# 2D HUMAN ANIMATION SYNTHESIS FROM VIDEOS USING GENERATIVE ADVERSARIAL NEURAL NETWORKS.

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#### **Declaration**

I declare that this dissertation does not incorporate, without acknowledgment, any material previously submitted for a Degree or a Diploma in any University and to the best of my knowledge and belief, it does not contain any material previously published or written by another person or myself except where due reference is made in the text. I also hereby give consent for my dissertation, if accepted, to be made available for photocopying and for interlibrary loans, and for the title and summary to be made available to outside organization.

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Supervised by	
Dr.Subha Fernando	Signature of the Supervisor
	Date:

## **Dedication**

I dedicate this thesis to my parents and my wife who were there for me for my successes and failures.

#### Acknowledgment

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Many thanks to my adviser Dr. Subha Fernando for her effort, patience and wisdom, and guidance provided throughout the project. Her expertise was the guiding light that enabled me to successfully formulate the research question and the methodology.

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#### **Abstract**

Synthesizing 2D human animation has many industrial applications yet is currently done manually by animators utilizing time and resources. Therefore, many types of research have been conducted to synthesize human animation using artificial intelligence techniques. However, these approaches lack the quality as well as capability to generalize to various visual styles. Thus, synthesizing high-quality human animations across different visual styles remains a research challenge

We hypothesize that given video references for motion and appearance, synthesizing high-quality human animations across a variety of visual styles can be achieved via generative adversarial networks.

Here we have come up with the solution known as HumAS-GAN, an acronym for **Hum**an Animation Synthesis Generative Adversarial Networks. HumAS-GAN accepts video references for motion and appearance and synthesis 2d Human animations. HumAS-GAN has three main modules, motion extraction, motion synthesis, and appearance synthesis. In motion extraction, the motion information is extracted via pre-trained human pose extraction [21], The motion synthesis module syntheses a motion representation matching the target human's body structure which is then combined with the human pose coordinates to be used by the appearance synthesis module to generate the Human animation. HumAS-GAN is focused on improving the quality of the animation as well as the ability to use cross-domain/visual-style references to generate animation. This solution will be beneficial for many multimedia-based industries as it is capable of generating high human animations and quickly switching to any visual style they prefer.

HumAS-GAN is evaluated against other methods using a custom dataset and a set of 3 experiments designed to evaluate the capability of generating human animations across various visual styles. Evaluations results prove the superiority of HumAS-GAN over other methods in synthesizing high-quality 2d human animations across a variety of visual styles.

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### **Abbreviations**

GAN Generative Adversarial Network

CGI Computer Generated imagery

Human Animation Synthesis Generative

Adversarial Network

cGAN Conditional Generative Adversarial Network

GPU Graphics Processing Unit

HD High Definition

SSIM Structural Similarity Index Measure

LPIPS Learned Perceptual Image Patch Similarity