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RAJAGIRI SCHOOL OF
ENGINEERING & TECHNOLOGY
(AUTONOMOUS)

Project Phase II Report on

**Learning to dance: A graph convolutional adversarial
network to generate realistic dance motions from
audio**

*Submitted in partial fulfillment of the requirements for the
award of the degree of*

Bachelor of Technology

in

Computer Science and Engineering

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CERTIFICATE

*This is to certify that the project report entitled "**Learning to dance: A graph convolutional adversarial network to generate realistic dance motions from audio**" is a bonafide record of the work done by **Gowri Sen (U2003090)**, **Gautham Sanil (U2003082)**, **Iris Orris (U2003097)**, **Joyce Boban (U2003112)**, submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

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Abstract

In this project, Graph Convolutional Networks (GCN) is used to synthesize realistic human dance motions from audio signals. By leveraging GCN for motion modeling and SoundNet for music style feature extraction, the method enables the generation of diverse and high-quality dance movements. The results demonstrate superior performance compared to existing methods, with a user study confirming the similarity of generated motions to real dance movements. The dataset and methodology presented in this work pave the way for advancements in generating human motions, with future plans to extend the method to infer 3D motions and expand the dataset with additional dance styles. The architecture manages audio data to synthesize motion, using a 1D-CNN classifier to define the input music style and a spatial-temporal correlated latent vector generated by a Gaussian process to condition a GCN architecture. The GCN is trained in an adversarial regime to predict 2D human body joint positions over time. The proposed method addresses the challenge of synthesizing motions from audio, providing plausible movements while maintaining the characteristics of different dance styles. The advantages of the method include its simplicity, ease of training, and the capability to generate more realistic motion styles. In comparison with the state-of-the-art method (D2M), the proposed approach outperforms the competitor. The user study shows that the proposed method received similar scores to real dance movements, indicating its capability to generate high-quality and recognizable dance motions. Therefore, the proposed method shows significant advancements over the state-of-the-art technique in human motion synthesis from music.

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List of Abbreviations

- GP: Gaussian Process
- CNN: Convolutional Neural Network
- FID: Fréchet Inception Distance
- 2D: Two-Dimensional
- U-Net: Convolutional Neural Network architecture
- GCN: Graph Convolutional Network
- CVPR: Conference on Computer Vision and Pattern Recognition
- ICML: International Conference on Machine Learning
- TVCG: IEEE Transactions on Visualization and Computer Graphics
- LSTM: Long Short-Term Memory
- GAN: Generative Adversarial Network
- D2M: Dance Dance to Music

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Chapter 1

Introduction

Providing reliable animation for virtual avatars, especially in the context of human motion, is a challenge in computer graphics, and this has led to the development of a new architecture for synthesizing human motion from auditory data. The aim of this work is to use networked network (GCN) and conflict learning to process data at different times. The basis of this study is the creation of multimodal files containing audio links, movement data and videos of dancers to different music. We aim to go beyond the most advanced methods to create unique and diverse campaigns. This introduction sets the stage for the goals of the project regarding the need for progress in human locomotor synthesis and the potential of the proposed method to meet this challenge.

1.1 Preamble

As a project aimed at advancing the field of human motion synthesis, our goal is to develop a novel architecture for generating diverse and realistic movement styles from auditory data. By leveraging a conditional graph convolutional network (GCN) and adversarial learning, we aim to surpass the limitations of existing methods and contribute to the evolution of human motion synthesis. Additionally, the creation of a multimodal dataset containing paired audio, motion data, and videos of people dancing different music styles will enable us to train and evaluate the proposed architecture effectively. Our project is motivated by the enduring challenge in Computer Graphics of providing plausible animations to virtual avatars, particularly in the context of human motion, and we are committed to addressing this challenge through innovative and impactful research.

1.2 Project Statement

The project aims to develop a novel architecture for synthesizing human motion from auditory data, with a focus on generating realistic and diverse movement styles. This will involve leveraging a conditional graph convolutional network (GCN) and adversarial learning to surpass the limitations of existing methods. The project will likewise involve generating a multimodal dataset that comprises of paired audio, motion data, and videos showing individuals dancing different music genres as a means of testing and assessing the suggested framework. The ultimate goal is to contribute to advancements in human motion synthesis, with potential applications in virtual avatars, animation, and entertainment industries.

1.3 Problem Definition

The aim of this project is to develop a new model for the synthesis of human movements from auditory data, focusing on creating realistic and diverse movements.

1.4 Scope and Motivation

Scope: The scope of this project encompasses the development of a cutting-edge architecture for synthesizing human motion from auditory data, with a specific emphasis on diverse dance styles. The project will engage creating and applying a multimodal dataset involving coupled audio, motion data, and videos displaying people practicing different music styles in dance steps. The architecture will be designed to surpass the limitations of existing methods and enable the generation of realistic and diverse movement styles. Additionally, the project will explore the potential extension of the method to infer 3D human motions and expand the dataset by adding more dance styles, thereby broadening the scope of applicability.

Motivation: The motivation behind this project stems from the enduring challenge in Computer Graphics of providing plausible animations to virtual avatars, particularly in the context of human motion. The limitations of existing methods in capturing the rich spatiotemporal distribution and endless variety of different motions have motivated the exploration of a novel architecture that leverages auditory data to enhance the re-

alism and diversity of synthesized human motion. By addressing these limitations and surpassing the state-of-the-art methods, the project aims to contribute to advancements in human motion synthesis, with potential applications in virtual avatars, animation, and entertainment industries.

1.5 Objectives

- To Device a method for synthesizing human motion from music using graph convolutional networks (GCN) trained with an adversarial regime.
- To create a mock-up model that is supported by GCN and is taught in a disputable way to produce human postures rows.
- To train a 1D-CNN classifier that characterizes the musical genre of the input and then merge the outcome of classification with a spatial-temporal correlated latent vector modeled using a Gaussian process (GP).
- To propose an architecture that manages audio data to synthesize motion and control the style of the movement using audio data while preserving the plausibility of the final motions.

1.6 Purpose and Need

Purpose: The purpose of our project is to address the enduring challenge in Computer Graphics of providing plausible animations to virtual avatars, particularly in the context of human motion. By developing a novel architecture for synthesizing human motion from auditory data, we aim to contribute to advancements in human motion synthesis, with potential applications in virtual avatars, animation, and entertainment industries.

Need: There is a pressing need to surpass the limitations of existing methods in capturing the rich spatiotemporal distribution and endless variety of different human motions. The limitations of current approaches have motivated the exploration of a novel architecture that leverages auditory data to enhance the realism and diversity of synthesized human motion. Our project is driven by the need to develop a cutting-edge

solution that can generate realistic and diverse movement styles, thereby addressing the challenges in human motion synthesis and advancing the field of Computer Graphics.

1.7 Assumptions

- The model assumes that the human skeleton can be represented as a graph structure, where each joint corresponds to a node in the graph.
- The dataset used for training and evaluation contains paired audio, motion data, and videos of people dancing different music styles.
- It assumes that conditioning the movement distributions on audio data can effectively capture and generate realistic human motions.
- The model assumes that human motions can be accurately represented and synthesized using a graph-structured model.
- The model assumes that the temporal and spatial relationships in human movements can be effectively learned and represented using graph convolutional networks.

1.8 Organization of the Report

The report begins with an introduction that provides context, outlines the problem and the scope and motivation for the project. It also underscores the assumptions and challenges undertaken in the process of generating realistic dance motions. The next section details the design principles for fusing human motion from audio data, including the role of different data sources and the use of linear networks, connections (GCNs), and learning conflicts. In the evaluation section, various indicators used to evaluate user studies and design are presented, and the results are carefully analyzed and compared with existing methods. The Results and Discussion section examines the results and quantitative measurements of user studies, describing the results and their implications for the advancement of human mobility. The conclusion presents the main findings and contributions of the project, discusses practical implications and future directions, and offers conclusions and recommendations for research. The report also includes a comprehensive

list of references and appendices that contain additional information such as detailed references and testimonials. To sum up, this chapter gave a thorough review of the state of the research, including the study's background, problem definition, scope, and motivation. The outlined goals and recognised difficulties prepared the groundwork for the discussion of important topics in the sections that followed. We emphasised the work's industrial importance while detailing the study process's underlying assumptions. The reader is guided towards a fuller comprehension of the research objectives and the context in which they are pursued by this foundational chapter, which also establishes the platform for the discussions and analyses that follow.

Chapter 2

Literature Survey

2.1 Learning to dance: A graph convolutional adversarial network to generate realistic dance motions from audio

2.1.1 Introduction

The paper [1] discusses about the challenges of providing realistic animations to virtual avatars has been a longstanding issue in Computer Graphics. Human motion, with its diverse spatiotemporal distribution and complex situational influences, presents a significant modeling challenge. Traditional motion capture systems have limitations in capturing the rich variety of human movements affected by factors such as auditory perception, physical conditions, and cultural background.

In response to this challenge, motion synthesis through learning techniques has gained popularity for applications in graphic animation, robotics, and multimodal graphic rendering engines. This has led to the emergence of Graph Convolutional Networks (GCNs) as a powerful tool for modeling human movements and classifying actions.

