Vid-ODE: Continuous-Time Video Generation with Neural Ordinary Differential Equation

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Abstract

Video generation models often operate under the assumption of fixed frame rates, which leads to suboptimal performance when it comes to handling flexible frame rates (e.g., increasing the frame rate of more dynamic portion of the video as well as handling missing video frames). To resolve the restricted nature of existing video generation models’ ability to handle arbitrary timesteps, we propose continuous-time video generation by combining neural ODE (Vid-ODE) with pixel-level video processing techniques. Using ODE-ConvGRU as an encoder, a convolutional version of the recently proposed neural ODE, which enables us to learn continuous-time dynamics, Vid-ODE can learn the spatio-temporal dynamics of input videos of flexible frame rates. The decoder integrates the learned dynamics function to synthesize video frames at any given timesteps, where the pixel-level composition technique is used to maintain the sharpness of individual frames. With extensive experiments on four real-world video datasets, we verify that the proposed Vid-ODE outperforms state-of-the-art approaches under various video generation settings, both within the trained time range (interpolation) and beyond the range (extrapolation). To the best of our knowledge, Vid-ODE is the first work successfully performing continuous-time video generation using real-world videos.

1 Introduction

Videos, the recording of continuous flow of visual information, inevitably discretize the continuous time into a predefined, finite number of units, e.g., 30 or 60 frames-per-second (FPS). This leads to the development of rather rigid video generation models assuming fixed time intervals, restricting the modeling of underlying video dynamics. Therefore it is challenging for those models to accept irregularly sampled frames or generate frames at unseen timesteps. For example, most video generation models do not allow users to adjust the framerate depending on the contents of the video (e.g., higher framerate for more dynamic portion). This limitation applies not only to extrapolation (i.e., generating future video frames), but also to interpolation: given a 1-FPS video between \( t = 0 \) and \( t = 5 \), most existing models cannot create video frames at \( t = 1.5 \) or \( t = 3.8 \).

This might not seem as a serious limitation at a first glance, since most videos we take and process are usually very dense enough to capture essential dynamics of actions. However, video models are widely applied to understand spatio-temporal dynamics not just on visual recordings, but also on various scientific spatio-temporal data which often do not follow the regular timestep assumption.

For instance, a climate video consists of multiple channels of climate variables (i.e., air pressure and ground temperature) instead of color density on the 2-D geographic grid. Due to the equipment cost, the time interval per each measurement often spans minutes to hours, which is insufficient to capture the target dynamics (e.g., creation and development of hurricanes). Consequently, existing video models often lead to sub-optimal prediction. Another challenge with datasets collected from a wild environment is frequently missing values, which in turn results in irregular timesteps.

To resolve this limitation, we propose a video generation model based on Ordinary Differential Equation (Vid-ODE) combined with a linear composition technique and adversarial training. The proposed Vid-ODE learns the continuous flow of videos from a sequence of frames (either regular or irregular) and is capable of synthesizing new frames at any given timesteps using the power of the recently proposed neural ODE framework, which handles the continuous flow of information (Chen et al. 2018).

Closely related to our work, ODE-RNN (Rubanova, Chen, and Duvenaud 2019) was recently proposed to handle arbi-
trary time gaps between observations, but limited to generating low-dimensional time-series data. In order to predict high-dimensional spatio-temporal data, Vid-ODE uses ODE convolutional GRU (ODE-ConvGRU), a convolution version of ODE-RNN, as an encoder to capture the spatio-temporal dynamics. Vid-ODE also employs adversarial training and a combination of pixel-level techniques such as optical flow and difference map to enhance the sharpness of the video. Overall, Vid-ODE is a versatile framework for performing continuous-time video generation with a single model architecture.

We propose Vid-ODE that predicts video frames at any given timesteps (both within and beyond the observed range). To the best of our knowledge, this is the first ODE-based framework to successfully perform continuous-time video generation on real-world videos.

• According to extensive experiments on various real-world video datasets (e.g., human-action, animation, scientific data), Vid-ODE consistently exhibits the state-of-the-art performance in continuous-time video generation. With ablation study, we validate the effectiveness of our proposed components along with their complementary roles.

• We demonstrate that Vid-ODE can flexibly handle unrestricted by pre-defined time intervals over the several variants of ConvGRU and neural ODEs on climate videos where data are sparsely collected.

2 Related Work

Neural ordinary differential equations Vid-ODE has parallels to neural ODE, an idea to interpret the forward pass of neural networks as solving an ODE, and several following works (Rubanova, Chen, and Duvenaud 2019) [Dupont, Doucet, and Teh 2019] [De Brouwer et al. 2019]. In particular, inspired by the application of neural ODE to the continuous time-series modeling, latent ODE (Rubanova, Chen, and Duvenaud 2019) equipped with ODE-RNN was proposed to handle irregularly-sampled time-series data. Recently, ODE²VAE (Yildiz, Heinonen, and Lahdesmaki 2019) attempted to decompose the latent representations into the position and the momentum to generate low-resolution image sequences. Although these prior works employing neural ODE show some promising directions in continuous time-series modeling, it is still an unanswered question whether they can scale to perform continuous-time video generation on complex real-world videos, since existing methods demonstrated successful results only on small-scale synthetic or low-resolution datasets such as sinusoids, bouncing balls, or rotating MNIST. Our model aims at addressing this question by demonstrating the applicability in four real-world video datasets.

Video Extrapolation The pixel-based video extrapolations, which are the most common approaches, predict each pixel separately, motion-based methods (Liu et al. 2017; Liang et al. 2015; Xingjian et al. 2015; Lotter, Kreiman, and Cox 2016; Wang et al. 2017; 2019a,b; Kwon and Park 2019). Alternatively, motion-based methods (Liu et al. 2017; Liang et al. 2017; Gao et al. 2019), which predict the transformation including an optical flow between two frames, generate sharp images, but the quality of outputs is degraded when it faces a large motion. To tackle this, the models combining generated frames and transformed frames using linear composition (Hao, Huang, and Belongie 2018) is proposed.

