Chhaya: Photorealistic Contextual Animation Generation

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***Abstract*—We introduce Chhaya, a derived process that allows to build a deep learning model that is able to create photorealistic frames of contextual animation. This model should be able to go through the textual description given by the user and generate photorealistic animation using deep understanding. This will allow people's creativity and research taken to another level.**

***Index Terms*—animation, image, description, network, frames**

I. Introduction

After the introduction of photorealistic text-to-image diffusion models [1], the research on this topic has become so popular that it led to industrial commercialization and constant creative improvements as per usage. Although text-to-image generation is still under research, our imagination does not stop here. If we can generate images from textual descriptions, can we animate them as well? Generating animation from scratch can be extremely difficult for a computer given the current technology we have. But can we make several frames of images from textual description so that it behaves like an animation? In this paper, we have generated images of same description several times and converted it into an animation using GLIDE method [2].

II. Related Previous Works

Ho et al. (2022) proposed and described Imagen Video, a text-conditional video generation system that uses a cascade of video diffusion models to generate high-definition videos. The authors claimed their system is designed to be scalable and to transfer findings from previous work on diffusion-based image generation to the video generation setting. It is capable of generating high-fidelity videos with a high degree of controllability and world knowledge, including the ability to generate diverse videos with text animations and 3D object understanding. The authors apply progressive distillation to their video models for fast, high-quality sampling. Overall, the authors presented a promising approach for generating videos from text. [3]

Singer et al. (2022) introduced Make-A-Video, an approach for generating videos from text that takes advantage of recent progress in text-to-image (T2I) generation. This approach uses paired text-image data to learn what the world looks like and how it is described, and unsupervised video footage to learn how the world moves. The approach has several advantages, including the ability to accelerate training of the T2V model, not requiring paired text-video data, and generating videos with the diversity of today's image generation models. The authors designed a spatial-temporal pipeline to generate high-resolution, high-frame-rate videos. The authors built 2 new datasets based on MNIST and CATER for their model. They claims that Make-A-Video sets the new state-of-the-art in text-to-video generation. The research paper was written professionally and in a simple standard. The work is done in details and seems effective. [4]

Hu et al. (2022) proposed a novel video generation task called Text-Image-to-Video generation (TI2V) that aims to generate videos from a static image and a text description. According to them, the key challenges of this task lie in aligning appearance and motion from different modalities and in handling uncertainty in text descriptions. To address these challenges, the authors propose a Motion Anchor-based video GEnerator (MAGE) that uses an innovative motion anchor structure to store appearance-motion aligned representations and allows for the injection of explicit conditions and implicit randomness. The authors also build two new datasets for evaluating their method. The authors claim their experiments to show that MAGE is effective and that the TI2V task has potential. They approach is generic and but the fact that they created datasets for their own was itself a dedicated approach. [5]

Fu et al. (2022) introduced a novel task called text-guided video completion (TVC), which involves generating a video from partial frames guided by a natural language instruction. To address this task, the authors propose a model called Multimodal Masked Video Generation (MMVG) that discretizes the video frames into visual tokens and masks most of them during training to perform video completion from any time point. At inference time, a single MMVG model can address all three cases of TVC (video prediction, rewind, and infilling) by applying the appropriate masking conditions. The authors evaluated MMVG on various video scenarios and show that it is effective in generating high-quality visual appearances with text guidance for TVC. they approach is quite different than most other from the year of publication. Although the quality of the output videos seem questionable. [6]

Villegas et al. (2022) presented Phenaki, a model that can

generate realistic videos from a sequence of textual prompts. To address the challenges of generating videos from text, such as the computational cost and limited quantities of high-quality text-video data, the authors introduce a new model for learning video representation that compresses the video into a small set of discrete tokens. This tokenizer uses causal attention in time, which allows it to work with variable-length videos. To generate video tokens from text, the authors use a bidirectional masked transformer conditioned on precomputed text tokens. The generated video tokens are then detokenized to create the actual video. The authors demonstrate that joint training on a large corpus of image-text pairs and a smaller number of video-text examples can result in generalization beyond what is available in the video datasets. The authors claim that compared to previous methods, Phenaki can generate arbitrary-length videos from time-variable prompts in the open domain and produces better spatiotemporal consistency than per-frame baselines. Overall, the authors presented a promising approach for generating videos from text. [7]