Within this framework, there is a new approach suggested on deriving human movements from music via graph convolution networks using an adversarial setting. The method is designed to produce motion styles that simulate actual movements and are measured using various quantitative metrics. It always has an upper hand over other methods in terms of perception of motion

2.1.2 Methodology

The methodology involves using graph convolutional networks trained with an adversarial regime to synthesize human motion from music. The approach conditions the motion generation on audio data and aims to produce realistic human movements with respect to a

specific dance style. The technique is analyzed according to both qualitative and quantitative performance measures in comparison with the leading Dancing to Music as the state of art approaches. The results have shown that the motion perception performance of the proposed method surpasses the performance of motion perception exhibited by other methods already available. Apart from this, it is evident that the method is capable of creating real movement examples

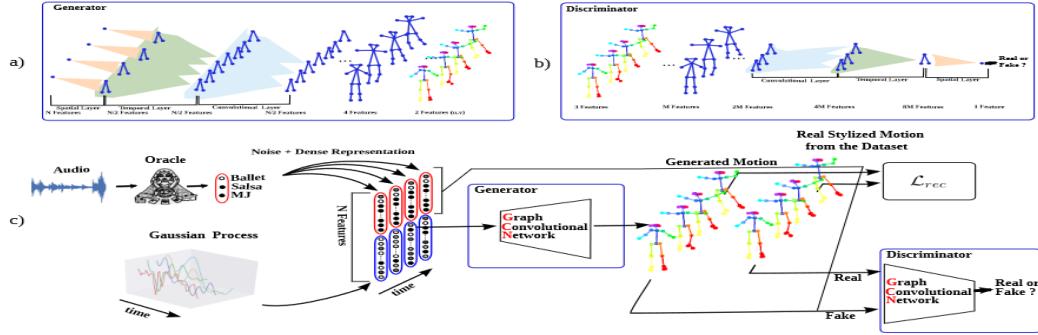


Figure 2.1: Architecture diagram 1

2.1.3 Conclusion

The proposed method for synthesizing human motion from music using graph convolutional networks trained with an adversarial regime has demonstrated significant advancements in motion generation. The approach successfully conditions motion generation on audio data, producing realistic human movements aligned with specific dance styles. Comparative evaluations against state-of-the-art methods indicate superior qualitative and quantitative performance, showcasing the method's ability to create highly discriminative and plausible dance movements. Overall, the approach presents a promising direction for synthesizing human motion from music, offering potential applications in various domains such as graphic animation and multimodal graphic rendering engines.

2.2 Music-Driven Choreography Generation Using Autoregressive Encoder-Decoder Network

2.2.1 Introduction

The paper [2] introduces a neural network centred approach for producing brand new and organic dances modeled with vast data collected from an online video sharing community. The model plans on acquiring the information about the relationship between music and dance through employing an auto-regressive encoder-decoder network that generates choreography reflecting the periodicity of music. The suggested model features two encoders and one decoder; incorporating causal dilated highway convolutional blocks (CDHC). The study includes an evaluation through a user study and autocorrelation analysis to assess the naturalness and alignment of the generated choreography with the music.

2.2.2 Methodology

The paper discusses the limitations of the proposed model, highlighting that the generated choreography reflects only the periodicity among various properties of music. It also mentions the need to create appropriate choreography according to various genres, moods, and contexts of music, as well as the difficulty of using 2-d skeleton position data for actual implementation such as in a robot. The study concludes by emphasizing the significance of using the relationship with music for choreography generation and outlines directions for future work, including the extension of the model to 3-d choreography generation using an improved 3-d pose estimation algorithm. The paper presents a detailed explanation of the proposed approach, the experimental setup, the evaluation process, and the results.

It also discusses related work and acknowledges the limitations of the proposed model while highlighting its significance in the area of learning-based choreography generation.

2.2.3 Conclusion

The proposed system for dance motion synthesis from audio input has shown promising results in generating diverse and high-quality dance sequences. The use of a two-stream motion transformer generative model has demonstrated its effectiveness in producing realistic and flexible motion sequences. Additionally, the introduction of new evaluation

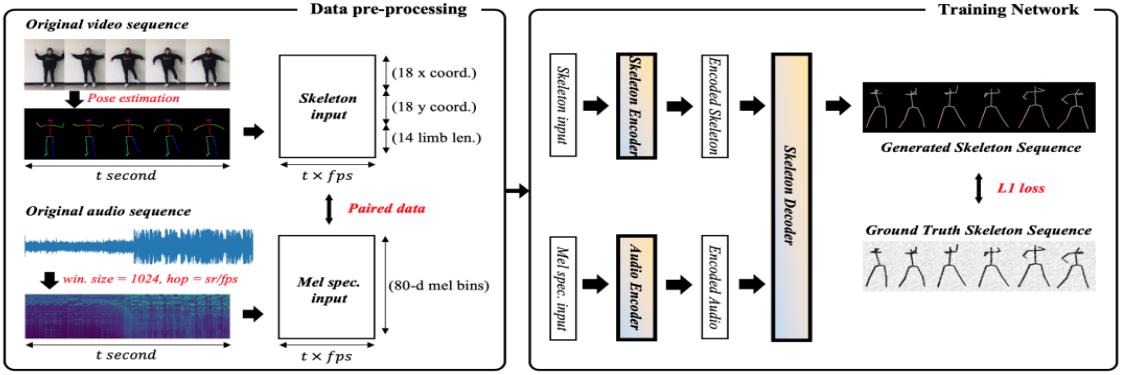


Figure 2.2: Architecture diagram 2

metrics has provided a comprehensive assessment of the quality of synthesized dance motions. The system’s ability to outperform existing methods and its potential applications in virtual concerts and professional animation pipelines make it a valuable contribution to the field of dance motion synthesis. The system’s ability to outperform existing methods and its potential applications in virtual concerts and professional animation pipelines make it a valuable contribution to the field of dance motion synthesis. The creation of a massive dance motion dataset from YouTube videos further enhances the system’s potential for training and validation. Overall, the system represents a significant advancement in the synthesis of expressive and diverse dance motions, with implications for both artistic and practical applications.

2.3 Music-to-Dance Motion Choreography with Adversarial Learning

2.3.1 Introduction

In this paper [3] the proposed method, DeepDance, utilizes adversarial learning to create realistic dance sequences based on input music and starting pose. It aims to model the correlation between music and dance motion and can generate long and plausible dance sequences of arbitrary length. The framework includes a generator to produce dance movements best-fit to the current music and a discriminator to evaluate the performance. Motion consistency constraints are added to create long, realistic dance sequences. The approach also introduces a method to create a large-scale dataset, YouTube-Dance3D, from open data sources. Extensive experiments demonstrate that the approach effectively captures the correlation between music and dance and can be used to choreograph

appropriate dance sequences. The impact of each component in the proposed approach is studied, and the model is shown to be capable of creating reasonable dances of different genres given the same input music. It highlights the strong correlation between music and body movements in choreography, where dancers react to rhythmic sounds with synchronized body movements. It sets the stage for the proposed method, DeepDance, which aims to leverage this correlation between music and dance motion to generate realistic and expressive dance sequences.

2.3.2 Methodology

DeepDance, is to model the correlation between music and dance motion and generate long and plausible dance sequences of arbitrary length. It aims to create realistic dance sequences based on input music and starting pose, effectively capturing the relationship between music and dance. The method utilizes adversarial learning and motion consistency constraints to achieve this objective. Additionally, the approach introduces a method to create a large-scale dataset, YouTube-Dance3D, from open data sources, further contributing to the objective of capturing the correlation between music and dance.

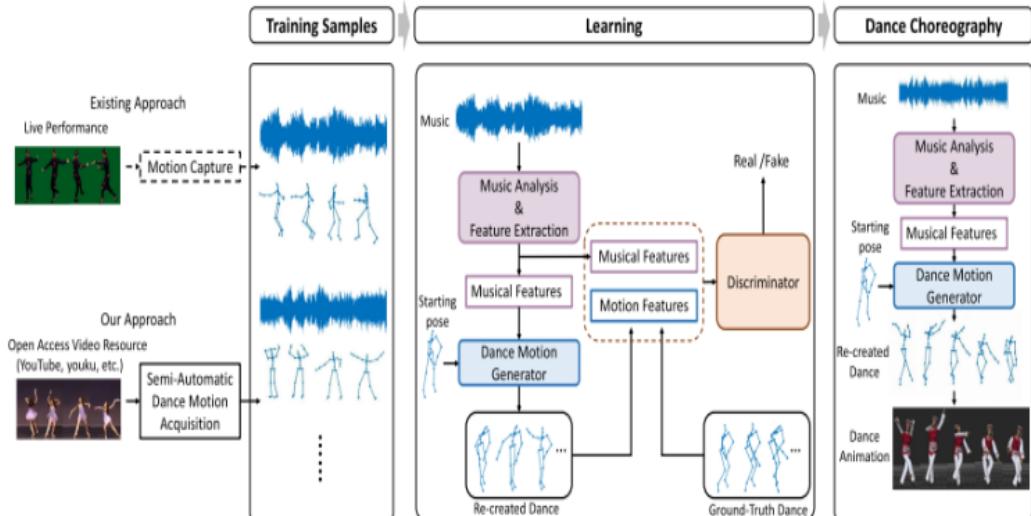


Figure 2.3: Architecture diagram 3

2.3.3 Conclusion

A vital subject of cross-modal analysis is the generation of ad-hoc dancing choreographies. The significant issue of the problem is how to establish an efficient probabilistic one-to-many mapping between music and choreography essential for realization of plausible dances in different genres. To solve this problem, we have introduced a GAN-based framework that connects two different types of data (dance motion and music). It is called DeepDance and it is aimed at generating from a given music input the appropriate dance sequence by correlating the two modalities. Its generator uses prior examples to selectively generate dance moves that suit the currently-playing music. A great number of tests have been conducted on the music-dance datasets available and the Youtube-Dance3D dataset in order to confirm that our method accurately takes note of the connection between dancing and music thereby enabling one to design correct dance sequences.

2.4 Music-Driven Dance Generation

2.4.1 Introduction

The paper [4] explores the origin of dousing actions caused by music, paying attention to problems met in identifying corresponding dance sequence and recommending ways of assessing the outcome of dances made. It presents the LSTM-SA model that employs the LSTM model together with attention mechanisms to deal with this problem of associating long multidimensional streams like movements so as to produce human-generative dance motions that are more compatible with music than earlier methods. The method involves feature extraction, human evaluation, and the creation of a new learning-based scoring model. The LSTM-SA framework is compared with other methods for synthesizing dance movements, and scoring results are obtained for both training and test datasets, demonstrating the effectiveness of the proposed approach.

2.4.2 Methodology

This involves the use of a Long Short-Term Memory with Self-Attention (LSTM-SA) network architecture, which includes an encoder with an attention mechanism and a decoder

network with an attention layer, three LSTM layers, and a dense layer. The framework aims to address the challenge of mapping music to dance movements and to evaluate the naturalness and alignment of the generated dance sequences with the music.

