2. Literature Review

This chapter discusses the various other related works. The first part explores some state of art autonomous vehicle simulators and identifies its key features, advantages and limitations. The subsequent part summarizes about the preceding approaches for defining a metric for the comparison of Autonomous vehicle simulators. The last part of this chapter discusses about the different types of Generative Adversarial networks (GANs), a Generative AI algorithm which is applied in this thesis and highlights the key advantages in those approaches.

2.1 State of art simulators

There are numerous simulators available in the market, however this section discusses about some of the relevant and popular simulators

2.1.1 CARLA

CARLA (Car learning to act) is an open-source software developed by the Computer Vision Centre (CVC) and the Barcelona Supercomputing Centre (BSC) in collaboration with the Toyota Research Institute for research and development of autonomous driving. It provides realistic and diverse environments with various urban scenarios, climates and sensors. It is developed using unreal engine 4 for rendering high quality visual effects and OpenDRIVE standard 1.4 to define roads and urban settings. The figure 1 depicts a scene from the simulators in various weather. The key feature of this simulator is that it is built as a server client architecture. The server handles the physics and computation of simulators whereas the user can control the simulator using C++ and python APIs making it scalable. Another upside of this simulator is that it facilitates the flawless process of developing, training and validating machine learning algorithms. Various algorithms like modular pipeline, Imitation learning, Reinforcement learning [2] can be trained and validated in this simulator making it one the best choices for researchers. Moreover, it provides variety of sensor data such as cameras, Lidars, various meta data and ground truth which makes it more beneficial and handy. This simulator also provides access to various digital assets (actors) in the environment carefully designed to maintain high level of realism. However, currently it supports only 2 pre-defined urban maps with 2.9 kms and 1.4 kms of driving failing to provide diversity and generalization.

2.1.2 LGVSL

LG Silicon Valley lab (LGSVL) is developed by LG electronics as an open-source simulation engine. It uses Unity gaming engine to render photo realistic environments and also takes advantage of technologies such as High-definition render pipeline (HDRP). The simulator is developed into two parts, Simulation engine and user autonomous driving (AD) stack. The simulation engine is open source and it receives input from the AD stack and simulates the environment, sensors and vehicle. The AD stack consist of three parts Perception, planning and control which can be configured by user. The AD stack and simulation engine are connected through communication bridge interface such as Cyber RT. The simulator comes with various default set of sensors such as camera Lidar, Radar… However, the one of the key feature of this simulator is that the user can built and configure their own sensor. In addition to default sensors, Model of real world sensors can be imported as a plug in. For Example, Velodyne VLP-16 LiDAR generate point clouds in the same format as real sensors. The sensor data and its position can be exported and defined using JSON formatted text which make it easy to use The unique feature of this simulator is it’s ability to use real world maps to build the environment. Maps in formats like Lanelet2, OpenDRIVE and Apollo 2 HD map can be and used as the virtual environment. This makes it more suitable for researchers in OEMs

2.1.3 SUMMIT

A Simulator for Urban Driving in Massive Mixed Traffic (SUMMIT) a open source simulator developed as an extension of CARLA simulator inheriting its physics and visual realism. It uses Python based APIs to communicate with CARLA Most of the other simulators simulates a rule-based traffic where all the actors acts according to a rule with minimal degree of randomness. However, the real world traffic is comparatively aggressive and chaotic. The distinguishable feature of SUMMIT is that is simulates the aggressive and chaotic behaviour of the traffic in real world. This attracts users who are interested in training and testing the algorithms which drives vehicles in un regulated traffic. In this simulator, a crowd behaviour algorithm “Context - GAMMA”, a velocity – space optimization algorithm is used to simulate the traffic behaviour geometrically and topologically. Moreover, it uses the real world map from OpenStreetMap to extract features such as roads, sidewalks, roundabouts, which can be further used in the simulator to replicate real world maps. The figure3 shows the Real map and its counterpart with un regulated traffic behaviour in SUMMIT of Magic- Roundabout, England. This feature of using real world map and taking advantage of Visual realism from CARLA and simulating chaotic traffic behaviour makes it even powerful.

