A Multi-Stage Advanced Deep Learning Graphics Pipeline

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Figure 1: Final renders from the proposed Advanced Deep Learning Graphics Pipeline. 18,225 input attribute files were used to generate each image. Bunny model courtesy of the Stanford University 3D Scanning Repository [Turk and Levoy 1994].

ABSTRACT

In this paper we propose the *Advanced Deep Learning Graphics Pipeline (ADLGP)*. ADLGP is a novel approach that uses existing deep learning architectures to convert scene data into rendered images. Our goal of generating frames from semantic data has produced successful renderings with similar structures and composition as target frames. We demonstrate the success of ADLGP with side-by-side comparisons of frames generated through standard rendering procedures. We assert that a fully implemented ADLGP framework would reduce the time spent in visualizing 3D environments, and help selectively offload the requirements of the current graphics rendering pipeline.

CCS CONCEPTS

• **Computing methodologies** → **Rendering**; Image processing; Machine learning algorithms.

KEYWORDS

Graphics pipeline, rendering pipeline, rendering technologies, machine learning, generative adversarial networks, text-to-image, super resolution, semantic data processing, image processing

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1 INTRODUCTION

Our goal is to train a framework of deep neural networks to learn the correspondence between semantic data within an animated 3D environment and rendered target frames. We propose the application of the Advanced Deep Learning Graphics Pipeline (ADLGP) to offload existing graphics rendering so that future visual experiences, such as 3D games, are more interactive. The system design displayed in Figure 2 shows how ADLGP could be used to supplement current graphics rendering with generated frames using trained machine learning architectures, thereby lowering the time and costs incurred by complex rendering calculations. In Figure 5 we present a total of six frames generated by our ADLGP framework, which was trained on the first and third frames of a source animation. Generated frames 2 and 4 through 6 are novel views with respect to the dataset. Our results show that ADLGP can be used to generate quality in-between frames and also predict plausible future frames, given they have the same dimensional features as those trained on. In a full implementation of our work, training would be dynamic; the framework would use frames generated from the standard graphics pipeline to dynamically train the generative models of the framework, and then use ADLGP to replace strategic future frames when low enough loss has been achieved.

2 RELATED WORK

Path tracing [Foley et al. 2013] is very computationally slow [Schied et al. 2017], however efforts using neural networks to improve

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Figure 2: Process diagram for a real-time application of the Advanced Deep Learning Graphics Pipeline framework.

image quality and rendering time have been gaining ground over the last few years. Image-based approaches [Chaitanya et al. 2017; Schied et al. 2017], and convolutional LSTMs [Mahjourian et al. 2017] for predicting frames are a few examples. Mathieu et al. use a multi-scale GAN approach [Mathieu et al. 2015] to address the major problems of exemplar prediction – lower output quality as convolutions may create blurry predictions. The convolutional encoder-decoder network, Deep Voxel Flow, borrows voxels from neighboring frames [Liu et al. 2017] requiring less processing than other image-to-image methods. Qiao et al. proposed improvements to the Attentional GAN model [Xu et al. 2018] with the LEarn, Imagine and CreAte GAN (LeicaGAN) [Qiao et al. 2019a]. Hong et al. created an intermediate semantic layout to further improve regional influence [Hong et al. 2018; Li et al. 2019], yet poor object prediction disqualifies it for use in novel image generation in our application.

Many architectures have also been created for the purpose of enhancing low quality images via super resolution. Dahl et al. at Google Brain extended PixelCNN [Oord et al. 2016] to address the problem of recursive super resolution [Dahl et al. 2017]. The Super-Resolution GAN (SRGAN) successfully translates between low and high resolution images [Goodfellow et al. 2016; Ledig et al. 2017]. Ledig et al. showed that their perceptual loss greatly improved the ability for the SRGAN model to create high resolution outputs of input images with improved perceived quality over models without perceptual loss [Ledig et al. 2017; Simonyan and Zisserman 2015; Zhou et al. 2018].