Developing a novel LSTM-SA framework for generating dance movements from music and pose features. Evaluating the generated dance sequences using scoring models and cosine similarity calculations. Investigating the use of deep learning techniques, such as recurrent neural networks (RNN) and LSTM, for cross-domain sequence analysis, including semantic manipulation of images, arousing human emotions through visual content, and generating an artistic poem from an image. Exploring the application of the proposed framework in the context of human motion synthesis and object detection.

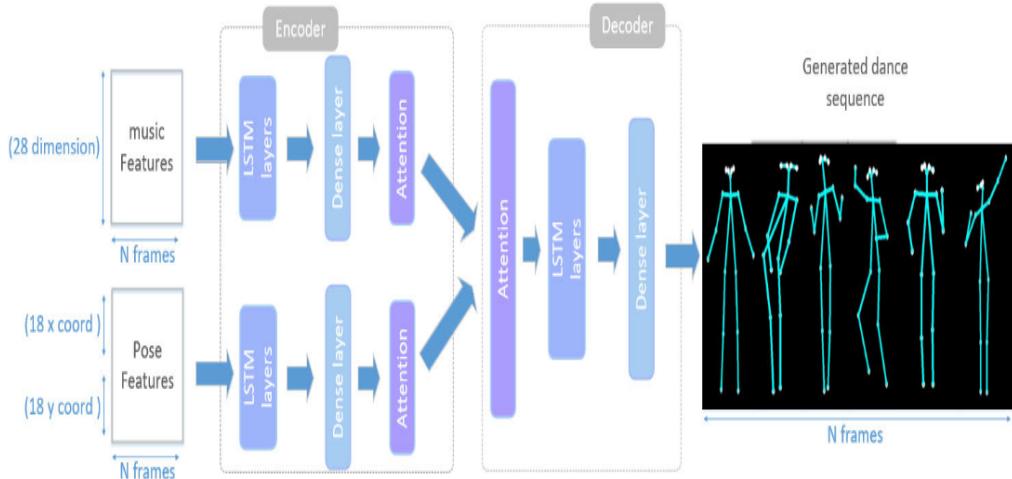


Figure 2.4: Architecture diagram 4

2.4.3 Conclusion

The paper provides valuable insights into the development of a model for music-driven dance generation, offering potential applications in virtual reality and related fields. The proposed LSTM-SA framework demonstrates promising results in synthesizing dance movements from music and pose features. Additionally, the paper discusses cross-domain sequence analysis, shedding light on innovative approaches such as semantically manipulating images and generating artistic poems from images. The limitations of traditional neural networks and the advantages of RNN and LSTM models are also highlighted.

Overall, the research contributes to the advancement of sequence generation methods and their potential impact on various domains.

2.5 Music Conditioned 3D Dance Generation with AIST++

2.5.1 Introduction

The paper [5] introduces the Full-Attention Cross-modal Transformer (FACT) network for generating 3D dance motion conditioned on music. It outlines the dataset AIST++, which contains 5.2 hours of 3D dance motions accompanied by music and multi-view images. The AIST++ dataset and the Full Attention Cross-Modal Transformer (FACT) model have been introduced to address the challenge of generating realistic 3D dance motion correlated with input music. The dataset contains 5.2 hours of 3D dance motions with music and multi-view images, making it the largest dataset of its kind. The FACT model is trained to predict multiple future motions, addressing issues of motion freezing or divergence. Extensive evaluations validate the design choices, including motion diversity and motion-music correlation. The dataset and code will be released for research purposes, providing a new benchmark for 3D dance generation conditioned on music.

2.5.2 Methodology

The FACT model is designed to predict future motion sequences and generate continuous motion in an auto-regressive manner. The success of the model relies on three key design elements: audio transformer, seed motion transformer, and cross-modal transformer. This paper provides extensive evaluations to validate the design choices, including motion diversity and motion-music correlation. Additionally, a novel metric called Beat Alignment Score (BeatAlign) is proposed to evaluate the motion-music correlation. This paper also references related work and datasets, highlighting the significance of the proposed model in generating 3D dance motion from music. The paper aims to introduce the AIST++ dataset, which contains 5.2 hours of 3D dance motions accompanied by music and multi-view images, and to demonstrate the effectiveness of the FACT model in preserving the correlation between music and 3D motion while generating realistic and diverse dance motions.

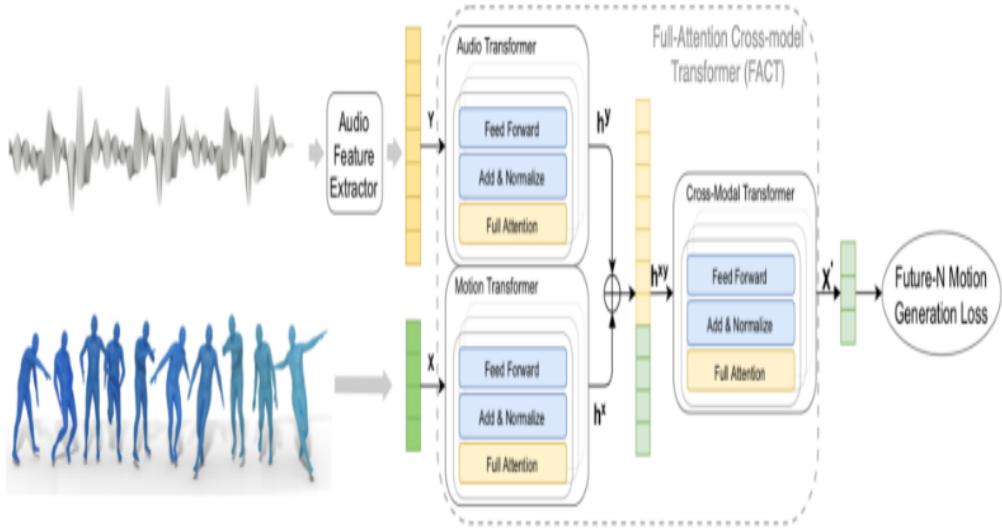


Figure 2.5: Architecture diagram 5

2.5.3 Conclusion

In this paper, the solution to the problem of generating lifelike 3D dance motion from music by introducing the AIST++ dataset and the Full Attention Cross-Modal Transformer (FACT) model. Thus, we deduce that the system isn't just put off by music alone but can also generate 3D motion of high quality. The results of many tests show that the model is better than all other known ways when it comes to movement quality, the disparity in production and the connection between motion and music. I will give the data set and my coding so as other researchers may use it as they wish: this will be helpful since it will enable them explore further on how 3D conditional movement can be managed and even people's way of thinking understood in a better way. Although the findings suggest a way forward, other lines of investigation also deserve to be pursued in order to address kinematic artifacts and discover how several realistic dances can be generated for each piece of music. This work's inputs offer fresh prospects in advancing music-conditioned 3D motion generation, as stated above.

Chapter 3

Requirements

3.1 Hardware and Software Requirements

- System: 16GB RAM or more , minimum of 32 bit CPU
- Programming Languages: Python
- Machine Learning Frameworks: TensorFlow
- Integrated Development Environment (IDE): Jupyter Notebooks

3.2 Functional Requirements (Numbered List/ Description in Use Case Model)

1. Music Style Classification: To condition the motion generating process, the system should be able to classify incoming music audio into specified dance genres, like Michael Jackson, Salsa, or Ballet.
2. Motion Generation Control: Using audio data, the system should enable control over the movement's style while maintaining the final motions' realism and distinctive qualities. To condition the motion generation, this entails creating a temporal coherent latent vector.
3. Adversarial Training for Motion Generation: Depending on the musical genre, the system must be able to train an adversarial generative model based on a graph convolutional neural network (GCN) to produce sequences of human poses.
4. User Research and Evaluation: The system ought to enable user research to compare the produced motions with actual dance moves. This should involve blind assess-

ments to determine whether the synthetic motions are believable and appropriate for whatever dance forms.

5. Quantitative Evaluation Metrics: To evaluate the effectiveness of the motion synthesis model, the system should include quantitative evaluation metrics as Frechet Inception Distance (FID), GAN-Train, and GAN-Test.
6. Dataset and Classifier Training: The system ought to facilitate the use of a multi-modal dataset comprising coupled audio, motion data, and videos of people dancing to various musical styles, as well as the training of a 1D-CNN classifier to specify the input music style.
7. Temporal Coherence and Spatial-Temporal Correlation: The system should maintain spatial coherence of the motion for each joint over time, using a spatial-temporal correlated latent vector generated by a Gaussian process (GP) to ensure the generation of varied and coherent poses.
8. Realistic Motion Synthesis: The system should be capable of synthesizing realistic human motions that align with specific dance styles, providing a large variety of motions while retaining individual characteristics and temporal relationships of the movements.

Chapter 4

System Architecture

In order to create lifelike animations for virtual avatars, a new way of synthesizing human movements by using sounds has been designed by means of graph convolution. Human motion synthesis based on auditory data presents an important problem in creating photorealistic animations for virtual avatars. Current motion capture system have limitations in regards to capturing richer spatiotemporal distribution and diversity of human movements with its diversity. Moreover such human motion is also influenced by complicated situational factors like acoustic feedbacks , psychophysical states and cultural affiliations.

In order to meet this challenge we've created a new graph-convolutional method of synthesize human movement from sound input that is more faithful with respect to both quality criteria as well as being more understandable by human beings than previous approaches. A conditional GCN architecture and innovative multimodal data sets with matching audio, movement data and videos of people dancing in various musical genres are used.

The approach consists of three main components a 1D-CNN classifier, spatial-temporal correlated latent vector and a graph convolutional network. For realistic motion generation a binary cross-entropy loss is minimized using adversarial training.

The method has demonstrated motion perception that is similar to true data and has surpassed the latest technique by far. Public availability of both the technique and the dataset makes them a great resource in the Synthesis of human motion field.