2.2 Comparative study on simulators

This section will analyse some other work involving in comparative study of Autonomous vehicle simulators and summarizes the analysis

In the work of Guan Yang, et.al., (2021) in the “Survey on autonomous vehicle simulation platform”, the team had conducted an extensive research on various autonomous vehicle simulation platform. They had broke down the objective of the simulator into 5 parts i.e., Static environment simulation, Dynamic environment and behaviour simulation, Traffic flow simulation, Sensor simulation and vehicle dynamics simulation. Moreover, for they have defined a taxonomy for existing simulator, They categorized the simulation platform into Point cloud based and 3D engine. Point based simulators are the one which simulates the sensory data and reconstructs the environment based on sensor data. Some example of this simulators are CarCraft from Waymo and Apollo from Baidu. Figure 4 shows the map from Apollo a point based simulation platform, whereas 3d engine based platform uses gaming 3 d engines such as Unity, Unreal to render a environments in accordance with laws of real physics. Figure 5 shows a map of PanoSim, a 3d engine based simulator. A Table with comparision simulators and its available feature is framed and the same is shown in figure 6. Thoug this table compares helps to compare the simulators the no of features is not enough for a concrete decision and there is no single metric which define the useability of that simulator to the user. It provides a categorization of simulators but a comparative method among simulator is not clearly defined

In the work of Md Salman Ahmed et.al (2016), an extensive research on connected vehicle simulator was discussed. The domain of connected vehicles includes Vehicle to vehicle communication, vehicle to server communication… and requires a simulator to train as it will be expensive to train in real world. In this paper several simulators which simulates the Vehicle communication system and compared based its memory consumption, computing environment (Sequential or Parallel) and no. of vehicles it can handle and the results are summarized. However these results corresponds to a specific domain of Connected and this method cannot hold for any other type of AV simulators.

2.3 Generative Advesarial Networks

Generative adversarial networks (GAN) is a Generative AI algorithm introduced in 2014 by Goodfellow et.al in the paper “Generative Adversarial Networks” [7]. From then it gained momentum in domain of Generative AI. In this Section, Some of the notable works in GANs will be discussed

2.3.1 VGAN

Video Genarative Adversarial Network (VGAN) was developed by Carl Vondrick [8] which generates videos with its scene dynamics. This model could generate video upto a second at full frame rate. The model is trained on over preprocessed 2 million videos available on the internet and categorized into 4 categories: Golf course, hospital room, beaches, train station. In terms of architecture the model uses a standard Genereator discriminator architecture. The generated video is segmented into 2 feautres, foreground and background and the authors assumes the camera to be static which results in static background. The generator is developed into two streams for foreground and background respectively. The foreground stream uses 5 layers of 3d spatio temporal convolution layer (time x width x height) with up samples f from a low dimensional latent code z sampled from standard normal distribution. A masking layer m is added before the last layer which describe the pixels of object in foreground. The second stream for background generate uses a 5 layer strided 2d convolution layers (width x height) and generates a background b. 2D convolution layer is used as the background is assumed to be static. The Foreground and background are synthesised using the as per the equation

The video of 32 frames with the dimension of 64x64 is generated from a 100 dimensional latent code sampled from a normal distribution. The Discriminator is designed to solve 2 problems, it should classify realistic scene and to recognize plausible motion between frames. In terms of architecture the same 5 layered spatio-temporal convolutional layers used in foreground generation in generator is used as discriminator with the replacement of downsampling instead of upsampling and the last layer outputs a binary classification (real or not). Batch normalization and ReLU activation function is used after every layer in generator and discriminator. The model was trained using Adam optimizar and with a batch size of 64. The results show that the model can able to generate videos with sharp background and a blurry foreground. The Figure 7 shows the results of various generated videos. Though the resolution of foreground is blurry, the dynamics of the generated foreground is plausible and convincing and the user doesn’t have control over the content of generation.