Video Interpolation Conventional approaches (Revaud et al. 2015) for interpolation often rely on hand-crafted methods such as a rule-based optical flow, resulting in limited applicability for real-world videos. Recently, several neural-net-based approaches (Dosovitskiy et al. 2015; Ilg et al. 2017; Jiang et al. 2018; Bao et al. 2019) exhibited a significant performance boost, taking advantage of end-to-end trainable models in a supervised fashion. In addition, an unsupervised training method for video interpolation (Reda et al. 2019) was explored, providing an indirect way to train the neural networks.

3 Proposed Method: Video Generation ODE

Notations. We denote $X_T = \{X_0, X_1, ..., X_L\}$ as a sequence of input video frames of length $L$, where each $X_i \in \mathbb{R}^{m \times n \times c}$ is a 2-D image of size $m \times n$ with $c$ channels at irregularly sampled timesteps $T \equiv \{t_1, t_2, ..., t_L\}$, where $0 < t_1 < t_2 < ... < t_L$. We additionally define $t_0 = 0$ as origin, and specially denote the last timestep $t_L = T$.

Problem Statement. Given an input video $X_T$, the goal of a continuous-time video generation problem is to generate video frames $X_S$ for another set of timesteps $S \equiv \{s_1, s_2, ..., s_K\}$. As a couple of special cases, this task reduces to interpolation if $0 \leq s_i \leq T$, but to extrapolation if $s_i > T$ for all $s_i \in S$. Generally speaking, the query timesteps $S$ may contain both inside and outside of the given range $T$.

Overview of Vid-ODE. As illustrated in Figure 2, Vid-ODE basically adopts an encoder-decoder structure. First, the encoder embeds an input video sequence $X_T$ into the hidden state $h_T$ using ODE-ConvGRU, our novel combination of neural ODE (Chen et al. 2018) and ConvGRU (Ballas et al. 2015) (Section Encoder: ODE-ConvGRU). Then, from $h_T$, the decoder utilizes an ODE solver to generate new video frames $X_S$ at arbitrary timesteps in $S$ (Section Decoder: ODE Solver + Linear composition). Additionally, we include two discriminators in our framework to improve the quality of the outputs via adversarial learning. We end this section by describing our overall objective functions (Section Objective Functions).

Encoder: ODE-ConvGRU

Prior approaches elaborating neural ODE (Chen et al. 2018; Rubanova, Chen, and Duvenaud 2019) [Dupont, Doucet, and Teh 2019] [De Brouwer et al. 2019] [Yildiz, Heinonen, and Lahdesmaki 2019] employ a fully-connected network $f$ to model the derivative of the latent state $h$ as

$$\frac{dh(t)}{dt} = f_\theta(h(t), t), \quad h(T) = h(0) + \int_0^T f_\theta(h(t), t) dt,$$

where $\theta$ is a set of trainable parameters of $f$. Although this approach successfully models temporal dynamics in irregular


Figure 2: Overview of Vid-ODE. First, input video frames \(X_T\) are fed into a Conv-Encoder \(E\), followed by ODE-ConvGRU. The final hidden state \(h_T\) is used as an initial value by another ODE solver, calculating the sequential hidden states \(h_{s_1}, h_{s_2}, \ldots, h_{s_K}\). Afterwards, the Conv-Decoder \(G\) generates three intermediate representations \(F_{s_1}, D_{s_1}, M_{s_1}\) at each timestep \(s_1\), which are combined via the linear composition \(\Psi\) to generate target video frames \(\{\hat{X}_{s_1}, \hat{X}_{s_2}, \ldots, \hat{X}_{s_K}\}\).

Formally, our decoder is described as

\[
\hat{X}_{s_1}, \hat{X}_{s_2}, \ldots, \hat{X}_{s_K} = \text{ODESolve}(f_\theta, h_{s_1}, (s_1, s_2, \ldots, s_K)),
\]

\[
F_{s_1}, D_{s_1}, M_{s_1} = G(h_{s_1}, h_{s_1-1}),
\]

\[
\hat{X}_{s_i} = \Psi(F_{s_i}, D_{s_i}, M_{s_i}, \hat{X}_{s_i-1}),
\]

Optical Flow

where \(\Psi := M_{s_i} \odot W(F_{s_i}, \hat{X}_{s_i-1}) + (1 - M_{s_i}) \odot D_{s_i}\).

Optical Flow \((F_{s_i})\). Optical flow is the vector field describing the apparent motion of each pixel between two adjacent frames. Compared to using static frames only, using the optical flow helps the model better understand the dynamics of the video to predict the immediate future or past by providing vector-wise information of moving objects [Dosovitskiy et al. 2015; Ig et al. 2017; Liu et al. 2017]. Combined with a deterministic warping operation, optical flow helps the model preserve the sharpness of outputs. In our model, we first predict the optical flow \(F_{s_i} \in \mathbb{R}^{m \times n \times 2}\) at an output timestep \(s_i\). Then, we apply the warping operation \(\mathcal{W}\) on the previous generated image \(\hat{X}_{s_i-1}\), producing a warped image \(\mathcal{W}(F_{s_i}, \hat{X}_{s_i-1})\).

Decoder: ODE Solver + Linear composition

The decoder generates a sequence of frames at target timesteps \(S \equiv \{s_1, s_2, \ldots, s_K\}\) based on the latent representation \(h_T\) of the input video produced by the encoder. Our decoder consists of an ODE solver, the Conv-Decoder \(G\), and the Linear composition \(\Psi\).
which can possibly have disappeared around large movements. Through combining these two outputs, we can obtain the improved results as seen in the last row of Figure 3.

