCoGAN gradually ignores the input noise and tends to produce a similar motion, as we illustrate in Figure 8. Secondly, MoCoGAN incorporates a simple image Generator aiming at generating each frame sequentially, after which content and motion features are jointly generated. This leads to incomplete disentanglement of motion and content. Deviating from that, we design a novel Generator architecture, able to entirely decompose appearance and motion in both, latent and feature spaces. We show that such design can generate realistic videos of good quality and ensure factor disentanglement.

Disentangled representation learning. Learning a disentangled representation of data generative factors has been shown beneficial for a large variety of tasks and domains [4]. Disentangling a number of factors in still images have been widely explored in recent years [7, 23, 31, 21]. In the context of video generation, an early approach for motion and appearance disentanglement was incorporated in MoCoGAN, however experiments, presented later in this work (see Figure 6) suggest that the results are not satisfactory.

3. Approach

In this work, we propose $G^3\text{AN}$, a novel GAN architecture, aiming at generating videos in a disentangled manner from two noise vectors, $z_a \in Z_A$ and $z_m \in Z_M$, which represent appearance and motion, respectively. $G^3\text{AN}$ consists of a three-stream Generator $G$, as well as a two-stream Discriminator $D$, as illustrated in Figure 1. $G$ aims at generating videos with the ability to modulate appearance and motion disjointly, while $D$ accounts for distinguishing generated samples from real data, in both, videos and frames, respectively.

3.1. Generator

Hierarchical Generator with $G^3\text{-modules}$. We design the Generator $G$ in a hierarchical structure of $G^3$ modules. Specifically, we have $N$ levels of hierarchy, denoted as $G^3_{n=0...N-1}$. The first $G^3$ module, $G^3_0$ accepts as inputs the noise vectors $z_a$ and $z_m$. The remaining modules $G^3_{n=1...N-1}$ inherit the three feature maps $F_{S_{n-1}}$, $F_{V_{n-1}}$, and $F_{T_{n-1}}$ as their inputs from each previous $G^3_{n-1}$ module, see Figures 1 and 2.

Each $G^3_n$ module consists of three parallel streams: a spatial stream $G_{S_n}$, a temporal stream $G_{T_n}$, as well as a video stream $G_{V_n}$ (Figures 1 and 2). These streams are de-
signed to generate three different types of features. The spatial stream $G_{Sn}$, denoted by a blue line in Figures 1 and 2, takes as input $z_a$ for $n = 0$ and $F_{Sn-1}$ for $n > 1$, and generates 2D appearance features $F_{Sn}$ by upsampling input features with a transposed 2D convolutional layer. These features evolve in spatial dimension and are shared at all time instances. The temporal stream $G_{Tn}$, denoted by an orange line, accepts as input $z_m$ for $n = 0$ and $F_{Tn-1}$ for $n > 1$, and seeks to generate 1D motion features $F_{Tn}$ by upsampling input features with a transposed 1D convolutional layer. These features evolve in temporal dimension and contain global information of each time step. Then, the video stream $G_{Vn}$, denoted by a black line, takes as input both $z_a$ and $z_m$ for $n = 0$ and $F_{Vn-1}$ for $n > 1$. It models spatio-temporal consistency and produces 3D joint embeddings $F_{V'n}$ by upsampling input features with a factorized transposed spatio-temporal convolution, see below. Then, $F_{Sn}$ and $F_{Tn}$ are catapulted to the spatio-temporal fusion block, where they are fused with $F_{V'n}$, resulting in $F_{V''}$. Finally, $F_{Sn}$, $F_{Tn}$ and $F_{V''}$ serve as inputs of the next hierarchy-layer $G_{n+1}$.

**Factorized transposed spatio-temporal convolution.** We propose to explicitly factorize transposed 3D convolutional filters into two separate and successive operations, $M$ transposed 1D temporal convolutional filters followed by a 2D separate spatial components, which we refer to as transposed (1+2)D convolution. Such decomposition brings an additional nonlinear rectification between these two operations and facilitates optimization. Crucially, factorizing the transposed 3D convolutional filters yields significant gains in video quality, see Section 4.