3 PROPOSED RESEARCH

Our work is based on the application of deep learning networks to the rendering process [Harris and Semwal 2021]. We use solely non-image semantic data extracted from the scene in order to create

images, the same inputs consumed in graphics rendering. We chose to use a sequence-to-sequence learning mechanism called attention, which follows an encoder-decoder structure similar to other sequence-to-sequence learning techniques, yet is better suited for longer sequences of data. Recently, attention was applied in conditional GANs for the purpose of improving text-to-image translation [Vaswani et al. 2017]. The AttnGAN model combines adversarial learning and attention to improve attribute correspondence and semantic relevance to input descriptors [Xu et al. 2018]. The first stage of ADLGP uses AttnGAN to convert 3D scene data in the form of semantic text attributes into a structural image representing a low resolution rendering of the scene. To improve further on the results of [Harris and Semwal 2021], we add a multi-stage framework. Multi-stage frameworks have been used by several other researchers to generate high-quality images with large resolutions ([Mathieu et al. 2015], [Karnewar et al. 2019], [Qiao et al. 2019b], [Li et al. 2019], and [Qiao et al. 2019a]). Using the SRGAN super resolution architecture [Ledig et al. 2017] trained on the structural outputs of the AttnGAN [Xu et al. 2018], we obtained significant increases in quality for predicting known and unknown views. We also tested the capabilities of ADLGP in generating different material types, including properties of diffuse, reflected, and refracted light (see Figure 5). The final ADLGP framework was used to generate realistic frame sequences for all of these materials.

Figure 3: Flow diagram of ADLGP, as applied in our evaluation. Bunny model courtesy of the Stanford University 3D Scanning Repository [Turk and Levoy 1994].

4 ADLGP IMPLEMENTATION

Our process is illustrated in Figure 3. We generated sets of training data by extracting image-text pairs from the source scene. Using

Figure 4: Sample 4×4 pixel image and corresponding text attributes extracted from the scene.

our novel image generation process [Harris and Semwal 2021], semantic text attributes are extracted from the animation software for every *frameblock* of the frame. A frameblock is a small portion of pixels which show significant change in the animation. An example of a text-image pair is displayed in Figure 4.

We used the Stanford Bunny [Turk and Levoy 1994] to evaluate the capabilities of our proposed system. We trained the AttnGAN pre-training and generative models, which were used to generate structural images off of the extracted text. The AttnGAN rendered adequate experimental images, however many aspects of the architecture limited the capacity of understanding scene attributes. A major drawback of AttnGAN is its limitations for recognizing the inherent semantic dependencies within data, such as the closeness of vector components. Semantic attributes which helped the most in generating good results were merely identifiers. In this implementation, we identified where in a frameblock an object resided using subdivision and clipping, as well as what part of the object was shown by grouping visible faces together. Because the sets of these values are not correlated to block location, they greatly improved recognition for the AttnGAN model overall. We found the use of these identifiers impacted our results more so than any numerical attributes. To improve recognition for numerical values, such as rotation, translation, and scale, the generative model used in ADLGP must be better equipped to handle such inherent relationships.

Once the AttnGAN model was trained, we created a dataset of intermediate frames to use in training the SRGAN model. To create an intermediate frame from outputs of AttnGAN, semantic attributes of the frame were used to generate all frameblocks which were then placed into their corresponding block positions of each frame. This gave us the structural base used to train and test the SRGAN model. Because SRGAN is trained on intermediate outputs, all known training frames must be generated and trained on to completely initialize the network. Any frame generated by AttnGAN can then be fed into the initialized SRGAN model to output the final enhanced image. Retraining is only required for large changes between frames, such as changes in scene. This process was completed for the sequence of the 6 frames we evaluated, only 2 of which were known to the training dataset.