Objective Functions

Adversarial Loss ⁴ We adopt two discriminators, one at the image level and the other at the video sequence level to improve the output quality both in spatial appearance and temporal dynamics. The image discriminator $D_{img}$ distinguishes the real image $X_{s_t}$ from the generated image $\hat{X}_{s_t}$ for each target timestep $s_t$. The sequence discriminator $D_{seq}$ distinguishes a real sequence $X_{\mathcal{S}}$ from the generated sequence $\hat{X}_{\mathcal{S}}$ for all timesteps in $\mathcal{S}$. Specifically, we adopt LS-GAN (Mao et al. 2017) to model $D_{img}$ and $D_{seq}$ as

$$
\min_{\text{Vid-ODE}} \max_{\text{D}_{img}} L_{adv} \equiv \mathbb{E}_{X_{s_t} \sim p(X_{\mathcal{S}})} \left( (D_{img}(X_{s_t}) - 1)^2 \right) + \mathbb{E}_{X_{T} \sim p(x_T)} \left( (D_{img}(\text{Vid-ODE}(X_{s_t} | X_{\mathcal{T}})) - 1)^2 \right)
$$

$$
\min_{\text{Vid-ODE}} \max_{\text{D}_{seq}} L_{adv} \equiv \mathbb{E}_{X_{t_1:s_t} \sim p(x_{\mathcal{T}, \mathcal{S}})} \left( (D_{seq}(X_{t_1:s_t}) - 1)^2 \right) + \mathbb{E}_{X_{t_1:s_{t-1}} \sim p(x_{\mathcal{T}, \mathcal{S}})} \left( (D_{seq}(X_{t_1:s_{t-1}} \mid \text{Vid-ODE}(X_{s_t} | X_{\mathcal{T}})) - 1)^2 \right),
$$

where $\mathcal{T} \cup \mathcal{S}$ is union of the timesteps $\mathcal{T}$ and $\mathcal{S}$, and $X_{t_1:s_t}$ is a sequence of frames from $t_1$ to $T$, concatenated with frames from $s_1$ to $s_t$, for some $i = 1, \ldots, K$.

Reconstruction Loss $L_{recon}$ computes the pixel-level $L_1$ distance between the predicted video frame $\hat{X}_{s_t}$ and the ground-truth frame $X_{s_t}$. Formally,

$$
L_{recon} = \mathbb{E}_{X_{s_t} \sim X_{\mathcal{S}}} \left( \| \hat{X}_{s_t} - X_{s_t} \|_1 \right).
$$

Difference Loss $L_{diff}$ helps the model learn the image difference $D_{s_t}$ as the pixel-wise difference between consecutive video frames. Formally,

$$
L_{diff} = \mathbb{E}_{\Delta X_{s_t} \sim X_{\mathcal{S}}} \left( \| D_{s_t} - \Delta X_{s_t} \|_1 \right),
$$

where $\Delta X_{s_t}$ denotes the image difference between two consecutive frames, i.e., $X_{s_t} - X_{s_{t-1}}$.

Overall Objective Vid-ODE is trained end-to-end using the following objective function:

$$
L = L_{recon} + \lambda_{diff} L_{diff} + \lambda_{img} L_{img} + \lambda_{adv} L_{adv},
$$

where we use $\lambda_{diff}$, $\lambda_{img}$, and $\lambda_{adv}$ for hyper-parameters controlling relative importance between different losses.

4 Experiments

Experimental Setup

We evaluate our model on two tasks: video interpolation and video extrapolation. In video interpolation, a sequence of five input frames are given, and the model is trained to reconstruct the input frames during the training phase. At inference, it predicts the four intermediate frames between the input time steps. In video extrapolation, given a sequence of five input frames, the model is trained to output the next five future

⁴Note that the adversarial loss formulation represented here is for video extrapolation. The formulation for video interpolation is provided in supplementary material.
We compare Vid-ODE against existing neural-ODE-based models such as ODE-VAE (Yildiz, Heinonen, and Lahdesmaki 2019) and latent ODE (Rubanova, Chen, and Duvenaud 2019). In addition, to verify the effectiveness of ODE-ConvGRU described in Section Encoder: ODE-ConvGRU, we design the variants of neural ODEs (e.g., ODE-FC, ODE-Conv) by removing ODE-ConvGRU; thus, both take the channel-wise concatenated frames as an input for the Conv-Encoder $E$. We call the variants depending on the types of the derivative function $f_{\phi}$: fully-connected layers (ODE-FC) and convolutional layers (ODE-Conv).

We conclude this section with the analysis of the role of each component of Vid-ODE, including an ablation study. Additional implementation details such as model architectures, hyper-parameters are provided in the supplementary material.

**Datasets.** For evaluate our model on the following real-world datasets: KTH Action (Schuldt, Laptev, and Caputo 2004) consists of videos of 25 subjects performing 6 different types of actions (walking, jogging, running, boxing, hand waving, and hand clapping). Moving GIF (Siarohin et al. 2019) consists of 1,000 videos including cartoons of moving animals. We use 900 for training and 100 for testing. Penn Action (Zhang, Zhu, and Derpanis 2013) contains 2,326 videos of 15 different actions, such as baseball swing, bench press, and bowling. CAM5 (Kim et al. 2019) is a hurricane video dataset, where we evaluate our model for video extrapolation from irregular input frames, in order to test the model’s ability to process irregular input. Details of each dataset are described in the supplementary materials.