Kim et al. (2020) proposed a novel training framework called Text-to-Image-to-Video Generative Adversarial Network (TiVGAN) for generating videos based on text descriptions. The authors trained their model gradually on more and more consecutive frames, starting with a single video frame, and this step-by-step learning process helps stabilize the training and enables the creation of high-resolution video based on the given text descriptions. The authors claim that experiments on various datasets show that the proposed method is effective. Although their use in proposed model was GAN, the quality of the videos is not high. [8]

Chen et al. (2020) proposed a novel Bottom-up GAN (BoGAN) method for generating videos from a text description. To ensure the coherence of the generated frames and match the language descriptions semantically, the authors design a bottom-up optimization mechanism to train BoGAN. This mechanism includes a region-level loss via attention mechanism to preserve local semantic alignment and draw details in different sub-regions of the video, as well as a frame-level and video-level discriminator to maintain the fidelity of each frame and the coherence across frames. The authors evaluate the effectiveness of BoGAN on two synthetic datasets and two real-world datasets. Although they used GNA in their model, the model seems to be suitable for only comparatively smaller textual descriptions. [9]

Deng et al. (2019) proposed and described a novel approach called Introspective Recurrent Convolutional GAN (IRC-GAN) for generating videos from given text. The authors used a recurrent transconvolutional generator that integrates LSTM cells with 2D transconvolutional layers to take both the definition of each video frame and temporal coherence into account, resulting in videos with better visual quality. They also uses mutual information introspection to measure the semantic consistency between the generated videos and the corresponding text. They compiled experiments on three datasets show that IRC-GAN is effective at generating plausible videos from given text and compares favorably with state-of-the-art methods. At the time of publication, the approach of GAN described in this paper was a success. But it appears that latest approaches on GAN performs a lot better than this one. [10]

III. Methodology

In this project, we have used the GLIDE approach for generating frames for our desired animation. GLIDE (Guided Language-to-Image Diffusion for Generation and Editing), a diffusion model achieves performance comparable to DALL-E despite utilizing only one-third of the parameters. In addition to producing images from text, GLIDE may be used to change existing images by using natural language text prompts to insert new objects, add shadows and reflections, conduct image inpainting, and so on. It can also convert basic line drawings into photorealistic photos, and it has powerful zero-sample production and repair capabilities for complicated circumstances.

GLIDE uses diffusion models [11] with deep neural network in it called *Imagen*. Imagen is trained on pre-trained BERT for text embedding. It is trained on the correlation between text and images. After GLIDE trained itself, it takes a text as sample input and generates N number of images of the same context. Then we have taken all images into account and combined them to produce an animation into graphics interchange format.

A. Diffusion Models

We consider the Gaussian diffusion models introduced by Sohl-Dickstein et al. (2015) and improved by Song Ermon (2020b); Ho et al. (2020). Given a sample from the data distribution x0 q(x0), we produce a Markov chain of latent variables x1, ..., xT by progressively adding Gaussian noise to the sample:

$$q(x_t|x_{t-1}) \coloneqq \mathcal{N}(x_t; \sqrt{\alpha_t}x_{t-1}, (1-\alpha_t)\mathcal{I})$$

If the magnitude 1 t of the noise added at each step is small enough, the posterior q(xt1—xt) is well-approximated by a diagonal Gaussian. Furthermore, if the magnitude 1 1...T of the total noise added throughout the chain is large enough, xT is well approximated by N (0, I). These properties suggest learning a model $p\theta(xt1|xt)$ to approximate the true posterior:

$$p_\theta(x_{t-1}|x_t) \coloneqq \mathcal{N}(\mu_\theta(x_t), \Sigma_\theta(x_t))$$

which can be used to produce samples $x0p\theta(x0)$ by starting with Gaussian noise xT N (0, I) and gradually reducing the noise in a sequence of steps xT 1, xT 2, ..., x0.