4.1 System Overview

To utilize musical genres, the purpose of the proposed system is to produce human gestures with the help of sound, specifically. It has three main components: classification of input music style using 1D-CNN classifier is done at the outset. Next is, with Gaussian

Process (GP), creating vessel motion based on a spatio-temporally correlated latent vector which, in turn, is influenced by the classification outcome. This latent vector should aim at maintaining spatial coherency over time for all joints' motions. Finally, a generative model based on graph convolutional network (GCN) along with adversarial training processed trained in order to generate human pose sequences. The system is capable of rendering animations of virtual characters performing the motion generated by the method, and it has been shown to outperform the state-of-the-art method in terms of generating plausible movements while maintaining the characteristics of different dance styles. The system's architecture and methodology have been thoroughly evaluated through user studies and quantitative metrics, demonstrating its effectiveness in synthesizing realistic human motions aligned with specific music styles.

4.2 Architectural Design

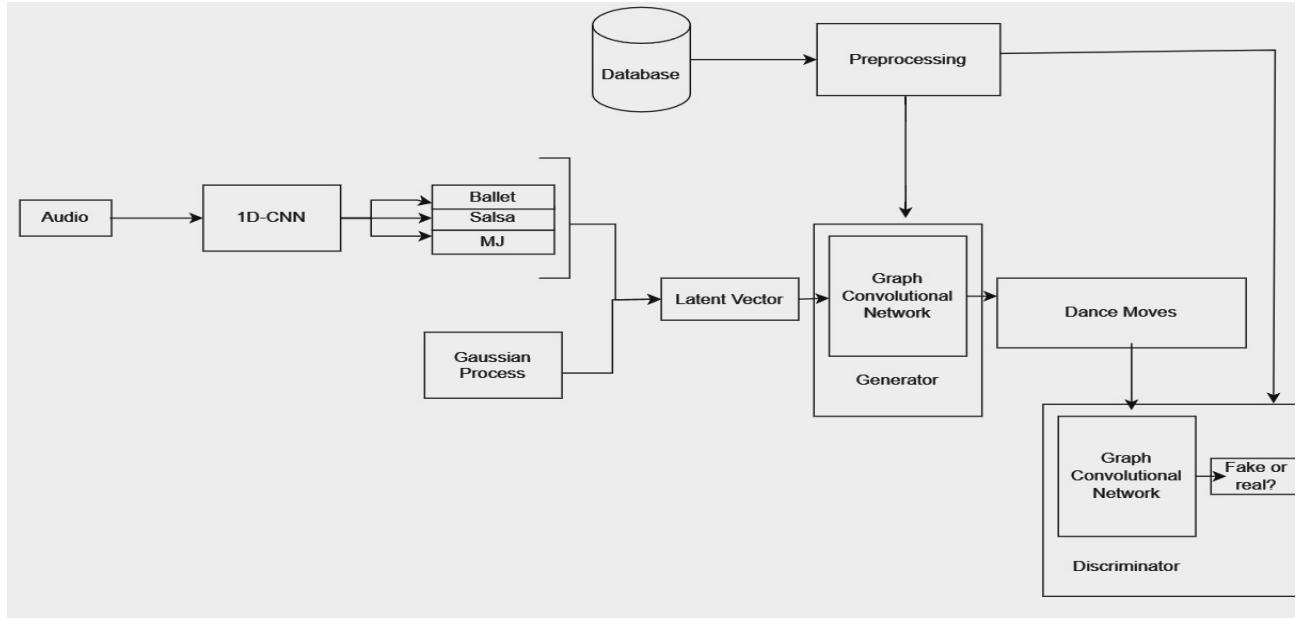


Figure 4.1: Architecture diagram

The architectural diagram depicts the process of synthesizing human motion styles based on music genres using a Generative Graph Convolutional Network (GGCN). The generator component consists of temporal and spatial layers, a Gaussian Process, and Graph Convolutional Network elements. On the other hand, the discriminator structure mirrors the generator but incorporates downsampling layers. This diagram visually rep-

resents how real and generated motion data flow through the network for classification purposes, showcasing the intricate interplay of components in the motion synthesis process.

4.3 Module Division

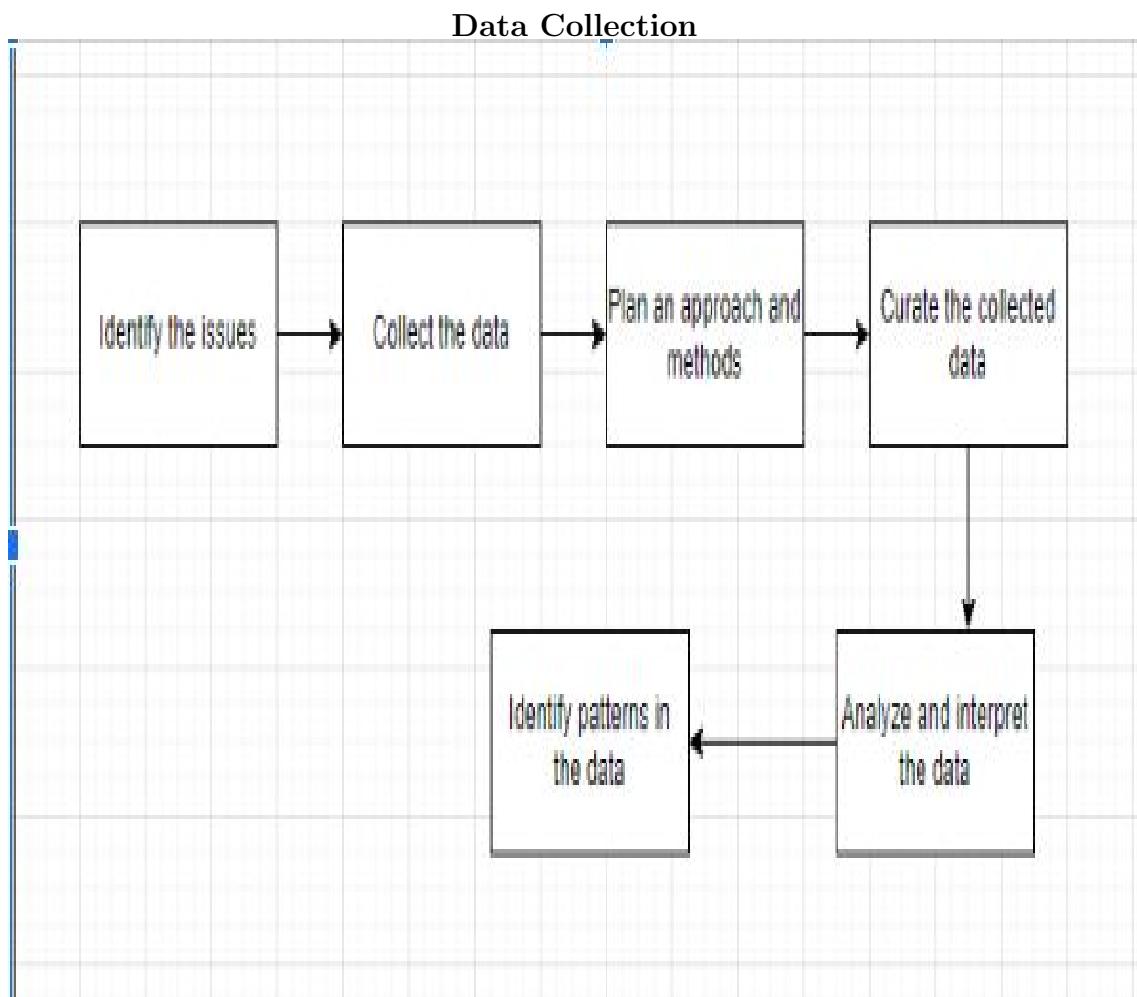


Figure 4.2: Data Collection

Beginning with defining the information you require and its sources, data collection is a systemic process. The next step involves selecting methods for collecting the same such as surveys or interviews. During collection, the data should be cleaned and confirmed for its accuracy ensuring that ethical considerations are upheld. Secured storage should be used while documentation done to ensure that the data meets future efficacy requirements. It is important to note that this meticulous procedure gives one credible facts for goal

attainment.

Data Preprocessing

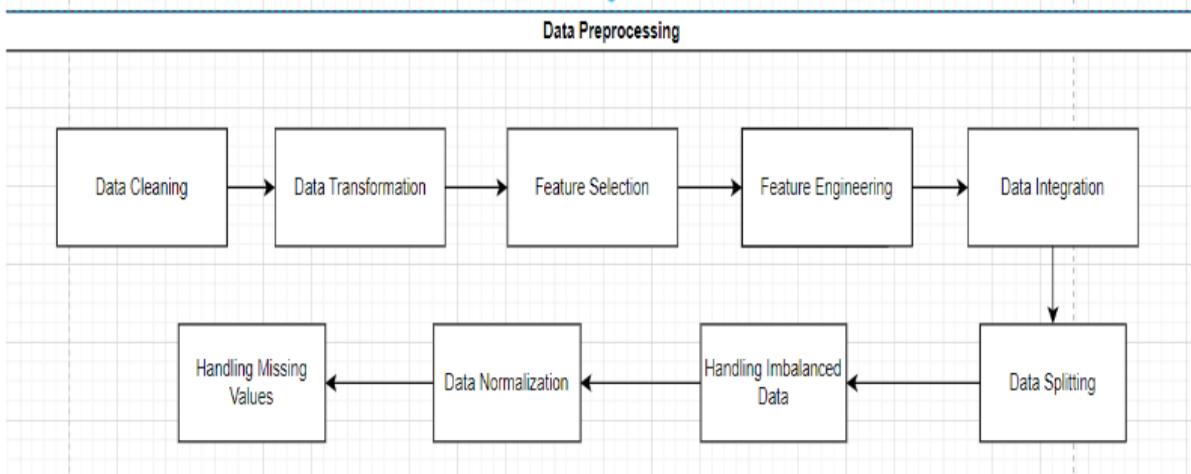


Figure 4.3: Data Preprocessing

Below is a visual representation of information pre-processing necessary for its examination: to represent cleaning the input information before it is worked upon, it may encompass filling missing information or normalizing it equalizing it out where necessary and managing data pointing out unequal distribution among given classes; possible modification involve transformation into a markdown style as well as narrowing down using identifying key features constructing intelligent systems.