**Comparison with Neural-ODE-based Models**

| Datasets | Model     | Video Interpolation | Video Extrapolation |
|----------|-----------|---------------------|---------------------|
|          |           | SSIM 2         | LPIPS 2 | PSNR 2 | SSIM 2 | LPIPS 2 | PSNR 2 |
| KTH Action | Latent ODE | 0.730          | 0.481   | 20.99  | 0.730  | 0.495   | 20.61  |
|          | ODE-VAE   | 0.752          | 0.456   | 23.28  | 0.755  | 0.430   | 23.19  |
|          | ODE-FC    | 0.749          | 0.444   | 22.96  | 0.750  | 0.442   | 23.00  |
|          | ODE-Conv  | 0.769          | 0.416   | 25.12  | 0.768  | 0.429   | 24.31  |
|          | Vid-ODE   | **0.911**      | **0.048** | **31.77** | **0.878** | **0.080** | **28.19** |
| Moving GIF | Latent ODE | 0.700          | 0.483   | 15.69  | 0.675  | 0.513   | 14.41  |
|          | ODE-VAE   | 0.715          | 0.456   | 16.49  | 0.704  | 0.471   | 15.91  |
|          | ODE-FC    | 0.717          | 0.446   | 16.55  | 0.704  | 0.452   | 15.86  |
|          | ODE-Conv  | 0.745          | 0.380   | 17.88  | 0.713  | 0.429   | 16.23  |
|          | Vid-ODE   | **0.815**      | **0.115** | **18.44** | **0.778** | **0.156** | **16.68** |
| Penn Action | Latent ODE | 0.377          | 0.762   | 15.63  | 0.374  | 0.775   | 15.32  |
|          | ODE-VAE   | 0.433          | 0.687   | 17.06  | 0.423  | 0.701   | 16.90  |
|          | ODE-FC    | 0.447          | 0.643   | 17.40  | 0.342  | 0.753   | 15.00  |
|          | ODE-Conv  | 0.550          | 0.538   | 19.25  | 0.557  | 0.514   | 19.23  |
|          | Vid-ODE   | **0.920**      | **0.033** | **26.73** | **0.880** | **0.045** | **23.81** |

| Datasets | Model     | SSIM 2 | LPIPS 2 | PSNR 2 |
|----------|-----------|--------|--------|--------|
| KTH Action | Vid-ODE   | 0.764  | 0.379  | 21.52  |
|          | PredNet   | 0.825  | 0.242  | 22.15  |
|          | DVF       | 0.837  | 0.129  | 26.05  |
|          | RCG       | 0.820  | 0.187  | 21.92  |
| Moving GIF  | Vid-ODE  | **0.878** | **0.080** | **28.19** |
|          | PredNet   | 0.467  | 0.532  | 11.49  |
|          | DVF       | 0.777  | 0.215  | 16.39  |
|          | RCG       | 0.593  | 0.491  | 11.17  |
| Penn Action | Vid-ODE  | **0.880** | **0.045** | **23.81** |
|          | PredNet   | 0.625  | 0.262  | 18.48  |
|          | DVF       | 0.790  | 0.102  | 21.90  |
|          | RCG       | 0.809  | 0.098  | 20.13  |

**Evaluation Metrics.** We evaluate our model using two metrics widely-used in video interpolation and video extrapolation, including Structural Similarity (SSIM) (Wang et al. 2004), Peak Signal-to-Noise Ratio (PSNR). In addition, we use Learned Perceptual Image Patch Similarity (LPIPS) (Zhang et al. 2018) to measure a semantic distance between a pair of the real and generated frames. Higher is better for SSIM and PSNR, lower is better for LPIPS.

We compare Vid-ODE against existing neural-ODE-based models such as ODE-VAE (Yildiz, Heinonen, and Lahdesmaki 2019) and latent ODE (Rubanova, Chen, and Duvenaud 2019). In addition, to verify the effectiveness of ODE-ConvGRU described in Section Encoder: ODE-ConvGRU, we design the variants of neural ODEs (e.g., ODE-FC, ODE-Conv) by removing ODE-ConvGRU; thus, both take the channel-wise concatenated frames as an input for the Conv-Encoder $E$. We call the variants depending on the types of the derivative function $f_{\phi}$: fully-connected layers (ODE-FC) and convolutional layers (ODE-Conv).

Table 1 shows that Vid-ODE significantly outperforms all other baselines both in interpolation and extrapolation tasks. This improvement can be attributed to the ODE-ConvGRU and the linear composition which helps Vid-ODE effectively maintain spatio-temporal information while preserving the sharpness of the outputs. This is also supported from an observation that ODE-Conv outperforms ODE-FC, achieving higher scores by simply using convolutional layers to estimate the derivatives of hidden states where spatial information resides. We find that the VAE architecture of ODE-VAE and Latent ODE makes the training unstable, as the KL divergence loss of high dimensional representations does not converge well. Due to this, these models often fail to generate realistic images, resulting in suboptimal performance.

**Datasets**

| Datasets | Model | SSIM 2 | LPIPS 2 | PSNR 2 |
|----------|-------|--------|--------|--------|
| KTH Action | DVF   | **0.954** | **0.037** | **36.28** |
|          | UVI   | 0.934  | 0.055  | 29.97  |
|          | Vid-ODE | 0.911  | 0.048  | 31.77  |
| Moving GIF | DVF   | **0.850** | **0.130** | **19.41** |
|          | UVI   | 0.700  | 0.163  | 17.13  |
|          | Vid-ODE | 0.815  | **0.115** | **18.44** |
| Penn Action | DVF   | **0.955** | **0.024** | **30.11** |
|          | UVI   | 0.904  | 0.042  | 25.21  |
|          | Vid-ODE | 0.920  | **0.033** | **26.73** |

**Table 2: Video extrapolation results**

**Table 3: Video interpolation results.** We compare Vid-ODE (unsupervised) with DVF (supervised) and UVI (unsupervised).
Comparison with Task-specific Models

We compare the performance of Vid-ODE against various state-of-the-art video interpolation (Liu et al. 2017; Reda et al. 2019) and extrapolation models (Ballas et al. 2015; Lotter, Kreiman, and Cox 2016; Kwon and Park 2019; Liu et al. 2017).