5 RESULTS

Our final results were generated from 540×540 pixel resolution frames using 4×4 pixel dimension frameblocks. Our outputs are visually very promising, as shown in Figure 5. To compare the results of the architecture between those from frame prediction and other baselines, we decided to measure differences between our outputs and the target images. A summary of these results are shown in Table 1. The AttnGAN architecture trained for 100 epochs

on each of our datasets, which contained approximately 24,000 training images. The SRGAN model was trained on the resulting 6 frames for 2000 epochs. Given the lack of training data compared to the case of AttnGAN, we found a higher number of epochs was necessary for convergence of the SRGAN architecture.

Figure 5: Sequence of six frames rendered with ADLGP for clay, gold, and glass materials. Bunny model courtesy of the Stanford University 3D Scanning Repository [Turk and Levoy 1994].

Our final results are shown in Figure 5. All images are structurally very similar to their targets. The architecture worked well for in-between frames, where the attributes of the frame were closer to those of known data. When these attributes were not highly correlated, rendering of the frame was less sharp, as in frames 5 and 6 generated by ADLGP. The closeness of generated and target frames both visually and numerically is very promising for future work in applying deep learning to the graphics pipeline, and shows the promise of ADLGP for rendering novel views of a scene.

During testing of ADLGP, We observed that extremely fine lighting and textural details were often incorrect. This is in large part due to the absence of textural and lighting information in our attributes. Future improvements to these qualities would improve ADLGP renderings. While the SRGAN model smoothed over clean edges, overall visual quality was greatly improved by the addition of the super resolution phase. In a subjective comparison, our ADLGP framework came close to or surpassed results for current frame prediction models. The Geometry-Based Next Frame Prediction model estimated scores between 24 and 25 PSNR and 0.92 and 0.93 SSIM, on average [Mahjourian et al. 2017]. Our results for PSNR exceed those ranges for most cases. The SSIM values for our highest scoring model neared 0.97 with an average value of 0.948, calculated from Table 1. SSIM and PSNR were also improved for our model when compared to STP [Finn et al. 2016] and Multi-Scale Video Prediction [Mathieu et al. 2015]. We concede there may be situations where our proposed framework performs more poorly than we recorded in our experiments. Regardless, our comparisons with current frame prediction networks show that our method has major promise and requires broader studies in future work [Zhou et al. 2020].

Table 1: Averaged results of MSE, SSIM and PSNR for intermediate and enhanced outputs. The best value of each column is shown in bold.

Intermediate Outputs			
Material	MSE	SSIM	PSNR
Clay	28.847	0.904	33.532
Gold	26.409	0.876	33.919
Glass	29.962	0.874	33.365
Enhanced Outputs			
Material	MSE	SSIM	PSNR
Clay	111.231	0.951	27.675
Gold	110.008	0.953	27.721
Glass	112.110	0.942	22.998

6 CONCLUSIONS AND FUTURE RESEARCH

In this paper, we studied the semantics available in the scene and exported the semantic information as textual attributes. Our novel approach of breaking the viewport into *frameblocks* greatly improved rendering results and reduced the chances of over-training. We explored various avenues of text-to-image translation, and described works from the related field of image-to-image frame prediction. We found that a multi-stage approach is preferable for complex image generation in most cases, where a structural image is first created and then later refined to generate the final enhanced output. Using the existing Attentional GAN [Xu et al. 2018] and Super-Resolution GAN [Ledig et al. 2017] architectures, we successfully implemented an Advanced Deep Learning Graphics Pipeline. Once trained, the pipeline was able to generate plausible novel frames without a commercial renderer. Evaluating our final results using MSE, SSIM, and PSNR, we found our approach to show great promise compared to current frame prediction strategies.

As the quality of ADLGP generated images in our paper are promising, we expect ADLGP to be implemented in the future alongside the standard graphics pipeline, as shown in Figure 2, to leverage the speed of ADLGP and remove barriers of computation inherent to the rendering process.

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