Feature Extraction

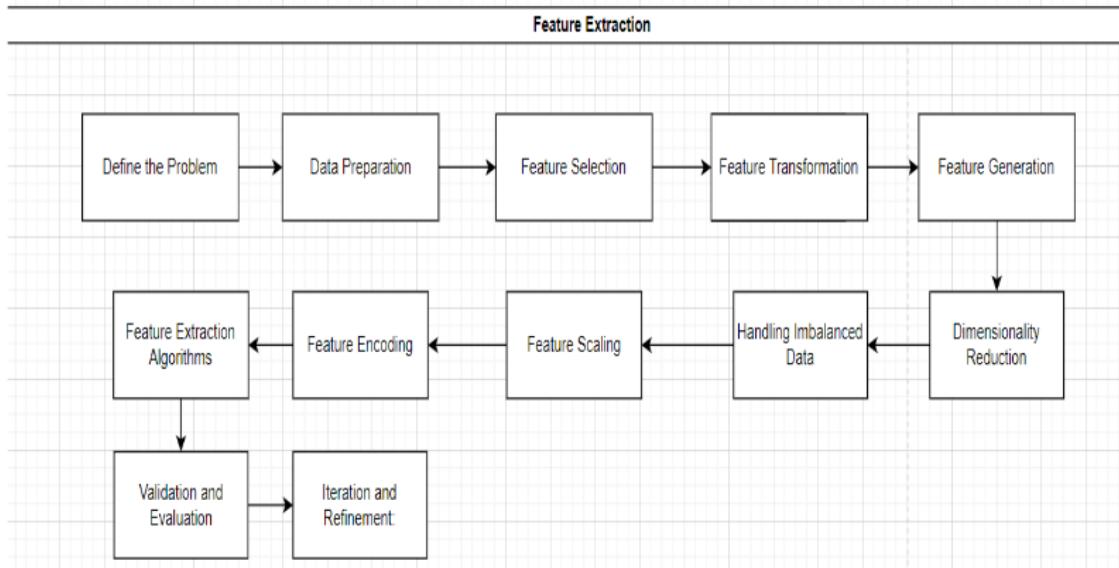


Figure 4.4: Feature Extraction

Feature extraction is an essential step in getting data ready for machine learning models, and this flowchart shows you how to do it. It begins with task definition, which is effectively the machine learning model's objective. The next step is data preparation, which involves formatting and cleaning the raw data to make analysis easier. Subsequently, the model selects features, or quantifiable properties. Here, the most pertinent elements from the given data are chosen for the particular task at hand. Feature transformation takes care of the data format, making sure it fits the model's requirements. Techniques for normalizing or scaling may be used in this. By developing completely new features based on the available data, feature generation goes one step further. Here, methods such as binning or polynomial expansion can be applied. For the model to comprehend categorical features—which stand for non-numerical attributes—they must be translated into numerical values. The process for doing this is feature encoding. By ensuring that each feature has a comparable range, feature scaling keeps certain characteristics from dominating other features during the model's analysis. The last two steps are crucial, however they aren't shown in the flowchart explicitly: Validation and assessment determine how well the selected features work, and the process can be improved for best results by iterating and refining it all depending on the findings.

Graph conditioning networks are an advanced type of neural architecture designed for effective handling of data having a graph structure. The primary components of the

Model Training

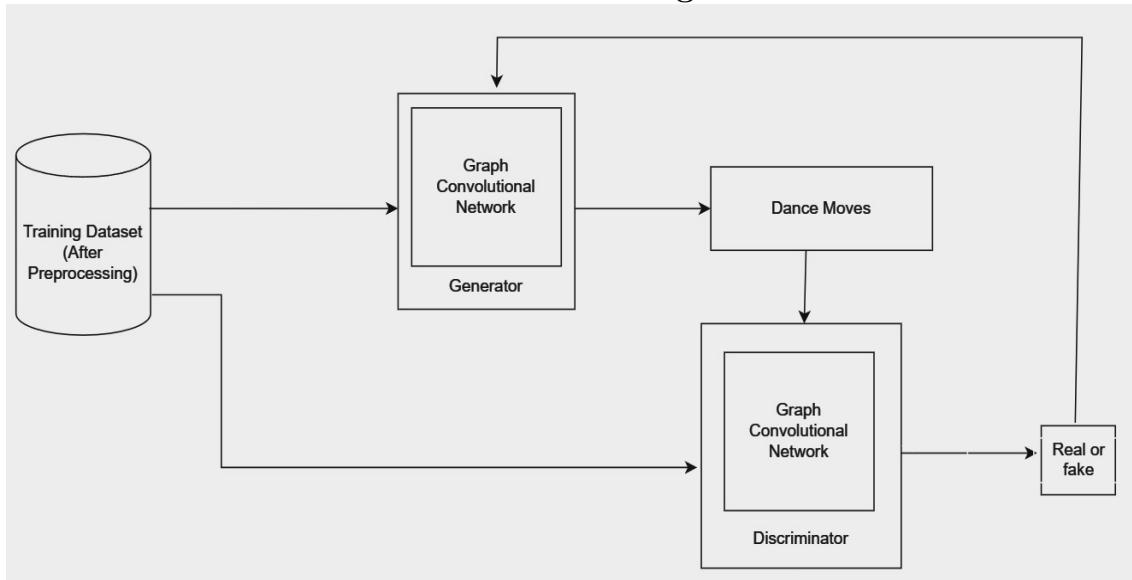


Figure 4.5: Model Training

network are nodes and edges encoded in a latent vector. The vector is processed by a Graph Convolutional Network (GCN), where the network structure and the latent vector are fused together. The GCN utilizes information from nearby nodes to improve representations of each node, capturing complex relationships within the graph. The network trains on a training dataset to update its parameters while evaluating its performance on unseen data using an evaluation dataset. A generator, which changes a latent vector into some output—like a synthesized graph or its properties—and a discriminator, which has to learn how to distinguish between fake and real graphs are what this network consists of. Through adversarial training, the generator learns how to create graphs that are quite similar to real ones, thus showcasing the networks capacity to produce the true graph data. Graph condition networks are utilized in various areas such as molecular chemistry, social network study and recommendation system where data is inherently of graph nature.

Model Evaluation

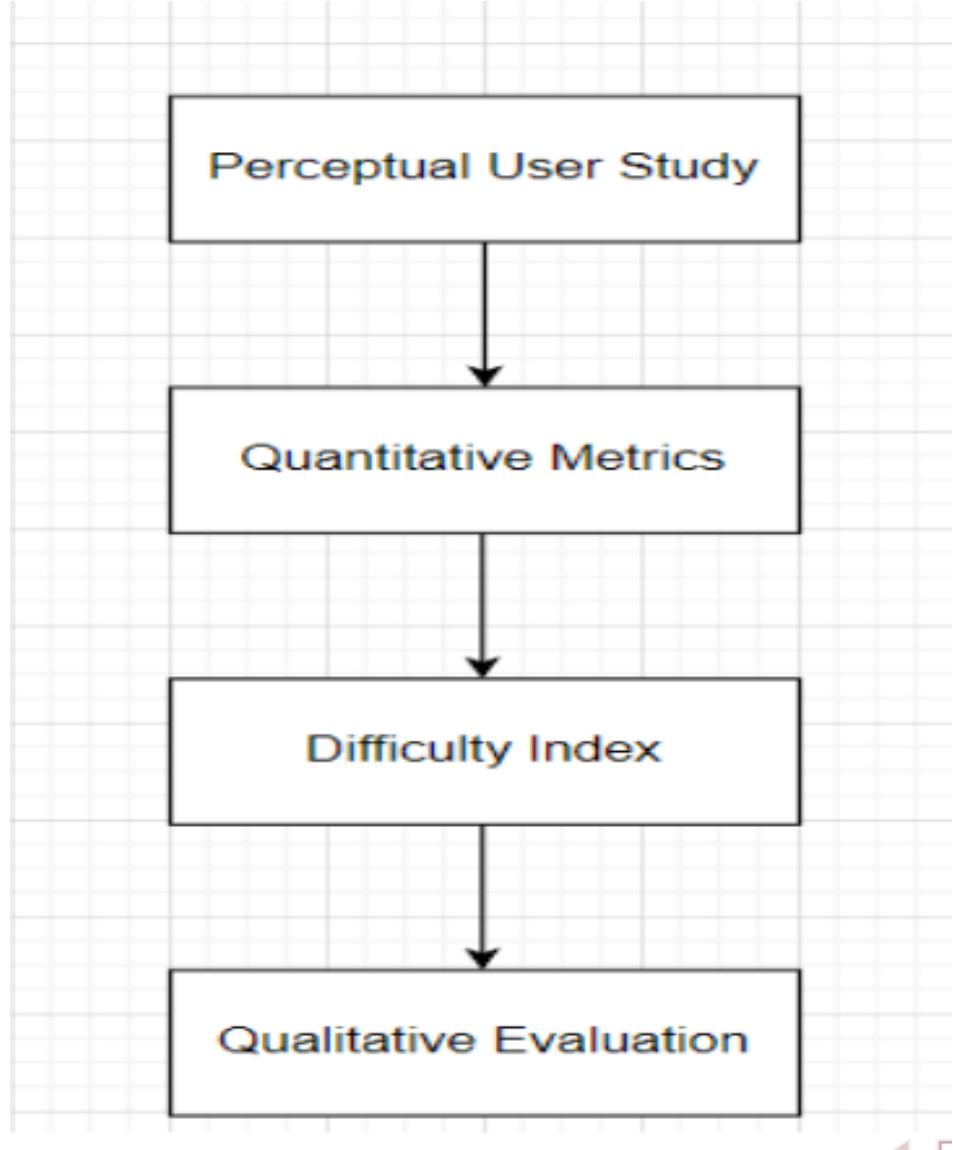


Figure 4.6: Model Evaluation

A perceptual user study is a comprehensive research methodology used in human-computer interaction and user experience research to delve into how users perceive and interact with a product or system. It involves a meticulous process starting with the clear definition of research objectives, followed by the recruitment of representative participants matching the product's user base. Researchers meticulously design a research plan detailing the tasks, scenarios, and evaluation techniques to be used during the study. Throughout the study, participants engage with the product while researchers observe, collect qualitative feedback, and sometimes employ additional methods like eye tracking or physiological measurements. After data collection, thorough analysis, including both quantitative metrics and qualitative insights, is conducted to uncover patterns and themes in user experiences. Findings are then synthesized into a comprehensive report, offering actionable recommendations for product improvement. This method provides valuable insights into user perceptions and behaviors, guiding iterative design processes to ultimately enhance user experience.