Video Extrapolation As baselines, we adopt PredNet (Lotter, Kreiman, and Cox 2016), Deep Voxel Flow (DVF) (Liu et al. 2017), Retrospective Cycle GAN (RCG) (Kwon and Park 2019). As shown in Table 2, Vid-ODE significantly outperforms all other baseline models in all metrics. It is noteworthy that the performance gap is wider for Moving GIF, which contains more dynamic object movements (compared to rather slow movements in KTH-Action and Penn-Action), indicating Vid-ODE’s superior ability to learn complex dynamics. Furthermore, qualitative comparison shown in Figure 4 demonstrates that our model successfully learns the underlying dynamics of the object, and generates more realistic frames compared to baselines. In summary, Vid-ODE not only generates superior video frames compared to various state-of-the-art video extrapolation models, but also has the unique ability to generate frames at arbitrary timesteps.

Video Interpolation We compare Vid-ODE with Unsupervised Video Interpolation (UVI) (Reda et al. 2019), which is trained to interpolate in-between frames in an unsupervised manner. We additionally compare with a supervised interpolation method, DVF (Liu et al. 2017), to measure the headroom for potential further improvement. As shown in Table 3, Vid-ODE outperforms UVI in all cases (especially in Moving GIF), except for SSIM in KTH-Action. As expected, we see some gap between Vid-ODE and the supervised approach (DVF).

Irregular Video Prediction One of the distinguishing aspects of Vid-ODE is its ability to handle videos of an arbitrary sampling rate. We use CAM5 to test Vid-ODE’s ability to cope with irregularly sampled input, where we force the model to extrapolate at a higher rate (i.e. every three hours) than the input’s sampling rate. We randomly sample 5 input frames from each hurricane video where the interval can be as large as 48 hours. For baselines, we use Latent ODE, ODE\textsuperscript{2}VAE (Yildiz, Heinonen, and Lahdesmaki 2019), ConvGRU-\Delta, and ConvGRU-Decay where the last two were implemented by replacing the RNN cell of RNN-\Delta and RNN-Decay (Che et al. 2018) to ConvGRU (Ballas et al. 2015). Table 4 shows that Vid-ODE outperforms baselines in both LPIPS and MSE, demonstrating the Vid-ODE’s ability to process irregularly sampled video frames. Furthermore, visual comparison shown in Figure 5 demonstrates the capacity of Vid-ODE to handle spatial-temporal dynamics from
Datasets | Model | LPIPS | MSE
---|---|---|---
CAM5 | ConvGRU-$\Delta t$ | 0.270 | 2.439
 | ConvGRU-Decay | 0.160 | 0.583
 | Latent ODE | 0.206 | 0.554
 | ODE$^2$VAE | 0.203 | 0.551
 | Vid-ODE | **0.092** | **0.515**

Table 4: Extrapolation results for irregularly-sampled input video from the CAM5 hurricane dataset. MSE ($\times 10^{-3}$)

Methods | Video Interpolation | Video Extrapolation
---|---|---
 | SSIM | LPIPS | PSNR | SSIM | LPIPS | PSNR
(A) ODE-Conv | 0.769 | 0.416 | 25.12 | 0.768 | 0.429 | 24.31
(B) Vanilla Vid-ODE | 0.864 | 0.247 | 27.81 | 0.853 | 0.262 | 26.49
(C) + Adversarial learning | 0.866 | 0.226 | 28.60 | 0.856 | 0.245 | 27.69
(D) + Optical flow warping | **0.912** | **0.052** | **31.60** | 0.862 | 0.085 | **28.30**
(E) + Mask composition | **0.911** | **0.048** | **31.77** | **0.878** | **0.080** | **28.19**

Table 5: Performance improvement by adding each component to the Vid-ODE suggesting the applicability of each component to improve performance of tasks.

**Analysis of Individual Components**

**Need for Learning the Continuous Video Dynamics** To emphasize the need for learning the continuous video dynamics using the ODE, we compare Vid-ODE to Vid-RNN, which replaces ODE components in both the encoder and decoder of Vid-ODE with ConvGRU while retaining all other components such as linear composition. Using Vid-RNN, we can obtain video representations at arbitrary timesteps by interpolating its decoder (ConvGRU) hidden states from two adjacent regular timesteps. If Vid-RNN could generate video frames at unseen timesteps as well as Vid-ODE, then an ODE-based video generation would be unnecessary. However, Figure 6 shows that is not the case. While Vid-ODE is successfully inferring video frames at unseen timesteps ($t = 2.25, t = 2.5, t = 2.75$) thanks to learning the underlying video dynamics, Vid-RNN generates unrealistic video frames due to simply blending two adjacent latent representations. The intuition behind such behavior is described in Figure 7, where the advantage of the ODE-based approach is evident when handling continuous time.

**Ablation Study** Table 5 depicts the effectiveness of each component of the Vid-ODE. Starting with a simple baseline ODE-Conv (A), we first compare vanilla Vid-ODE (B) equipped with the proposed ODE-ConvGRU. We see a significant boost in performance, meaning that the ODE-ConvGRU cell better captures spatio-temporal dynamics in the video and is able to generate high quality frames. As depicted by (C) in Table 5, adding the adversarial loss to (B) improves performance, especially in LPIPS, suggesting that the image and sequence discriminators help the model generate realistic images. From (C) to (D), we add the optical flow warping (Eq. 2), which significantly enhances the performance by effectively learning the video dynamics. As a last component, we add the linear composition $\Psi$ (E). The performance boost from (B) to (E) might seem marginal. Comparing the warped image with the final product in Figure 3, however, demonstrates that using the image difference to fill in the disappeared pixels in the warped image indeed enhances the visual quality of the output.

