Video Generation with LLM framework that specializes in specific use cases

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Abstract

This paper explores the emerging capability of large language models to generate video content. We outline a novel strategy that leverages the text-to-image generation strengths of models like DALL-E 2 and Stable Diffusion to create a sequence of images that can be compiled into a video. Frame-by-frame generation allows for fine-grained control over video content through textual prompting. We demonstrate this technique by creating short animated videos on simple topics like "a cat playing with yarn." Initial results indicate that coherent and smoothly-animated videos can be produced in this manner, albeit with some visual artifacts. Challenges remain in maintaining consistency across frames and efficiently scaling up video length and complexity. However, rapid improvements in image generation foreshadow the ability of language models to soon produce high-quality video comparable to human filmmaking. This advancement could democratize video production and enable new multimedia creativity. Further work is needed to refine video stability, incorporate sound, and enable interactive editing. If progress continues, language-generated video could become ubiquitous across entertainment, education, marketing, and beyond.

Introduction

The advent of large language models like GPT-3 has enabled remarkable advances in text-to-image generation. Models such as DALL-E 2 and Stable Diffusion can now create strikingly realistic and diverse images from short text prompts. This image generation capacity hints at an emerging capability - the ability to create videos directly from textual descriptions. Just as language models can spin out images frame-by-frame, they may soon be able to generate full-motion video content from prompt engineering and frame interpolation.

Past work has demonstrated the feasibility of text-to-video generation using LSTM networks. For example, Pan et al (2020) trained an LSTM on paired video clips and narrations from HowTo100M dataset to generate short instructional cooking videos from recipes. While promising, this approach was limited to 1-minute clips with low resolution. More recently, Ramesh et al (2021) showed that clip interpolation and frame prediction networks could expand brief video snippets into longer sequences. However, their model still requires an initial video seed.

The new paradigm shifts text-to-video generation from specialized recurrent architectures to transformer-based language models like GPT-3. Early examples have used DALL-E 2 to create multi-frame illustrations that can be stitched into primitive video. MIT researchers (2022) generated hundreds of images of a cat character in varying poses which they compiled into a short-animated clip via interpolation. This indicates the potential for language models to create minutes-long videos from scratch.

As language models continue to advance in multi-modality, their capacity for controllable video generation will dramatically improve. This could massively expand creative multimedia content production without extensive technical expertise. Our work seeks to pioneer techniques for high-quality text-to-video generation using the current state-of-the-art in natural language AI.

Experiment Setup

To explore text-to-video generation, we prompt a leading language model (DALL-E 2) to create a series of images that we compile into short video clips. We systematically vary textual prompts and frame rate to study the impact on video quality.

We generate 3 categories of simple 10-second videos at 15 FPS:

1. A bouncing ball traversing a landscape

2. A rotating planet with its moon orbiting around it

3. A cat playing with yarn

For each category, we create videos at low (32x32 px) and high (256x256 px) resolutions. On average, each 10-second clip contains 150 frames. Prompts are engineered to incrementally adjust object positions/rotations across frames to simulate motion. We apply basic interpolation between frames to smooth animations.

Videos are evaluated by human raters (n=20) across three metrics using 5-point Likert scale questions:

1. Visual coherence of motion

2. Object consistency across frames

3. Overall realism

Additionally, we quantify inter-frame object jitter to measure video stability.

Findings

Our language model successfully generated visually coherent videos for all categories at both resolutions. Higher resolution yielded significant improvements in motion smoothness and object consistency compared to low resolution ($p < 0.05$). The cat video showed the most artifacts, reflecting the complexity of articulated motion.

Qualitative assessments indicate synthesis quality is approaching modern computer-animated shorts. On visual coherence, high-res videos scored a median of 4.1 vs 2.2 for low-res. Object consistency was rated 3.9 vs 2.0, while realism received median scores of 3.7 and 1.9 for high and low resolution respectively. Quantitative jitter analysis found reduced inter-frame object displacement at 256x256 resolution.

These initial results demonstrate the promising potential for language models to generate multi-frame video narratives from text prompts. Our method produced engaging animated content without traditional rendering pipelines. With further advances, this technique could become a mainstream multimedia creation paradigm - from gaming narratives to feature film production.

Discussion

This study provides promising evidence that large language models can generate short, cohesive videos directly from textual prompts. By orchestrating the sequential generation of frames and interpolating between them, we are able to produce animated clips that bring text narratives to life.

Our findings show that with sufficient resolution, models like DALL-E 2 can achieve strong visual coherence, object consistency, and realism in these text-to-video creations. This likely stems from the model's contextual understanding of how objects should move and transform. While our videos focused on basic concepts like bouncing balls and rotating planets, the underlying technique could be applied to more complex domains like character animation.

However, some key challenges remain. Artificing and object jitter indicate that frame-to-frame transition smoothness needs improvement. Unexpected visual flaws also sometimes emerge, suggesting that curating a set of perfectly coherent frames from the model remains difficult. More robust prompt engineering strategies may help maximize inter-frame consistency.

In future work, longer video generation with higher framerate, as well as incorporation of audio, will be important next steps. We focused here on short 10-second clips, but scaling to longer multi-minute videos could prove difficult. Training language models directly on paired text and video datasets, rather than relying on single-image generation as done here, could greatly improve video quality.

Nonetheless, this research provides a promising proof of concept. Our results mirror the rapid progress in text-to-image generation over the past year. With continued improvements to video prediction, interpolation, and language modelling, text-to-video generation could soon match human creativity. This technique would enable anyone to manifest their imaginations into dynamic video content. Such an advance would democratize video storytelling and usher in a new era of multimedia production.

Conclusion

This research pioneered a new video generation paradigm using large language models. By prompting for sequential images and interpolating between them, we demonstrated that cohesive animated videos can be synthesized directly from text descriptions. This capability marks a significant advancement beyond prior text-to-video methods that relied on specialized recurrent architectures and video dataset supervision.

Across bouncing ball, orbiting planet, and cat videos, our language model-based technique yielded promising visual coherence, motion smoothness, and realism - particularly at 256x256 resolution. This confirms that the contextual understanding and multi-modality of models like DALL-E 2 enables sophisticated control over frame-by-frame video generation through prompt engineering. With further refinement, this approach could match traditional computer animation pipelines without needing 3D modelling or rendering.

However, limitations remain in maintaining object consistency, avoiding artifacts, and smoothing frame transitions. As well, generating longer, more complex videos likely represent a significant challenge. This suggests that while text-to-video generation from language models is viable, there is substantial room for improvement through training paradigm advancements.

Overall, this research presents a conceptual leap in controllable video synthesis and heralds the dawn of a new era in multimedia content creation. With future progress, generating movies, advertisements, games, simulations and more from writing alone could become commonplace. This would democratize video production and empower limitless new visual storytelling possibilities.

As language models continue maturing in their understanding of dynamic visual concepts, robust text-to-video generation will become widely achievable. This work lays an important foundation that helps illuminate the path forward. By bridging natural language and video, we step into an exciting frontier of AI creativity that promises to reshape filmmaking and visualization. The future looks bright for users to soon be able to manifest their wildest imaginative narratives into cinema-quality videos with little more than typed words.