While there exists a tractable variational lower-bound on log p(x0), better results arise from optimizing a surrogate objective which re-weighs the terms in the VLB. To compute this surrogate objective, we generate samples xt q(xt—x0) by applying Gaussian noise to to x0, then train a model to

predict the added noise using a standard mean-squared error loss: $L_{\text{simple}} \coloneqq E_{t\sim[1,T],x_0\sim q(x_0),\epsilon\sim\mathcal{N}(0,\mathbf{I})}[||\epsilon-\epsilon_\theta(x_t,t)||^2]$

B. Classifier-free Guidance

Ho Salimans (2021) recently proposed classifier-free guidance, a technique for guiding diffusion models that does not require a separate classifier model to be trained. For classifier-free guidance, the label y in a class-conditional diffusion model $\theta(xt|y)$ is replaced with a null label $\emptyset$ with a fixed probability during training. During sampling, the output of the model is extrapolated further in the direction of $\theta(xt|y)$ and away from $(xt|\emptyset)$ as follows:

$$\hat{\epsilon}_\theta(x_t|y) = \epsilon_\theta(x_t|\emptyset) + s\cdot(\epsilon_\theta(x_t|y) - \epsilon_\theta(x_t|\emptyset))$$

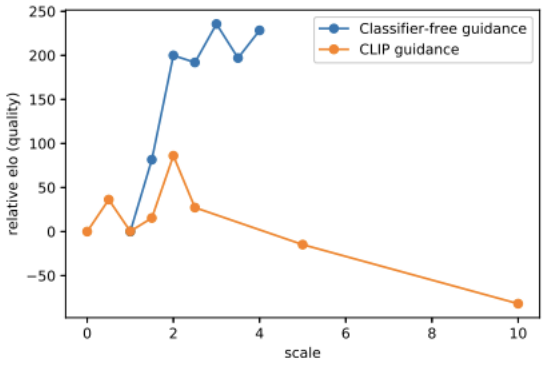
C. Training

For our main experiments, we train a 3.5 billion parameter text-conditional diffusion model at 64 × 64 resolution, and another 1.5 billion parameter text-conditional upsampling diffusion model to increase the resolution to 256 × 256. For CLIP guidance, we also train a noised 64 × 64 ViT-L CLIP model (Dosovitskiy et al., 2020).

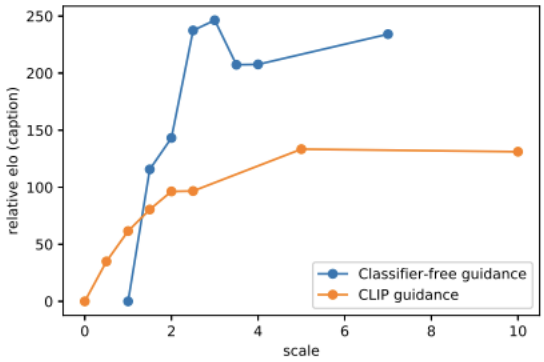
1) Text-conditional Models: We adopt the ADM model architecture proposed by Dhariwal Nichol (2021), but augment it with text conditioning information. For each noised image xt and corresponding text caption c, our model predicts p(xt1—xt, c). To condition on the text, we first encode it into a sequence of K tokens, and feed these tokens into a Transformer model (Vaswani et al., 2017). The output of this transformer is used in two ways: first, the final token embedding is used in place of a class embedding in the ADM model; second, the last layer of token embeddings (a sequence of K feature vectors) is separately projected to the dimensionality of each attention layer throughout the ADM model, and then concatenated to the attention context at each layer. We train our model on the same dataset as DALL-E (Ramesh et al., 2021). We use the same model architecture as the ImageNet 64 × 64 model from Dhariwal Nichol (2021), but scale the model width to 512 channels, resulting in roughly 2.3 billion parameters for the visual part of the model. For the text encoding Transformer, we use 24 residual blocks of width 2048, resulting in roughly 1.2 billion parameters. Additionally, we train a 1.5 billion parameter upsampling diffusion model to go from 64 × 64 to 256 × 256 resolution. This model is conditioned on text in the same way as the base model, but uses a smaller text encoder with width 1024 instead of 2048. Otherwise, the architecture matches the ImageNet upsampler from Dhariwal Nichol (2021), except that we increase the number of base channels to 384. We train the base model for 2.5M iterations at batch size 2048. We train the upsampling model for 1.6M iterations at batch size 512. We find that these models train stably with 16-bit precision and traditional loss scaling (Micikevicius et al., 2017). The total training compute is roughly equal to that used to train DALL-E.