**5 Conclusions**

In this paper, we propose Vid-ODE which enjoys the continuous nature of neural ODEs to generate video frames at any given timesteps. Combining the ODE-ConvGRU with the linear composition of optical flow and image difference, Vid-ODE successfully demonstrates its ability to generate high-quality video frames in the continuous time domain using four real-world video datasets for both video interpolation and video extrapolation. Despite its success in continuous-time video generation, Vid-ODE tends to yield degraded outcomes as the number of predictions increases, because of its autoregressive nature. As future work, we plan to study how to adopt a flexible structure to address this issue.
Ethical Impact

Our proposed Vid-ODE model learns the continuous flow of videos from a sequence of frames from potentially irregular training data, and is capable of synthesizing new frames at any given timesteps. Our framework is applicable to broad scope of spatio-temporal data without limiting to multi-media data. For example, as discussed in the main sections, this can be especially useful for scientific data where the assumption of regularly sampled time step does not always hold. Specifically, the application of proposed model to climate data, where the measurement is costly and sparse while it is sometimes beneficial to forecast at denser rate is critical. This can potentially bring significant impact on weather forecasting with improved estimation quality as well as with less cost compared to traditional scientific models. For instance, in disaster prevention plans for extreme climate events, the decision makers often rely on simulation or observation data with sparse timestep which is only available out there. This limits the capability to forecast in more frequent timesteps and thus prevent solid decisions based on accurate disaster scenario. Our Vid-ODE takes a significant step towards fully data-driven approach to forecast extreme climate events by addressing this issue.

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Supplementary Material

A. Datasets

For our evaluation, we employ and preprocess the four real-world datasets as follows.

**KTH Action** (Schuldt, Laptev, and Caputo 2004) consists of 399 videos of 25 subjects performing six different types of actions (walking, jogging, running, boxing, hand waving, and hand clapping). We use 255 videos of 16 (out of 25) subjects for training and the rest for testing. The spatial resolution of the original dataset is 160 × 120, but we center-crop and resize it to 128 × 128 for both training and testing.

**Moving GIF** (Siarohin et al. 2019) consists of 1,000 videos of animated animal characters, such as tiger, dog, and horse, running or walking in a white background. We use 900 for training and 100 for testing. The spatial resolution of the original dataset is 256 × 256, and each frame is resized to 128 × 128 pixels. Compared to other datasets, Moving GIF contains relatively larger movement, especially in the legs of cartoon characters.

**Penn Action** (Zhang, Zhu, and Derpanis 2013) consists of videos of humans playing sports. The dataset contains 2,326 videos in total, involving 15 different sports actions, including baseball swing, bench press, and bowling. The resolution of the frames are within the size of 640 × 480. For training and testing, we center-crop each frame and then resize it to 128 × 128 pixels. We use 1,258 videos for training, and 1,068 for testing.

**CAMS** (Kim et al. 2019) is a hurricane video dataset, where we evaluate our model on video extrapolation for irregular-sampled input videos. This dataset contains the frames of the global atmospheric states for every 3 hours with around 0.25° resolution, using the annotated hurricane records from 1996 to 2015. We use zonal wind (U850), meridional wind (V850), and sea-level pressure (PSL) out of multiple physical variables available in each frame. We take only those time periods during which hurricane actually occurs, resulting in 319 videos. We use 280 out of these for training and 39 for testing. To fit large-scale global climate videos into GPU memory, we split the global map into several non-overlapping basins of 60° × 160° sub-images.

B. Implementation Details

We employ Adamax (Kingma and Ba 2014), a widely-used optimization method to iteratively train the ODE-based model. We train Vid-ODE for 500 epochs with a batch size of 8. The learning rate is set initially as 0.001, then exponentially decaying at a rate of 0.99 per epoch. In addition, we find that Vid-ODE shows a slight performance improvement when the input frames are in a reverse order. A horizontal flip and a random rotation in the range of -10 to 10 degrees are used for data augmentation. For the implementations of existing baselines, we follow the hyperparameters given in the original papers and conduct the experiments with the same number of epochs, the batch size and data augmentation as our model. For hyperparameters of Vid-ODE, we use \( \lambda_{\text{diff}} = 1.0, \lambda_{\text{img}} = 0.003, \) and \( \lambda_{\text{seq}} = 0.003. \) As for training ODEs, Vid-ODE required only 7 hours for training on KTH Action dataset using a single NVIDIA Titan RTX (using 6.5GB VRAM).

Adversarial Loss for Interpolation

For video interpolation, we make the generated sequence \( \hat{X}_S \) for all timesteps by alternatively substituting a real frame in \( X_T \) with a fake frame \( X_{s,i}. \) Formally, \( L_{\text{adv}}^{\text{img}} \) and \( L_{\text{adv}}^{\text{seq}} \) are formulated as

\[
\min_{\text{Vid-ODE}} \max_{D_{\text{adv}}} L_{\text{adv}}^{\text{img}} = \mathbb{E}_{X_{s,i} \sim P(X_S)} \left[ (D_{\text{img}}(X_{s,i}) - 1)^2 \right] + \mathbb{E}_{X_T \sim P(X_T)} \left[ (D_{\text{img}}(\text{Vid-ODE}(\hat{X}_{s,i}|X_T)) - 1)^2 \right]
\]

\[
\min_{\text{Vid-ODE}} \max_{D_{\text{adv}}} L_{\text{adv}}^{\text{seq}} = \mathbb{E}_{X_T \sim P(X_T)} \left[ (D_{\text{seq}}(X_T) - 1)^2 \right] + \mathbb{E}_{X_T \sim P(X_T)} \left[ (D_{\text{seq}}(\text{Vid-ODE}(\hat{X}_{s,i}|X_T); \hat{X}_{s,i+1:t_L})) - 1)^2 \right],
\]

where \( X_{t_0:t_{i-1}}; \text{Vid-ODE}(\hat{X}_{s,i}|X_T); \hat{X}_{t_{i+1}:t_L} \) denotes a modified input sequence in which an intermediate frame \( \hat{X}_{s,i} \) is replaced by the predicted frame \( X_{s,i} \) (Recall that \( s_i = t_i \) for interpolation). Note that \( \hat{x}_{t_0:t_L} = \hat{x}_{t_L}; t_L = 0, \) meaning that concatenation only occurs at backward or forward when \( i = 1 \) and \( i = L - 1, \) respectively.