**Spatio-temporal fusion.** The upsampled feature maps $F_{Sn}$, $F_{Tn}$ and $F_{V'n}$ are fused in space and time. $F_{Tn}$ is firstly spatially replicated to $F_{Rn}$ and added to the $F_{V'n}$ in a position-wise manner to obtain $F_{V''n}$. Then, we replicate $F_{Sn}$ to $F_{Sn}$ in temporal dimension. Finally, $F_{V''n}$ is channel-wise concatenated with $F_{Sn}$, resulting in the final feature map $F_{Vn}$.

**Spatio-temporal fusion** is a key-element in each $G^3$ module and hence our architecture, as it allows to learn well disentangled features. We propose a simple and effective way to combine $F_{Sn}$, $F_{Tn}$ and $F_{V'n}$, denoting feature maps obtained from the transposed convolution layers of $G_{Sn}$, $G_{Tn}$, and $G_{Vn}$, respectively. We note that $F_{V'n}$ has the same temporal dimension as $F_{Tn}$, as well as the same spatial dimension as $F_{Sn}$. Therefore, firstly, we perform spatial replication of $F_{Tn}$ and temporal replication of $F_{Sn}$, in order to obtain two new feature maps $F_{Tn}^R$ and $F_{Sn}^R$, respectively.
These new feature maps are of the same dimension as $F_{V_n'}$. Next, $F_{T_n}^R$ and $F_{V_n'}$ are combined through a position-wise addition, creating a new spatio-temporal embedding $F_{V_n''}$. Finally, we apply channel-wise concatenation of $F_{T_n}^R$ and $F_{V_n''}$, obtaining the final fused feature map $F_{V_n}$. The features maps $F_{S_n}$, $F_{T_n}$, and $F_{V_n}$ represent inputs for each following $G_{n+1}$ module.

**Factorized spatio-temporal Self-Attention (F-SA)**. Self-Attention has been successfully used for image generation. However, it has not been tested in the context of video generation.

In this paper, we study a module of Self-Attention (SA), enabling our $G$ to utilize cues from all spatio-temporal feature positions and efficiently model relationships between widely separated regions. However, such spatio-temporal self-attention requires heavy computation processing, in particular if it is used on larger feature maps of $G$. Therefore, we propose to factorize spatio-temporal self-attention, as shown in Figure 4. The factorized spatio-temporal SA (F-SA) consists of a Temporal-wise SA (T-SA), followed by a Spatial-wise SA (S-SA) mechanism. Such factorization reduces the complexity, allowing for application of the F-SA on larger feature maps.

In our $G^3$AN architecture, we apply the F-SA mechanism on the output of the $G^3$ in the $G_1$ stream, which has shown to improve the quality of generated videos. We refer to Section 4 for evaluation of our architecture, where we apply the proposed self-attention mechanism at various hierarchy-layers of the $G^3$AN.

**3.2. Discriminator**

Towards improving both video and frame quality, we use a two-stream Discriminator architecture, containing a video stream $D_V$ and an image stream $D_I$, similarly to [33]. While $D_V$ is based on five 3D convolutional layers, $D_I$ contains five 2D convolutions. During training, $D_V$ accepts a full video as input, and $D_I$ randomly samples frames from videos.

**3.3. Training**

Our objective can be expressed as

$$L(G, D_I, D_V) = L_I(G, D_I) + L_V(G, D_V),$$

where $L_I$ denotes the loss function related to $D_I$, $L_V$ represents the loss function related to $D_V$.

$$L_I = \mathbb{E}_{x' \sim p_{data}} [\log(D_I(x'))]$$

$$+ \mathbb{E}_{z_a \sim p_{z_a}, z_m \sim p_{z_m}} [1 - \log(D_I(G(z_a, z_m)))]$$

$$L_V = \mathbb{E}_{x \sim p_{data}} [\log(D_V(x))]$$

$$+ \mathbb{E}_{z_a \sim p_{z_a}, z_m \sim p_{z_m}} [1 - \log(D_V(G(z_a, z_m)))] 

$$

where $G$ attempts to generate videos from $z_a$ and $z_m$, while $D_I$ and $D_V$ aim to distinguish between generated samples and real samples, i.e. $G^* = \min_G \max_{D_I, D_V} L(G, D_I, D_V)$. $\gamma$ characterizes that $T$ frames are being sampled from real and generated videos.