2.3.2 ImaGINator

ImaGINator is a conditional GAN developed to generate videos of human faces with different expressions by Yaohui Wang et.al. The video generated is conditioned on class label denoting expressions Unlike VGAN [8], the generated video is segmented into spatial and temporal information as a hypothesis. In terms of construction the ImaGINator has a generator and 2 discriminator. The Generator is designed to be encoder decoder architecture , with skip connections, The Generator accepts a static image with a face of a person and encodes onto a latent vector p. The one hot encoded class label is concatenated into the latent vector. In this way the spatial and temporal information are embedded into the laten vector. In addition a random noise sampled from a standard normal distribution is concatenated onto the latent vector. The decoder is designed to be (1+2) D convolution layer, explicitly splitting temporal and spatial information. Moreover, it mirrors the encoder architecture and skip connections for feature maps are designed from every layer in encoder to its corresponding decoder layer. In addition, the embedded class label vector is also passed to every layer in decoder, which makes sure that every layer in decoder has embedded spatial and temporal information. The no of frames in the generated video is fixed and outputs one step at time.

Two Discriminator are used with each has its unique purpose, The discriminator Di takes the frames of the generated video and classifies it real or fake base on its apperance, whereas the Discriminator Dv takes the all the frames in order and the class label as input and classifies the dynamics in the frame real or fake. The combined loss function from both the discriminator and the reconstruction loss for corresponding frames are used to optimize the generator and each discriminator loss is used to optimize the corresponding discriminators. ADAM optimizer with same learning rate is used for all generators and discriminator trainings. Various Evaluation metrics like Frechet Inception Distance (FID), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure are used to evaluate the performance of generated videos and to monitor the training. Figure 8 illustrates the frames of the generated video. The Model is trained on various popular datasets like MUG Facial expression dataset, NATOPS aircraft handling signal dataset, Weizmann Action dataset, UvA -NEMO smile dataset are used for training and the results are compared. In terms of Image quality this method had outperformed the VGAN , Moreover the content of the generated video can be controlled using class labels which finds various application.

2.3.3 MoCoGAN

MoCOGAN is Video Generation GAN proposed by Sergey Tulyakov et. al. in 2016. This GAN architecture has segmented the video into Content and Motion and sample input from the Content Subspace and Motion subspace respectively. This unique architecture equip the Model to generate videos of a same content different action and same action by different content. This GAN is designed to generate videos of shorter duration but the duration of the video is need not to be fixed length. Considering the fact that the duration of the video is shorter, the subject in the video is designed to be remain the same. In terms of architecture, the model has 4 networks, a Recurrent Neural Network Rm, Generator G1, Image Discriminator Di, Video Discriminator Dv. The Generator generates images sequentially frame by frame. It takes latent image Z as input which contains zc, zm. The Random vector zc corresponds to content in the video is sampled from the standard normal distribution and it is used for all the times, as the subject in the video is constant. The latent vector Zc is generated by Rm recursively by sampling from standard normal distribution at every timestep. The Network generates a trajectory in the motion subspace which results in the motion of the subject in the video. The parameters of the Rm is learned during the training as not all the motion trajectory is actually possible. The Zc and Zm is fed into the generator which generates video frames. The Image discriminator evaluates the quality of images in each frame, whereas the video discriminator evaluates the motion of the subject in the video. The RNN network is trained solely on Video discriminator loss and the entire Generator network is trained on the combined loss of the discriminators. The Model is trained on Weizmann Database [15] and Tai-Chi database and the performance evaluation was summarized. The Average Content distance (ACD) is used for evaluation. Figure 9 shows the frames of video clips generated from then MoCoGAN model. It had outperformed the VGAN and TGAN in terms of quality of images in the video. Moreover it has the advantage of generating videos of variable length. However, the control over the content creation is missing as it is sampled randomly from the motion subspace.