Model Architecture

Vid-ODE architectures are shown in Table 6. The notations used are as follows: N: the number of the output channels, K: the kernel size, S: the stride size, P: the padding size, BN: batch normalization, Up: bilinear upsampling ×2.

C. Architectures of Vid-ODE and Vid-RNN

We compare Vid-ODE and Vid-RNN to demonstrate the superior capability of the ODE component to learn continuous video dynamics. Vid-RNN is built by replacing ODE components in Vid-ODE with ConvGRU while retaining all other components such as adversarial losses and the linear composition. Figure 8 shows the architectures of Vid-ODE and Vid-RNN. To clearly illustrate the main components of the architectures, we omit the detailed components of decoding phase such as optical flow and linear composition.
| Part                  | Layer            | Output Shape          | Layer Information                  |
|----------------------|------------------|-----------------------|------------------------------------|
| Input Image          | -                | (h, w, c)             | -                                  |
| Conv-Encoder E       | Downsamp         | (h/2, w/2, 32)        | Conv-(N32, K3×3, S1, P1), BN, ReLU |
|                      | Downsamp         | (h/2, w/2, 64)        | Conv-(N32, K4×4, S2, P1), BN, ReLU |
|                      | Downsamp         | (h/4, w/4, 128)       | Conv-(N32, K4×4, S2, P1), BN, ReLU |
| ODE-ConvGRU          | ConvGRU          | (h/4, w/4, 128)       | Conv-(N128, K3×3, S1, P1)          |
|                      | ODE Func fθ      | (h/4, w/4, 128)       | Conv-(N128, K3×3, S1, P1), Tanh    |
|                      | ODE Func fθ      | (h/4, w/4, 128)       | Conv-(N128, K3×3, S1, P1), Tanh    |
|                      | ODE Func fθ      | (h/4, w/4, 128)       | Conv-(N128, K3×3, S1, P1), Tanh    |
|                      | ODE Func fθ      | (h/4, w/4, 128)       | Conv-(N128, K3×3, S1, P1), Tanh    |
|                      | ODE Func fθ      | (h/4, w/4, 128)       | Conv-(N128, K3×3, S1, P1), Tanh    |

Table 6: Encoder architecture of our model.

| Part                  | Layer            | Output Shape          | Layer Information                  |
|----------------------|------------------|-----------------------|------------------------------------|
| ODE Solver           | ODE Func fθ      | (h/4, w/4, 128)       | Conv-(N128, K3×3, S1, P1), Tanh    |
|                      | ODE Func fθ      | (h/4, w/4, 128)       | Conv-(N128, K3×3, S1, P1), Tanh    |
|                      | ODE Func fθ      | (h/4, w/4, 128)       | Conv-(N128, K3×3, S1, P1), Tanh    |
|                      | ODE Func fθ      | (h/4, w/4, 128)       | Conv-(N128, K3×3, S1, P1), Tanh    |
|                      | Upsample         | (h/2, w/2, 128)       | Up, Conv-(N128, K3×3, S1, P1), BN, ReLU |
|                      | Upsample         | (h, w, 64)            | Up, Conv-(N64, K3×3, S1, P1), BN, ReLU |
|                      | Upsample         | (h, w, c + 3)         | Up, Conv-(N(c+3), K3×3, S1, P1)    |

Table 7: Decoder architecture of our model.

| Part                  | Layer            | Output Shape          | Layer Information                  |
|----------------------|------------------|-----------------------|------------------------------------|
| Input Image          | -                | (h, w, c)             | -                                  |
| Discriminator D_img  | Downsamp         | (h/2, w/2, 64)        | Conv-(N64, K4×4, S2, P1), LeakyReLU |
|                      | Downsamp         | (h/4, w/4, 128)       | Conv-(N128, K4×4, S2, P1), LeakyReLU |
|                      | Downsamp         | (h/8, w/8, 256)       | Conv-(N256, K4×4, S2, P1), LeakyReLU |
|                      | Downsamp         | (h/8, w/8, 512)       | Conv-(N512, K4×4, S1, P2), LeakyReLU |
|                      | Downsamp         | (h/8, w/8, 64)        | Conv-(N64, K4×4, S1, P2)           |
| Input Sequence       | -                | (h, w, c × t)         | -                                  |
| Discriminator D_seq  | Downsamp         | (h/2, w/2, 64)        | Conv-(N64, K4×4, S2, P1), LeakyReLU |
|                      | Downsamp         | (h/4, w/4, 128)       | Conv-(N128, K4×4, S2, P1), LeakyReLU |
|                      | Downsamp         | (h/8, w/8, 256)       | Conv-(N256, K4×4, S2, P1), LeakyReLU |
|                      | Downsamp         | (h/8, w/8, 512)       | Conv-(N512, K4×4, S1, P2), LeakyReLU |
|                      | Downsamp         | (h/8, w/8, 64)        | Conv-(N64, K4×4, S1, P2)           |

Table 8: Discriminator architecture of our model.