2) Fine-tuning: After the initial training run, we fine-tuned our base model to support unconditional image generation. This training procedure is exactly like pre-training, except 20token sequences are replaced with the empty sequence. This way, the model retains its ability to generate text-conditional outputs, but can also generate images unconditionally.

3) Image Inpainting: Most previous work that uses diffusion models for inpainting has not trained diffusion models explicitly for this task (Sohl-Dickstein et al., 2015; Song et al., 2020b; Meng et al., 2021). In particular, diffusion model inpainting can be performed by sampling from the diffusion model as usual, but replacing the known region of the image with a sample from q(xt—x0) after each sampling step. This has the disadvantage that the model cannot see the entire context during the sampling process (only a noised version of it), occasionally resulting in undesired edge artifacts in our early experiments. To achieve better results, we explicitly fine-tune our model to perform inpainting, similar to Saharia et al. (2021a). During fine-tuning, random regions of training examples are erased, and the remaining portions are fed into the model along with a mask channel as additional conditioning information. We modify the model architecture to have four additional input channels: a second set of RGB channels, and a mask channel. We initialize the corresponding input weights for these new channels to zero before fine-tuning. For the upsampling model, we always provide the full lowresolution image, but only provide the unmasked region of the high-resolution image.



(a) Photorealism



(b) Caption Similarity

[H]

4) Limitation of GLIDE: While our model can often compose disparate concepts in complex ways, it sometimes fails to capture certain prompts which describe highly unusual objects or scenarios. In Figure 8, we provide some examples of these failure cases. Our unoptimized model takes 15 seconds to sample one image on a single A100 GPU. This is much slower than sampling for related GAN methods, which produce images in a single forward pass and are thus more favorable for use in real-time applications.

IV. Result

For testing, we have given the following text as an input and generated 6 frames for instance in order to make the animation.

"A black bird flying freely in the sky"

Then our model produces the following frames for our animation.

Fig. 1. Frames of our animation

"a corgi wearing a bow tie and a birthday hat"

"a fire in the background"

"only one cloud in the sky today"

V. Discussion

Although our approach could somehow generate frames for our animation, they are yet to be clearer and more contextual. The generated animation appears like a slideshow of images instead of an actual animation. We had to derive Imagen diffusion models and pre-trained BERT for training GLIDE, due to the limitation of time and resources. But it is believed that with more time, resources and manpower, we will be able to improve this and make a better approach in text-to-anomation synthesis.

VI. Conclusion

As the name suggests, this is a project that is aimed to build *Chhaya*, an approach to produce compositional animations from textual descriptions given by the users as per their

imaginations. This project will help people enhancing their creativity and imaginations about what is possible and what not. It will also help in academic presentations for students and researchers. With further development of this project and meeting its limitations, this can be treated as an easy tool for commercial production in film industries as well. Although a study has been done on Guided Language-to-Image Diffusion for Generation and Editing, this project will take animation production to the next level by using photorealistic image frames and merging them together. The output of this project will be unique every time and generate varieties of beautiful contextual animations in real time that does not exist in the real world opening windows to people's creative imaginations.

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