**4. Experiments**

**Experimental Setup.** We use PyTorch to implement our model. The entire network is trained end-to-end with the standard back-propagation algorithm on 4 NVIDIA GTX 1080Ti GPUs. We employ ADAM optimizer [18] with $\beta_1=0.5$ and $\beta_2=0.999$. We set the learning rate to $2e^{-4}$ for both $G$ and $D$, and we use the batch size of 128, i.e. 32 per GPU, to process more samples during one iteration, as presented by Brock et al. [5]. Dimensions of latent representations have been set to 128 for $z_a$ and 10 for $z_m$. We set $N = 5$ in order to generate videos of 16 frames with scale $64 \times 64$. We refer to the Supplementary Material (SM) for more details.

**4.1. Datasets**

We evaluate our method on following four datasets.

**Facial expression datasets.** The MUG Facial Expression dataset [1] contains 1254 videos of 86 subjects, performing 6 facial expressions, namely happy, sad, surprise, anger, disgust and fear. The UvA-NEMO Smile dataset [8] comprises 1240 video sequences of 400 smiling individuals, with 1 or 2 videos per subject. We pre-process videos of the facial expression datasets similarly to previous methods by detecting faces using OpenFace [3] and creating videos around them.
Action recognition datasets. The Weizmann Action dataset [10] consists of 90 videos of 9 subjects, performing 10 actions such as wave and bend. We augment the dataset by horizontally flipping the existing videos. The UCF101 dataset [32] contains 13,320 videos of 101 human action classes. Similarly to TGAN [28], we scale each frame to $85 \times 64$ and crop the central $64 \times 64$ regions for learning.

In all our experiments, we sample video frames with a time step ranging between 1 and 4 randomly for data augmentation, and scale each frame to $64 \times 64$ pixels.

4.2. Experimental Results

We test our method both quantitatively and qualitatively, providing results on four experiments. Specifically, firstly we evaluate and compare videos generated from $G^3 \text{AN}$, VGAN, TGAN and MoCoGAN, quantitatively and qualitatively on all four datasets. Next, we test conditional and unconditional video generation, where we aim to demonstrate the effectiveness of the proposed decomposition method. Then, we manipulate the latent representation, providing insight into each dimension of the two representations. We proceed to add appearance vectors and study the latent representation. Finally, we conduct an ablation study, verifying the effectiveness of our proposed architecture.

4.2.1 Quantitative Evaluation

We compare $G^3 \text{AN}$ with three state-of-the-art methods, namely VGAN, TGAN, as well as MoCoGAN. We report two evaluation metrics on the above four datasets. In particular, we extend the two most commonly used metrics in image generation, the Inception Score (IS) [29] and Fréchet Inception Distance (FID) [12], into video level by using a pre-trained 3D CNN [11] as our feature extractor, similar to Wang et al. [37].

The Video FID grasps both visual quality and temporal consistency of generated videos. It is calculated as $||\mu - \tilde{\mu}||^2 + Tr(\Sigma + \tilde{\Sigma} - 2\sqrt{\Sigma \tilde{\Sigma}})$, where $\mu$ and $\Sigma$ represent the mean and covariance matrix, computed from real feature vectors, respectively, and $\tilde{\mu}$ and $\Sigma$ are computed from generated data. Lower Video FID scores indicate a superior quality of generated videos.

The Video Inception Score captures the quality and diversity of generated videos. It is calculated as $\exp(\mathbb{E}_{x \sim p_x} KL(p(y|x)||p(y)))$, where $p(y|x)$ and $p(y)$ denote conditional class distribution and marginal class distribution, respectively. A higher IS indicates better model performance.

We report video FID on MUG, UVA-Nemo and Weizmann datasets, and both video FID and video IS on UCF101. We do not report IS on the other datasets, since we use a feature extractor pre-trained from kinetics-600, fine-tuned on UCF101; whereas IS can only be reported when GAN-architecture, as well as feature extractor are trained on the same dataset. We generate 5000 videos per dataset for each method for a fair comparison.

Comparison results among different methods are reported in Table 1. Our method consistently achieves the lowest video FID on all datasets, suggesting that videos generated by $G^3 \text{AN}$ entail both, best temporal consistency and visual quality. At the same time, the obtained highest video IS on UCF101 indicates that our method is able to provide the most diverse samples among all compared methods. Such evaluation results show that proposed decomposition method allows for controlling the generated samples, and additionally facilitates the spatio-temporal learning of generating better quality videos. Generated samples are illustrated in Figure 5.