4.4 Work Schedule

| | Month 1 | Month 2 | Month 3 | Month 4 | Month 5 |
|--------|-----------------|--------------------|--------------------|----------------|---------|
| Step 1 | Data Collection | | | | |
| Step 2 | | Data Preprocessing | | | |
| Step 3 | | | Feature Extraction | | |
| Step 4 | | | | Model Training | |
| Step 5 | | | | | Testing |

Figure 4.7: Work Schedule

Chapter 5

Results

Our project successfully developed a novel method for generating realistic human motions in dance scenarios from audio inputs. Through the use of graph-convolutional networks, we achieved superior performance compared to existing techniques.

User studies further validated the quality of our generated motions, showing similarity to real dance movements. The dataset created for training and evaluation purposes proved instrumental in enhancing the accuracy and diversity of motion synthesis across different dance styles. Our approach not only outperformed previous methods but also showcased potential for future applications in animation frameworks. The comparison with the state-of-the-art method, referred to as D2M, involved various quantitative metrics and a user study. The quantitative evaluation included the use of the Fréchet Inception Distance (FID) metric, GAN-Train, and GAN-Test metrics, which are well-known metrics for evaluating generative models. The results of these evaluations demonstrated that the proposed method achieved superior performance compared to the state-of-the-art technique. Additionally, a user study was conducted, where participants were able to accurately identify the dance style of the generated dance moves, further indicating the effectiveness of the proposed method. Moving forward, we aim to expand the dataset with more dance styles and explore 3D motion inference to further advance the realism and variety of generated human motions.

Work Done During 30%

During our 30% evaluation we have developed a user interface as shown below.

Learning To Dance

Home Register Login



Register

Your Name

Your Email

Password

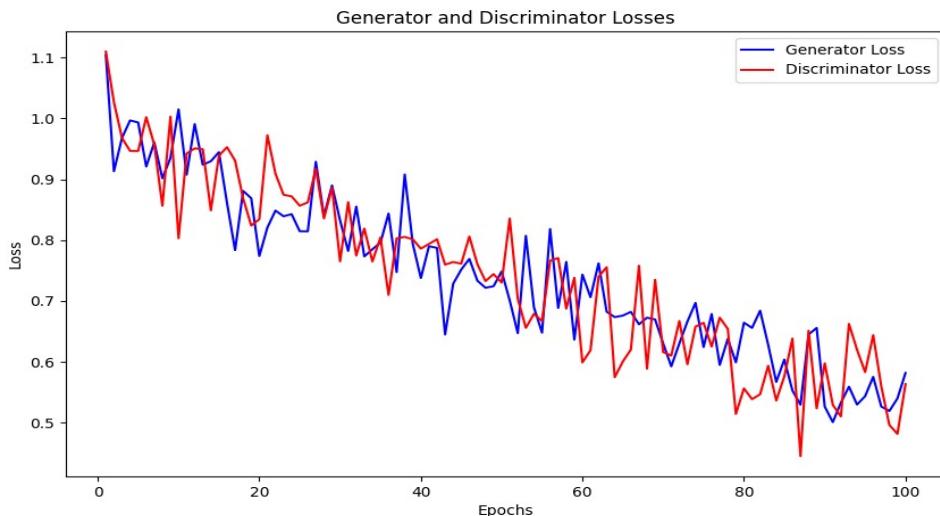
Submit

Login

Work Done During 60%

During our 60% of our project we have sucessfully trained our models(Generator and descriminator) using GCN method. Generator is responsible for generating dance moves and discriminator is responsible for validating dance moves generated by generator. We have also obtained the graph show the reduction in the loss with the increase in the no of epoch for each generator and descriminator resulting in much efficient 2 models capable of generating dance moves.

| | | | |
|--|---------------------|---------|-----------|
|  discriminator.pt | 01-03-2024 07:38 PM | PT File | 18,231 KB |
|  generator.pt | 01-03-2024 07:38 PM | PT File | 13,126 KB |



Work Done During 100%

The project aims in generating dance motion using generation graph convolutional networks. The dataset collected included audio and visual data for training and evaluating motion synthesis algorithms, aiming to generate realistic human motions in dance scenarios. The method involved training a 1D-CNN classifier to define music style input, combining it with a spatial-temporal correlated latent vector generated by a Gaussian process for motion generation. The study aimed to foster new approaches for generating human motions, with future work focusing on inferring 3D human motions and expanding the dataset with more dance styles.

Learning To Dance

[Home](#) [Test](#) [view results](#) [Logout](#)

Upload

Choose File ball...p3

Result

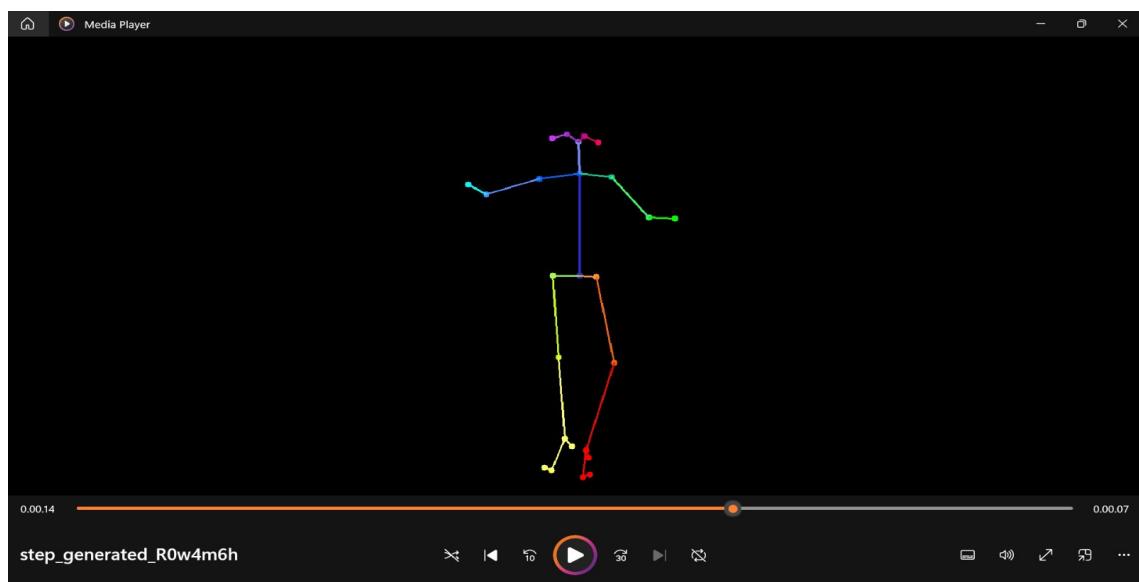
AUDIO

RESULT

▶ 0:00 / 0:23



download



Chapter 6

Conclusions & Future Scope

In conclusion the project proposes a method for synthesizing human motion from music using a graph convolutional network (GCN) architecture. The method involves encoding sound signals to extract music styles using a CNN architecture and conditioning a GCN architecture with the music style and a spatial-temporal latent vector. The GCN is trained in an adversarial regime to predict 2D human body joint positions over time. In summary, the comparison with the state-of-the-art technology involved the use of quantitative metrics such as FID, GAN-Train, and GAN-Test, as well as a user study to assess the performance of the proposed method in synthesizing dance movements from audio in comparison to the D2M technique. The results indicated that the proposed method achieved superior performance compared to the state-of-the-art technique.

The project opens up several avenues for future extensions and enhancements. Firstly, exploring the integration of additional modalities, such as text or other forms of sensory input, could further enrich the synthesis of human movements. Additionally, investigating the application of the graph-convolutional approach to real-time motion generation and interactive systems would be a valuable direction. Furthermore, delving into the potential for transfer learning and adaptation of the approach to different domains or cultural contexts could broaden its applicability. Finally, conducting user studies and evaluations in diverse settings and with larger sample sizes would provide deeper insights into the perceptual quality and effectiveness of the synthesized motion styles.

References

- [1] J. Li, Y. Yin, H. Chu, Y. Zhou, T. Wang, S. Fidler, and H. Li, “Learning to generate diverse dance motions with transformer,” *arXiv preprint arXiv:2008.08171*, 2020.
- [2] J. Lee, S. Kim, and K. Lee, “Listen to dance: Music-driven choreography generation using autoregressive encoder-decoder network,” *arXiv preprint arXiv:1811.00818*, 2018.
- [3] G. Sun, Y. Wong, Z. Cheng, M. S. Kankanhalli, W. Geng, and X. Li, “Deepdance: music-to-dance motion choreography with adversarial learning,” *IEEE Transactions on Multimedia*, vol. 23, pp. 497–509, 2020.
- [4] Y. Qi, Y. Liu, and Q. Sun, “Music-driven dance generation,” *IEEE Access*, vol. 7, pp. 166 540–166 550, 2019.
- [5] R. Li, S. Yang, D. A. Ross, and A. Kanazawa, “Ai choreographer: Music conditioned 3d dance generation with aist++,” in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2021, pp. 13 401–13 412.

Appendix A: Final Presentation

Learning to dance: A graph convolutional adversarial network to generate realistic dance motions from audio

U2003082 - Gautham Sanil

U2003090 - Gowri Sen

U2003097 - Iris Orris

U2003112 - Joyce Boban

RSET

May 2, 2024

Contents

- Problem Definition
- Project Objective
- Novelty of Idea and Scope of Implementation
- Literature Review
- Methodology
- Architecture Diagram
- Results
- Work Division among Team Members
- Conclusion
- Future Scope
- References

Problem definition

To create synthesised dance movements from music using adversarial training and a convolutional graph network architecture, aiming to generate natural motions that preserve the characteristics of different music styles.