| Model    | KTH Action | Moving GIF | Penn Action |
|----------|------------|------------|-------------|
|          | SSIM↑ | LPIPS↓ | PSNR↑ | SSIM↑ | LPIPS↓ | PSNR↑ | SSIM↑ | LPIPS↓ | PSNR↑ |
| SVG-FP   | 0.848 | 0.156 | 26.34 | 0.682 | 0.254 | 15.62 | 0.815 | 0.099 | 21.53 |
| SVG-LP   | 0.843 | 0.157 | 22.24 | 0.710 | 0.233 | 15.95 | 0.814 | 0.117 | 21.36 |
| SAVP     | **0.885** | 0.089 | 27.40 | 0.722 | 0.163 | 15.66 | 0.822 | 0.074 | 22.23 |
| SRVP     | 0.831 | 0.113 | 27.99 | 0.667 | 0.263 | 16.23 | 0.877 | 0.056 | 22.10 |
| Vid-ODE  | 0.878 | **0.080** | **28.19** | **0.778** | 0.156 | **16.68** | **0.880** | **0.045** | **23.81** |

Table 9: Additional video extrapolation comparisons. We report the baseline results by taking the average of three samples.
Figure 8: The architectures of Vid-ODE and Vid-RNN for continuous video interpolation. The main difference between Vid-ODE and Vid-RNN lies in how to obtain the representations at unseen timesteps. In order to generate the frames at unseen timesteps, we interpolate the hidden states of Vid-RNN decoder from two observed timesteps. The unseen frames are not used during training of Vid-RNN to make the same settings as Vid-ODE.

D. Additional Experiments

This section presents additional experiments as follows:

- Quantitative comparison results against the stochastic video prediction baselines.
- Quantitative comparison results given irregularly sampled inputs at different sampling rates.
- Qualitative comparison results with the video interpolation and extrapolation baselines.
- Continuous video generation results in varying time intervals based on 5-FPS input videos.
- High-resolution (e.g., 256 × 256) video interpolation and extrapolation results on Penn Action dataset.

Additional comparison with baselines In order to further evaluate our method, we additionally compare Vid-ODE with SVG-FP, SVG-LP (Denton and Fergus 2018), SAVP (Lee et al. 2018), and SRVP (Franceschi et al. 2020) for extrapolation. We used the official codes provided by the authors and followed the hyperparameters as presented in the official codes. Table 9 shows Vid-ODE consistently outperforms these existing approaches (except for one metric).

Effect of Irregularity To further investigate the effect of irregularity of inputs, we evaluated MSE and LPIPS on CAM5 dataset while changing the input’s sampling rate. We adjusted the sampling rate of CAM5 inputs as {100%, 50%, 33%, 25%} and measured the corresponding MSE and LPIPS scores. As shown in Figure 9, all models perform worse as the sampling rate decreases, demonstrating the difficulty of handling the sparsely sampled inputs. Nonetheless, Vid-ODE outperforms the baselines at the irregularly sampled inputs as well as regularly sampled inputs (i.e., 100% sampling rate), which verify its superior capability to cope with irregular inputs.

Figure 9: Changes of MSE(×10⁻³) and LPIPS at different sampling rates. Vid-ODE outperforms the baselines at all sampling rates and shows relatively small declines in performance as inputs are sparsely drawn.

Video Interpolation Figures 10–12 illustrate video interpolation, where we generate 4 frames in-between the given 5 input frames. The locations with highly dynamic movements are marked with rectangles (red for inputs and ground truth, green for Vid-ODE results).

Video Extrapolation Figure 13 shows a Bouncing ball experiment on a synthetic data, which consists of three moving balls with a resolution of 32 × 32. We demonstrate the superiority of Vid-ODE even on a low-dimensional dataset. Figures 14–16 illustrate video extrapolation on KTH, Moving GIF, and Penn Action datasets, where we compare the 5 predicted future frames given 5 previous input frames. We mark the areas with highly dynamic movements in the same manner as video interpolation.

Continuous Video Interpolation In Figures 17–18, we generate future frames in various FPS (e.g., 8, 11, 14, 17, and 20 FPS) after the last input frame.

Continuous Video Extrapolation In Figures 19–20, we generate future frames in various FPS (e.g., 8, 11, 14, 17, and 20 FPS) after the last input frame.

High-resolution video generation As shown in Figure 21–22 we further demonstrate that Vid-ODE works well for higher resolution (256 × 256) videos. Moving parts and their directions are marked with yellow arrows.
Figure 10: Qualitative comparisons with interpolation baselines on the KTH Action dataset.

Figure 11: Qualitative comparisons with interpolation baselines on the Moving GIF dataset.
Figure 12: Qualitative comparisons with interpolation baselines on the Penn Action dataset.

Figure 13: Qualitative comparisons with ODE-based baselines on the Bouncing ball dataset.
Figure 14: Qualitative comparisons with extrapolation baselines on the KTH Action dataset.

Figure 15: Qualitative comparisons with extrapolation baselines on the Moving GIF dataset.
Figure 16: Qualitative comparisons with extrapolation baselines on the Penn Action dataset.
Figure 17: Generated video frames in diverse time intervals based on a 5-FPS input video with the Moving GIF dataset. *(Top row: Input to Vid-ODE. Remaining rows: Videos generated in various FPS between the start frame and the end frame.)*

Figure 18: Generated video frames in diverse time intervals based on a 5-FPS input video with the KTH Action dataset. *(Top row: Input to Vid-ODE. Remaining rows: Videos generated in various FPS between the start frame and the end frame.)*
Figure 19: Based on a 5-FPS input video of the KTH Action dataset, predicting and extrapolating video frames generated in diverse time intervals. (First row: Input to Vid-ODE. Second row: Ground truth frames. Remaining rows: Predicted or extrapolated frames in various FPS.)
Figure 20: Based on a 5-FPS input video of the Penn Action dataset, predicting and extrapolating video frames in diverse time intervals. (*First row:* Input to Vid-ODE. *Second row:* Ground truth frames. *Remaining rows:* Predicted or extrapolated frames in various FPS.)
Figure 21: 256 × 256 resolution video interpolation results with Penn Action dataset.
Figure 22: 256 × 256 resolution video extrapolation results with Penn Action dataset.