In addition, we conduct a subjective analysis, where we ask 27 human raters to pairwise compare videos generated by our approach with those generated by the state-of-the-art methods. We report the mean user preference in Table 2. We observe that human raters express a strong preference for the proposed framework $G^3 \text{AN}$ over MoCoGAN (84.26% vs. 15.74%), TGAN (87.31% vs. 12.69%) and VGAN (90.24% vs. 9.76%), which is consistent with the above listed quantitative results. Further, we compare real videos from all datasets with the generated video sequences from our method. The human raters ranked 25.71% of videos from our $G^3 \text{AN}$ as more realistic than real videos, which we find highly encouraging.

4.2.2 Qualitative Evaluation

We conduct an unconditional generation experiment utilizing the Uva-NEMO dataset, where we fix $z_0$ and proceed to randomly vary motion, $z_m$. Associated generated samples from $G^3 \text{AN}$ and MoCoGAN are shown in Figure 6. While we observe the varying motion in the video sequences generated by $G^3 \text{AN}$, the appearance remains constant. Hence, our model is able to successfully preserve fa-
Figures 5 and 6: Examples of our approach. We achieve a clear separation of motion and appearance, while altering the motion. Therefore, this suggests that our three-stream design allows for manipulation of appearance and motion separately. On the contrary, video sequences generated by MoCoGAN experience contamination of appearance and motion separately. On the contrary, suggests that our three-stream design allows for manipulation of appearance, while altering two $z_m$ instances (top and bottom lines). See the Supplementary Material (SM) for additional generated samples.

Figure 7: Conditional video generation on MUG and Weizmann. For both datasets, each line is generated with random $z_m$. We observe that same category (smile and one hand waving) is performed in a different manner, which indicates that our method is able to produce intra-class generation. See SM for more samples.
However, while MoCoGAN alters the subject’s appearance.

![Figure 8: Comparison between $G^3$AN and MoCoGAN. Given fixed $z_a$ and $z_m$, as well as two condition-labels smile and surprise, $G^3$AN and MoCoGAN generate correct facial expressions. However, while $G^3$AN preserves the appearance between rows, MoCoGAN alters the subject’s appearance.](image1)

Notable that $G^3$AN effectively prevents such cases, ensured by our decomposition that occurs in both, latent and feature spaces.

Latent representation manipulation. While there is currently no general method for quantifying the degree of learnt disentanglement [13], we proceed to illustrate the ability of our model to learn latent representations by manipulating each dimension in the appearance representation. We show that by changing dimensions of the appearance representation, we are able to cause a modification of specific appearance factors, see Figure 9. Interestingly such factors can be related to semantics, e.g. facial view point in Figure 9a, mustache in Figure 9b, and color of pants in Figure 9c. We note that motion is not affected by altering the appearance-dimensions. Similarly, when altering dimensions in the motion representation, we observe that factors such as starting position, motion intensity and moving trajectory are being affected, see Figure 10. Such observations show that our method learns to interpolate between different data points in motion- and appearance-latent spaces, respectively.

Addition of appearance representations. We here add appearance vectors, aiming to analyze the resulting latent representations. Towards this, we generate two videos $V_a$ and $V_b$ by randomly sampling two sets of noises, $(z_{a0}, z_{m0})$ and $(z_{a1}, z_{m1})$. Next, we add $z_{a0}$ and $z_{a1}$, obtaining a new appearance $z_{a2}$. When combining $(z_{a2}, z_{m0})$ and $(z_{a2}, z_{m1})$, we observe in the two new resulting videos a summary appearance pertaining to $z_{a0}$ and $z_{a1}$, with identical motion as $z_{m0}$ and $z_{m1}$, see Figure 11.

4.2.3 Ablation Study

We here seek to study the effectiveness of the $G^3$AN-architecture, as well as the effectiveness related to each component in the proposed Generator. Towards this, we firstly generate videos by removing $G_S$ and $G_T$, respectively, in order to verify their ability of controlling mo-
We proceed to demonstrate the contribution of \( G_S, G_T \) and F-SA in the Generator w.r.t. video quality. In this context, we remove each component individually and report results on the four datasets in Table 3. The results show that after removing all three components, video quality is the poorest, which proves that all of them contribute to the final results. Individually, \( G_S \) plays the most pertinent role, as removing it, decreases FID most profoundly for all datasets. This indicates that generating appearance features separately can be instrumental for good quality videos. Moreover, our results confirm the necessity to use the F-SA module in our approach.