Project Objective

- ① To design sequence of 2D human poses resembling a human dancing according to a music style, aiming to estimate a motion that provides the best fit for a given input music audio.
- ② To develop a multi-step approach involving generative model training using a graph convolutional neural network in an adversarial manner to generate sequences of human poses.

Scope of project

- The project aims to solve the problem of choreographer availability and reduce costs.
- This automated approach provides a more accessible and cost-effective way to create diverse and expressive dance poses that align with different music styles.
- The purpose of this project is to advance the field of dance generation by introducing a novel graph-convolutional approach that outperforms existing methods.

PAPER 1

MUSIC-DRIVEN CHOREOGRAPHY GENERATION USING AUTOREGRESSIVE ENCODER-DECODER NETWORK

The proposed method uses an autoregressive encoder-decoder network to generate dance motion from music.

Causal convolution layer, dilated convolution, and highway network architecture are used in the network.

The network is trained using music-choreography pairs as input and is able to generate musically meaningful and natural dance movements.

| PROS | CONS |
|---|---|
| The model is trained on a large dataset of music and choreography pairs thus produces musically meaningful and natural choreography . | Difficulty in generalizing choreography across various music genres, and contexts, as well as the difficulty in using the generated 2D choreography data for practical implementations such as with robots. |

PAPER 11

Learning to Generate Diverse Dance Motions with Transformer

For the propose of dance motions generation a new approach using a large-scale dance motion dataset and a conditional auto-regressive generative model with Transformers. The dataset was collected from online dance videos Implemented using Two-Stream Motion Transformer (TSMT) and provides insights into the diversity and results of the proposed model.

| PROS | CONS |
|---|---|
| The proposed Two-Stream Motion Transformer model offers an efficient and scalable solution for generating diverse and realistic dance motions from a large-scale dataset, while also being able to capture long-term dependencies . | The model's reliance on online videos for data collection may result in limitations in the number of joints and the quality of 3D pose sequences, potentially impacting the expressiveness of the synthesized dance data. |

PAPER 111

Music-Driven Dance Generation

The paper discusses a LSTM-SA model, for synthesizing dance movements from music sequences, using a sequence to sequence learning architecture with LSTM and Self-Attention mechanism. The paper integrates LSTM and Self-Attention models to LSTM-SA. It works by first understanding features in both music and dance sequences.

Then, it uses a special network to learn how music and dance are related. The resulting dance sequences are then evaluated.

| PROS | CONS |
|--|---|
| Parallelisation for reduced training time Ability to maintain original pose to fit in music better | Compresses the entire input sequence into a fixed representation, limiting flexibility of the model |

PAPER 1V

Full-Attention Cross-modal Transformer for Music Conditioned 3D Dance Motion Generation.

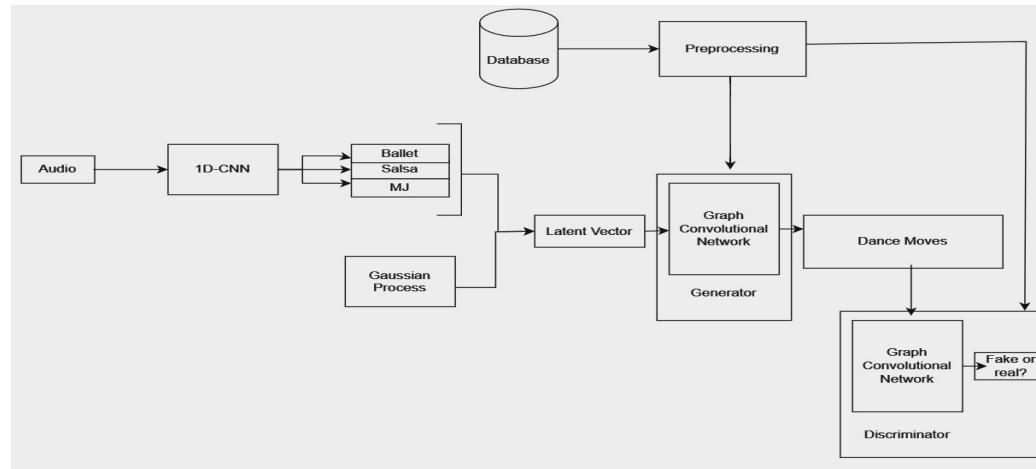
Full-Attention Cross-Modal Transformer (FACT) model is proposed to generate 3D dance motion from music.
AIST++ dataset is used, containing 5.2 hours of 3D dance motions accompanied with music and multi-view images

| PROS | CONS |
|---|--|
| Produce realistic 3D dance motion. Improved motion Quality | Kinematics limitations Complexity in processing |

Methodology

- The project introduces a novel method based on graph convolutional networks (GCN). The proposed GCN model uses an adversarial learning scheme conditioned on the input music audios to create natural motions preserving the key movements of different music styles.
- The method consists of three main components: a 1D-CNN classifier to define the input music style, a spatial-temporal correlated latent vector generated by a Gaussian process (GP), and a graph convolutional network (GCN) for human motion generation.
- The proposed approach aims to synthesize human movements using GCN and audio data, allowing control over the style of the movement while preserving the plausibility of the final motions.

Architecture Diagram



Work done during 30% Evaluation

User Interface

- Home Page
 - Registration Page
 - Login page created using Django framework

Data Preprocessing and Feature Extraction

- Standardise fps
 - Extract audio
 - Filter open pose
 - Preprocessing

Work done during 30% Evaluation



Work done during 60% Evaluation

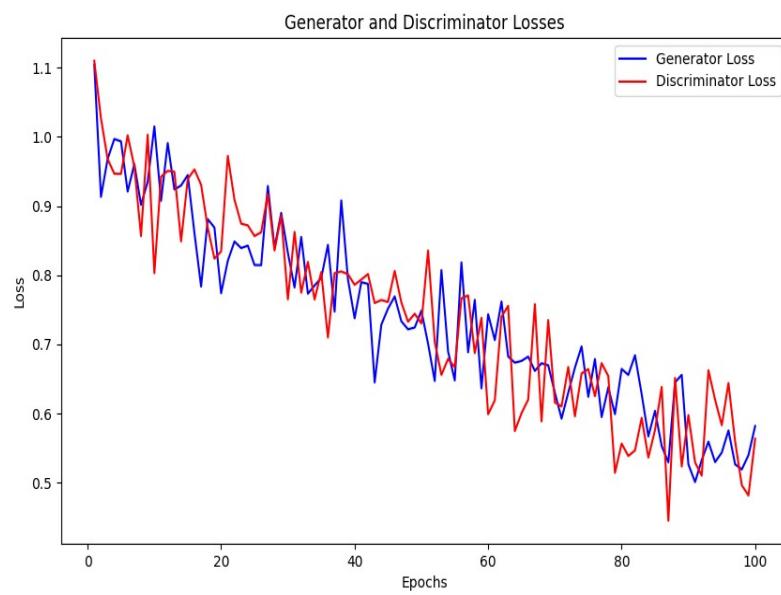
- ① Pytorch framework is used for training purpose which is the commonly used framework for training network in the form of graph i.e graph convolutional network.
 - ② Gcn models are trained in batches for each epoch.
 - ③ As a result of training 2 well trained gcn models i.e generator_network.pt and discriminator.pt will be generated.

Work done during 60% Evaluation

| Name | Date modified | Type | Size |
|--|---------------------|---------|-----------|
| ▼ Last month | | | |
|  discriminator.pt | 01-03-2024 07:38 PM | PT File | 18,231 KB |
|  generator.pt | 01-03-2024 07:38 PM | PT File | 13,126 KB |

Learning to dance: A graph convolutional adversarial network to generate realistic dance motions from audio

Work done during 60% Evaluation



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Work to be Completed (100% Evaluation)

① Model Testing

- ② User interface which generates dance move corresponding to music

Work done during 100% Evaluation(Testing)

A screenshot of a file explorer window. The path is shown as: Downloads > test_code > output > michael >. The window lists files and folders: labels.txt (Text Document, 1 KB), michael_black.mp4 (MP4 File, 2,936 KB), michael_white.mp4 (MP4 File, 2,404 KB), vid2vid_spline (File folder), and vid2vid (File folder). The 'michael_black.mp4' and 'michael_white.mp4' files are highlighted with a red border.

| Name | Date modified | Type | Size |
|-------------------|---------------------|---------------|----------|
| Yesterday | | | |
| labels.txt | 06-04-2024 11:40 PM | Text Document | 1 KB |
| michael_black.mp4 | 06-04-2024 11:40 PM | MP4 File | 2,936 KB |
| michael_white.mp4 | 06-04-2024 11:40 PM | MP4 File | 2,404 KB |
| vid2vid_spline | 06-04-2024 11:40 PM | File folder | |
| vid2vid | 06-04-2024 11:40 PM | File folder | |

Work done during 100% Evaluation

Learning To Dance

[Home](#) [Test](#) [view results](#) [Logout](#)

Upload

Choose File ball...p3

Submit

☰ ↺ 🔍 ↻
19 / 26

Results(100% Evaluation)

Learning To Dance

[Home](#) [Test](#) [view results](#) [Logout](#)