2.3.4 pix2Pix GAN

Pix2Pix is an image translation techinique introduced in 2016 by Philip Isola et al [11] which uses Conditional GAN. Image translation is the method of transferring image in one domain to other. For example, translating grayscale image to colour images. In the paper [12], the author had used this method to translate satellite terrain images to google map style images. The conditional GAN has similar structure to Normal GAN, with a Generator and a discriminator. In terms of architecture, the generator is built using a encoder decoder architecture. The encoder and decoder are built using blocks, each block contain a convolution layer, Batch norm and ReLU activation function. The decoder part is mirrored version of encoder, where every layer in the decoder is connected with encoder through the skip connection referred to a U-Nets. This architecture prevents the loss of information from input to output layer when flowing only through a bottle neck [11]. The Generator is designed to take image from input domain and outputs image in target domain. The discriminator takes paired images from both the domain as input. It uses a standard convolutional layer with a final layer predicting weather the given image is real/fake. The discriminator segments the image in 70x70 patches and the outputs binary classification for each patch, this type of Gan is called PatchGAN. Reconstruction loss between the generated image and the target image is computed and the gradients of the generators are optimized to reduce this reconstruction loss. The composed model is trained on weighted sum of Discriminator loss and reconstruction loss. The model is trained on the satellite image to google map image dataset with 1097 images. Figure 10 illustrates the satellite images and its corresponding google map images and generated image after 10 epochs. This problem of image translation finds application in various fields. However, this method demands paired dataset which is difficult to obtain in various scenarios.

**CLEAN TEXT**

2. Literature Review

This chapter explores different works related to the topic. The initial section examines the existing state-of-the-art autonomous vehicle simulators. The second part provides a summary of previous methodologies used to define a comparative metric for evaluating autonomous vehicle simulators. The last part of this chapter discusses about the different types of Generative Adversarial networks (GANs), a type of Generative AI algorithm utilized in this thesis. It identifies the key advantages associated with these approaches.

2.1 State-of-the-Art Simulators

Numerous simulators are available in the market, but this section highlights some relevant and popular simulators and highlighting their advantages, limitations and applications.

2.1.1 CARLA

CARLA, (Car Learning to Act) is an open-source software developed collaboratively by the Computer Vision Centre (CVC) and the Barcelona Supercomputing Centre (BSC) in partnership with the Toyota Research Institute. It is primarily designed for autonomous driving research and development, which provides diverse and realistic environments, various climates and wide range of sensors. CARLA operates on a server-client architecture, built on Unreal Engine 4 and utilizing the OpenDRIVE standard 1.4 to define roads and urban settings. This unique structure allows the server to manage simulator physics and computation while enabling user to communicate the server through C++ and Python APIs, providing scalability.

A notable feature of CARLA is its seamless support for developing, training, and validating machine learning algorithms. Researchers can employ various algorithms like modular pipelines, imitation learning, and reinforcement learning within this simulator [2], making it a preferred choice for researchers. Leveraging Unreal Engine 4, CARLA offers high-quality, realistic rendering of environments. Figure 1 showcases scenes from the simulator in different weather conditions. Additionally, it provides an array of sensor data such as cameras, LiDAR’s, various metadata, and ground truth, enhancing its useability. Moreover, CARLA offers access to diverse digital assets (actors) within the environment, meticulously designed to maintain a high level of realism. However, it currently offers support for only two pre-defined urban maps covering 2.9 km and 1.4 km, which limits its diversity and generalization capabilities.

Figure1: Scenes from the CARLA simulator in different weather conditions.

2.1.2 LGVSL

LG Silicon Valley Lab (LGSVL) is an open-source simulation engine developed by LG Electronics. It utilizes the Unity gaming engine to render photorealistic environments and taking advantage of technologies like the High-Definition Render Pipeline (HDRP) from Unity.