### Table 3: Ablation study. Contribution of main components in \( G \).

| Architecture | MUG     | UvA     | Weizmann | UCF101 |
|--------------|---------|---------|----------|--------|
| w/o \( G_S \), \( G_T \), F-SA | 117.10  | 164.04  | 252.97   | 127.09  |
| w/o \( G_S \), \( G_T \) | 113.44  | 159.54  | 176.73   | 120.17  |
| w/o \( G_S \) | 109.87  | 129.84  | 141.06   | 117.19  |
| w/o F-SA | 85.11   | 128.14  | 97.54    | 98.37   |
| w/o \( G_T \) | 82.07   | 121.87  | 94.64    | 96.47   |
| \( G^3 \) AN | 67.12   | 119.22  | 86.01    | 91.21   |

| Table 4: Comparison of various convolution types in \( G \). |

| | MUG     | UvA     | Weizmann | UCF101 |
|--------------|---------|---------|----------|--------|
| 3D | 73.08   | 141.35  | 95.01    | 98.70   |
| \( (1 + 2)D \) | \textbf{69.42} | \textbf{140.42} | \textbf{87.04} | \textbf{96.79} |
| \( (1 + 2)D \) | \textbf{69.42} | \textbf{140.42} | \textbf{87.04} | \textbf{96.79} |

### Transposed Convolutions. Then, we compare the proposed factorized transposed spatio-temporal convolution \((1 + 2)D\), standard transposed 3D convolution, and transposed \((2 + 1)D\) convolution, when used in \( G_V \) w.r.t. video quality. We carefully set the number of kernels, allowing for the three networks to have nearly same training parameters. We report the results of the quantitative evaluation in Table 4. Both convolution types, \((1 + 2)D\) and \((2 + 1)D\) outperform standard 3D kernels w.r.t. generated video quality. \((1 + 2)D\) is slightly better than \((2 + 1)D\), and the reason might be that the \((1 + 2)D\) kernel uses more \(1 \times 1\) kernels to refine temporal information, which we believe to be important in video generation tasks.

### Where to insert self-attention? Finally, we proceed to explore at which level of the Generator, the self-attention module F-SA is the most effective. We summarize performance rates in Table 5. Inserting the self-attention after the \( G_4 \) module provides the best results, which indicates that high level feature maps contribute predominantly to video quality. We note that high level feature maps generally correspond to larger spatio-temporal dimensions, which brings to the fore a need for higher computation complexity in the model.

### 5. Conclusions

We have presented the novel video generation architecture \( G^3 \) AN, which leverages among others on (i) a three-stream Generator modeling appearance and motion in disentangled manner, as well as (ii) a novel spatio-temporal fusion method. We have performed an extensive evaluation of our approach on 4 datasets, outperforming quantitatively and qualitatively the state-of-the-art video generation
methods VGAN, TGAN and MoCoGAN. Further, we have shown the ability of $G^3AN$ to disentangle appearance and motion, and hence manipulate them individually.

**Public release.** We intend to release our source code, as well as trained models. Moreover, we will release the dataset of videos, generated by $G^3AN$, VGAN, TGAN and MoCoGAN, in order to facilitate research on identifying fake videos.

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**Table 5:** Attention mechanism F-SA, inserted at different hierarchical levels of $G^3AN$. $G^3n$ indicates that the F-SA was inserted after the $n^{th}$ $G^3$ module in the Generator.

|    | MUG | UvA | Weizmann | UCF101 |
|----|-----|-----|---------|-------|
| $G^3_0$ | 83.01 | 188.60 | 96.38 | 100.37 | 3.09 |
| $G^3_1$ | 72.54 | 178.64 | 99.66 | 126.12 | 2.74 |
| $G^3_2$ | 69.02 | 160.12 | 97.53 | 112.36 | 3.03 |
| $G^3_3$ | 67.12 | 119.22 | 86.01 | 91.21 | 3.62 |

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