Result

AUDIO

RESULT

▶ 0:00 / 0:23 ━━ ⏪ ⏹

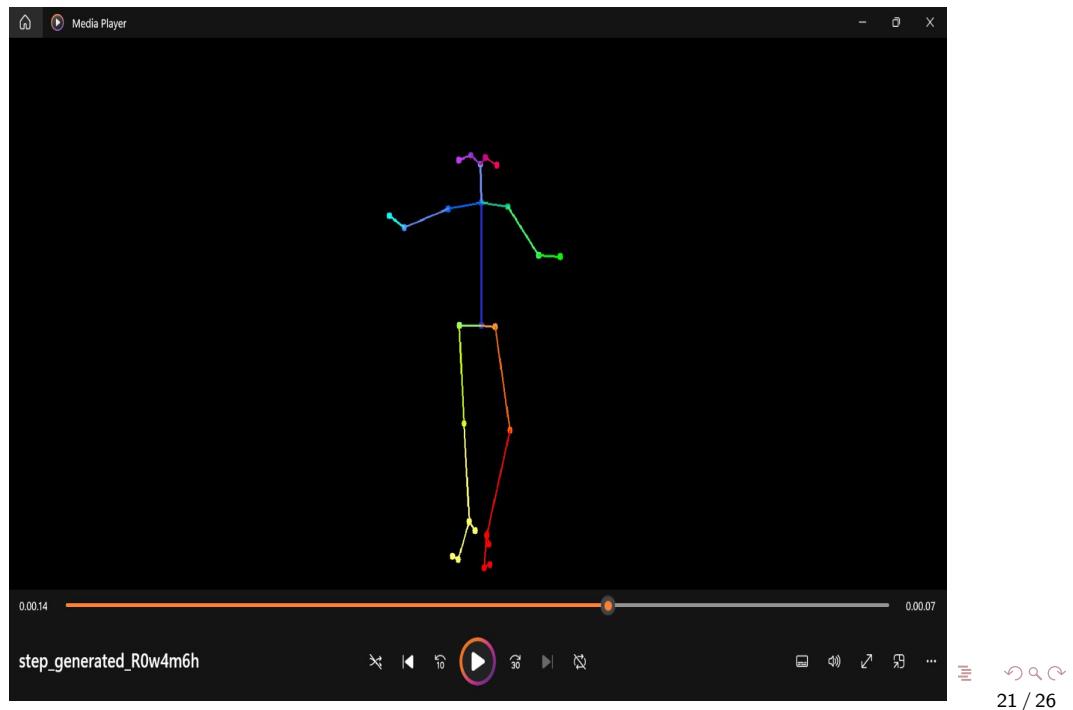
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Work done during 100% Evaluation



Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

- 3. Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
- 4. Conduct investigations of complex problems:** Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
- 5. Modern Tool Usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
- 6. The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
- 7. Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
- 8. Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
- 9. Individual and Team work:** Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.
- 10. Communication:** Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.
- 11. Project management and finance:** Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.
- 12. Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills

The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills

The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills

The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix C: CO-PO-PSO Mapping

CO-PO AND CO-PSO MAPPING

| | P O1 | P O2 | P O3 | P O4 | P O5 | P O6 | P O7 | P O8 | P O9 | PO 10 | PO 11 | PO 12 | PSO 1 | PSO 2 | PSO 3 |
|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|----------|----------|----------|----------|----------|----------|
| C O1 | 2 | 2 | 2 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 2 | 3 | | |
| C O2 | 2 | 2 | 2 | | 1 | 3 | 3 | 1 | 1 | | 1 | 1 | | 2 | |
| C O3 | | | | | | | | | 3 | 2 | 2 | 1 | | | 3 |
| C O4 | | | | | 2 | | | 3 | 2 | 2 | 3 | 2 | | | 3 |
| C O5 | 2 | 3 | 3 | 1 | 2 | | | | | | | 1 | 3 | | |
| C O6 | | | | | 2 | | | 2 | 2 | 3 | 1 | 1 | | | 3 |

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING & CO-PSO MAPPING

| MAPPING | LOW/MEDIUM/ HIGH | JUSTIFICATION |
|-----------------------------|---------------------|---|
| 100003/ CS722U.1-P O1 | M | Knowledge in the area of technology for project development using various tools results in better modeling. |
| 100003/ CS722U.1-P O2 | M | Knowledge acquired in the selected area of project development can be used to identify, formulate, review |

| | | |
|-----------------------------|---|---|
| | | research literature, and analyze complex engineering problems reaching substantiated conclusions. |
| 100003/ CS722U.1-P O3 | M | Can use the acquired knowledge in designing solutions to complex problems. |
| 100003/ CS722U.1-P O4 | M | Can use the acquired knowledge in designing solutions to complex problems. |
| 100003/ CS722U.1-P O5 | H | Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions. |
| 100003/ CS722U.1-P O6 | M | Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices. |
| 100003/ CS722U.1-P O7 | M | Project development based on societal and environmental context solution identification is the need for sustainable development. |
| 100003/ CS722U.1-P O8 | L | Project development should be based on professional ethics and responsibilities. |
| 100003/ CS722U.1-P O9 | L | Project development using a systematic approach based on well defined principles will result in teamwork. |

| | | |
|------------------------------|---|--|
| 100003/ CS722U.1-P O10 | M | Project brings technological changes in society. |
| 100003/ CS722U.1-P O11 | H | Acquiring knowledge for project development gathers skills in design, analysis, development and implementation of algorithms. |
| 100003/ CS722U.1-P O12 | H | Knowledge for project development contributes engineering skills in computing & information gatherings. |
| 100003/ CS722U.2-P O1 | H | Knowledge acquired for project development will also include systematic planning, developing, testing and implementation in computer science solutions in various domains. |
| 100003/ CS722U.2-P O2 | H | Project design and development using a systematic approach brings knowledge in mathematics and engineering fundamentals. |
| 100003/ CS722U.2-P O3 | H | Identifying, formulating and analyzing the project results in a systematic approach. |
| 100003/ CS722U.2-P O5 | H | Systematic approach is the tip for solving complex problems in various domains. |
| 100003/ CS722U.2-P O6 | H | Systematic approach in the technical and design aspects provide valid conclusions. |

| | | |
|------------------------------|---|---|
| 100003/ CS722U.2-P O7 | H | Systematic approach in the technical and design aspects demonstrate the knowledge of sustainable development. |
| 100003/ CS722U.2-P O8 | M | Identification and justification of technical aspects of project development demonstrates the need for sustainable development. |
| 100003/ CS722U.2-P O9 | H | Apply professional ethics and responsibilities in engineering practice of development. |
| 100003/ CS722U.2-P O11 | H | Systematic approach also includes effective reporting and documentation which gives clear instructions. |
| 100003/ CS722U.2-P O12 | M | Project development using a systematic approach based on well defined principles will result in better teamwork. |
| 100003/ CS722U.3-P O9 | H | Project development as a team brings the ability to engage in independent and lifelong learning. |
| 100003/ CS722U.3-P O10 | H | Identification, formulation and justification in technical aspects will be based on acquiring skills in design and development of algorithms. |
| 100003/ CS722U.3-P O11 | H | Identification, formulation and justification in technical aspects provides the betterment of life in various domains. |
| 100003/ CS722U.3-P O12 | H | Students are able to interpret, improve and redefine technical aspects with mathematics, science and |

| | | |
|------------------------------|---|---|
| | | engineering fundamentals for the solutions of complex problems. |
| 100003/ CS722U.4-P O5 | H | Students are able to interpret, improve and redefine technical aspects with identification formulation and analysis of complex problems. |
| 100003/ CS722U.4-P O8 | H | Students are able to interpret, improve and redefine technical aspects to meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations. |
| 100003/ CS722U.4-P O9 | H | Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions. |
| 100003/ CS722U.4-P O10 | H | Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools for better products. |
| 100003/ CS722U.4-P O11 | M | Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices. |
| 100003/ CS722U.4-P O12 | H | Students are able to interpret, improve and redefine technical aspects for demonstrating the knowledge of, and need for sustainable development. |

| | | |
|------------------------------|---|--|
| 100003/ CS722U.5-P O1 | H | Students are able to interpret, improve and redefine technical aspects, apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice. |
| 100003/ CS722U.5-P O2 | M | Students are able to interpret, improve and redefine technical aspects, communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions. |
| 100003/ CS722U.5-P O3 | H | Students are able to interpret, improve and redefine technical aspects to demonstrate knowledge and understanding of the engineering and management principle in multidisciplinary environments. |
| 100003/ CS722U.5-P O4 | H | Students are able to interpret, improve and redefine technical aspects, recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change. |
| 100003/ CS722U.5-P O5 | M | Students are able to interpret, improve and redefine technical aspects in acquiring skills to design, analyze and develop algorithms and implement those using high-level programming languages. |
| 100003/ CS722U.5-P O12 | M | Students are able to interpret, improve and redefine technical aspects and contribute their engineering skills in |

| | | |
|------------------------------|---|--|
| | | computing and information engineering domains like network design and administration, database design and knowledge engineering. |
| 100003/ CS722U.6-P O5 | M | Students are able to interpret, improve and redefine technical aspects and develop strong skills in systematic planning, developing, testing, implementing and providing IT solutions for different domains which helps in the betterment of life. |
| 100003/ CS722U.6-P O8 | H | Students will be able to associate with a team as an effective team player for the development of technical projects by applying the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems. |
| 100003/ CS722U.6-P O9 | H | Students will be able to associate with a team as an effective team player to Identify, formulate, review research literature, and analyze complex engineering problems |
| 100003/ CS722U.6-P O10 | M | Students will be able to associate with a team as an effective team player for designing solutions to complex engineering problems and design system components. |
| 100003/ CS722U.6-P O11 | M | Students will be able to associate with a team as an effective team player, use research-based knowledge and research methods including design of experiments, analysis and interpretation of data. |

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| 100003/ CS722U.6-P O12 | H | Students will be able to associate with a team as an effective team player, applying ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice. |
| 100003/ CS722U.1-P SO1 | H | Students are able to develop Computer Science Specific Skills by modeling and solving problems. |
| 100003/ CS722U.2-P SO2 | M | Developing products, processes or technologies for sustainable and socially relevant applications can promote Programming and Software Development Skills. |
| 100003/ CS722U.3-P SO3 | H | Working in a team can result in the effective development of Professional Skills. |
| 100003/ CS722U.4-P SO3 | H | Planning and scheduling can result in the effective development of Professional Skills. |
| 100003/ CS722U.5-P SO1 | H | Students are able to develop Computer Science Specific Skills by creating innovative solutions to problems. |
| 100003/ CS722U.6-P SO3 | H | Organizing and communicating technical and scientific findings can help in the effective development of Professional Skills. |