This simulator is developed in two parts: the Simulation Engine and the User Autonomous Driving (AD) Stack. The Simulation Engine, an open-source platform, receiving its inputs from AD stack and simulate the environment, sensors, and vehicle dynamics. The AD Stack comprises three key elements: Perception, Planning, and Control, offering various user-configurable functionalities. The AD Stack and the Simulation Engine is connected through communication bridge interface, such as Cyber RT, ensuring seamless integration. While the simulator comes with a default sensors including cameras, LiDAR, and Radar, its unique feature lies in its adaptability. Users can build and configure their own sensors, even importing models of real-world sensors as plugins. For instance, the plugin for Velodyne VLP-16 LiDAR replicates point cloud generation similar to its actual counterpart [3]. These sensors' data and its positions are defined through JSON-formatted text, simplifying their utilization. Figure 2 showcases the array of default sensors accessible within this simulator.

Figure 2: Different types of sensors. Left (top to bottom): Fish-eye camera,LiDAR, Radar; Right (top to bottom): Segmentation, Depth, 3D Bounding Box.

A distinguishing aspect of this simulator is its capability to incorporate real-world maps to construct virtual environments. Map formats like Lanelet2, OpenDRIVE, and Apollo 2 HD map can be imported and used as the virtual environment. This features of LGSVL appeals to engineers of automakers and making it a highly suitable tool for their research.

2.1.3 SUMMIT

SUMMIT (The Simulator for Urban Driving in Massive Mixed Traffic) is an open-source simulator developed as an extension of the CARLA simulator, inheriting its physics and visual realism. Unlike many other simulators that predominantly simulate rule-based traffic with minimal randomness, SUMMIT stands out for its ability to replicate the aggressive and chaotic nature of real-world traffic. This distinctive feature attracts users interested in training and testing algorithms for vehicles navigating unregulated traffic scenarios. SUMMIT employs the 'Context-GAMMA', a velocity-space optimization crowd behaviour algorithm [4] to geometrically and topologically simulate traffic behaviour. Additionally, it utilizes real-world maps from OpenStreetMap, extracting features such as roads, sidewalks, and roundabouts. These features are then incorporated into the simulator, enabling the replication of real-world maps. An illustrative example can be seen in Figure 3, which showcases the comparison between a real map and its counterpart with unregulated traffic behaviour in SUMMIT at the Magic Roundabout in England.

Figure3: Scenes in the real world and corresponding scenes in SUMMIT

SUMMIT's utilization of real-world maps, combined with CARLA's visual realism and the simulation of chaotic traffic behaviour, significantly enhances its capabilities.

2.2 Comparative Study on Simulators

This section examines notable studies that compare autonomous vehicle simulators and summarizes their results.

In Guan Yang et al.'s work (2021), "Survey on Autonomous Vehicle Simulation Platforms," [5] the team extensively researched different autonomous vehicle simulation platforms. They broke down the simulator's objectives into five parts: Static environment simulation, Dynamic environment and behaviour simulation, Traffic flow simulation, Sensor simulation, and Vehicle dynamics simulation. They also established a taxonomy for existing simulators, categorizing them into Point Cloud-based and 3D Engine-based platforms. Point-based simulators, such as CarCraft from Waymo and Apollo from Baidu, reconstruct the environment based on sensor data. Figure 4 displays the map from Apollo, a point-based simulation platform. On other hand, 3D engine-based platforms, like PanoSim, utilize gaming engines like Unity and Unreal to render environments following laws of physics (Figure 5).

Figure 4: Scene from Apollo simulator

Figure 5: Scene from PanoSim simulator

They further created a table comparing simulators and their available features [5] (Figure 6) .

Figure 6 : A Comparison table of various simulator

Although this table aids in comparing simulators, it doesn’t compare sufficient features for making a concrete decision, and lacks a single metric defining the level of usability of the simulator for a user. While the categorization of simulators is provided, a clear comparative method among simulators is not clearly defined.

In Md Salman Ahmed et al.'s work (2016), an extensive study on connected vehicle simulators was presented [6]. The focus was on the domain of connected vehicles, including vehicle-to-vehicle and vehicle-to-server communication. The paper assessed several simulators based on their memory consumption, computing environment (Sequential or Parallel), and the number of vehicles they could handle. However, these results are specific to the connected vehicle domain and may not be applicable to other types of autonomous vehicle simulators.

2.3 Generative Adversarial Networks

Generative adversarial networks (GAN) marks a significant advancement in the domain of Generative AI, first introduced by Goodfellow et al. in their 2014 paper "Generative Adversarial Networks" [7]. Since then, GANs have gained substantial momentum in the field of Generative AI especially in image generation. This section discusses some noteworthy works within the domain of GANs.

2.3.1 VGAN (Video Generative Adversarial Network)

VGAN, developed by Carl Vondrick et al. [8], specializes in generating videos with its scene dynamics. The model is capable of generating videos up to a second at full frame rate. Its training involves utilizing over 2 million pre-processed videos sourced from the internet, categorized into four distinct groups: golf courses, hospital rooms, beaches, and train stations.

The architecture of VGAN employs a standard Generator-Discriminator structure. The generated video is segmented into two features: foreground and background, assuming a static camera resulting in a static background. The generator comprises two streams dedicated to foreground and background, respectively. The foreground stream consist five layers of 3D spatiotemporal convolution layers (time x width x height), which upsamples the information from a low-dimensional latent code z, sampled from a standard normal distribution. A masking layer 'm' is introduced before the final layer, outlining the pixels of objects in the foreground. Meanwhile, the background stream utilizes five layers of 2D convolution layers (width x height), responsible for generating a background 'b'. The background stream uses 2D convolution layers as the background is assumed to be static. The synthesis of foreground and background follows the equation

The resultant video, comprising 32 frames with dimensions of 64x64, is generated from a 100-dimensional latent code sampled from a normal distribution. The Discriminator is designed for two primary objectives: classifying realistic scenes and recognizing plausible and smooth motion between frames. It mirrors the architecture of the foreground stream of generator with a five-layered spatiotemporal convolutional setup, employing downsampling instead of upsampling. The final layer outputs a binary classification (real or not). Batch normalization and ReLU activation functions are used after every layer in both the generator and discriminator.

The GAN is trained using Adam optimizer with a batch size of 64. Results demonstrate the model's ability to generate videos with a sharp background and a slightly blurry foreground. While the resolution of the foreground might be blurred, the dynamics of the generated foreground are convincing, but the user had no control over the content of generation. Figure 7 illustrated the frames of various generated videos.

Figure 7: Videos generated using VGAN

2.3.2 ImaGINator

ImaGINator is a conditional Generative Adversarial Network (GAN) developed by Yaohui Wang et al [9]. Its primary aim is to produce human videos depicting various expressions. Unlike VGAN [8], this model generates videos conditioned on specific class labels for expressions. The generated videos are segmented into spatial and temporal segments. ImaGINator comprises a generator and two discriminators. The generator adopts an encoder-decoder architecture with skip connections. It takes a static image featuring a person's face and encodes it into a latent vector 'p'. In addition, this vector is concatenated with one-hot encoded class label c, representing the expression, and random noise sampled from a standard normal distribution. This fusion embeds spatial (p) and temporal information (c) into the latent vector. The decoder, structured as a (1+2)D convolution layer, explicitly separates temporal and spatial information. It mirrors the dimensions of the encoder's architecture and had skip connections from encoder, ensuring that each decoder layer retains embedded spatial details. Moreover, the embedded class label vector is integrated into every decoder layer, ensuring the preservation of temporal information throughout the model. The generated video consists of a fixed number of frames and the last layer of the generator outputs an image with all the frames.

Two discriminators serve distinct purposes: 'Di' evaluates individual frames of the generated video to classify real from fake based on appearance, while 'Dv' examines the sequence of frames alongside the class label to classify the dynamics within the frames as real or fake. The Generator is optimized on the combined loss function from both discriminators and a reconstruction loss for corresponding frames. Each discriminator's loss function optimizes its corresponding discriminator. The ADAM optimizer with the same learning rate is used across all generator and discriminator components.

Evaluation metrics such as Frechet Inception Distance (FID), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure are used to evaluate the performance of the generated videos and to monitor the training progress. Figure 8 in the document provides a visual representation of the frames within the generated video.

Figure 8: Frames of the video generated using ImaGINator

The model was trained on various widely used datasets like MUG Facial Expression Dataset [13], NATOPS Aircraft Handling Signal Dataset [14], Weizmann Action Dataset [15], and UvA-NEMO Smile Dataset [16]. Comparative analysis shows the superior image quality compared to VGAN. Furthermore, the model's ability to control the content of generated videos using class labels holds significant potential across various applications.

2.3.3 MoCoGAN

MoCOGAN, a Video Generation GAN introduced by Sergey Tulyakov et al. in 2016 [10], operates on a unique architecture that segments videos into Content and Motion. This segmentation allows the model to sample inputs separately from the Content and Motion subspaces (unsupervised). Notably, this architecture enables the model to generate videos depicting the same content with different actions or the same action with different content. While designed for shorter video durations, MoCOGAN doesn't require a fixed length for the generated videos. Given the shorter duration, the video's subject is assumed to remain constant.

The model comprises four networks: a Recurrent Neural Network (Rm), Generator (G1), Image Discriminator (Di), and Video Discriminator (Dv). The Generator sequentially produces frames by taking a latent image Z as input, containing zc and zm. The random vector zc represents the video's content and is sampled from a standard normal distribution, remaining constant throughout the video as the subject remains unchanged. On the other hand, the latent vector Zc, which determines the motion trajectory of the subject, is recursively outputted by Rm by sampling from a standard normal distribution at each timestep.

The Rm's parameters are learned during training, as not all motion trajectories are physically possible. Zc and Zm are inputted into the generator to produce video frames. The Image Discriminator assesses frame quality, while the Video Discriminator evaluates subject motion in the video. The RNN is trained exclusively on the Video Discriminator loss, while the entire Generator network is trained on the combined loss of the discriminators.

The model's training utilizes the Weizmann Dataset [15] and Tai-Chi Dataset [17], and its performance was assessed using the Average Content Distance (ACD). Visual representations in Figure 9 depict video clip frames generated by the MoCoGAN model.

Figure 9: Frames of video generated by MoCoGAN

Notably, MoCoGAN had outperformed VGAN [8] and TGAN in image quality within the videos and offers the flexibility of generating videos of varying lengths. However, it lacks direct control over content creation like ImaGINator as content is randomly sampled from the

2.3.4 Pix2pix GAN

Pix2Pix, introduced in 2016 by Philip Isola et al [11], is an image translation technique using Conditional GANs. Image translation involves transforming images from one domain to another, such as converting grayscale images to colour images. In [12], the method was applied to translate satellite terrain images into Google Maps style images.

The structure of the conditional GAN resembles that of a Normal GAN, comprising a Generator and a Discriminator. In [12], the generator adopts an encoder-decoder architecture, consisting of blocks that include a convolution layer, Batch Normalization, and ReLU activation function. The decoder mirrors the encoder, employing skip connections (known as U-Nets) between corresponding layers to retain information and prevent loss during transmission through bottle necks [11]. The Generator takes an image from the input domain and produces an image in the target domain. On the other hand, the Discriminator intakes the paired images from both domains, uses standard convolutional layers, converging in a final layer that determines the given image (real or fake). Using PatchGAN, the Discriminator segments images into 70x70 patches and performs binary classification for each patch making the discriminator suitable for any given image size.

Training involves computing the reconstruction loss between the generated image and the target image. The generator's gradients are optimized to minimize this loss. The composed model training combines the Discriminator loss and the reconstruction loss using a weighted sum. The dataset used for training, consisting of 1097 paired images of satellite and Google Maps images. Each image is pre processed and rescaled to 256X256 pixels before training. Figure 10 illustrates the satellite images and its corresponding google map image and generated image.

Figure 10: The satellite images and its corresponding google map image and generated image after 10 epochs

While image translation using this method has diverse applications, this method often requires paired datasets, which is difficult to obtain in various scenarios.

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