Mesopotamian journal of Big Data
Vol. **(2024)**, 2024, **pp**. 40–47
DOI: https://doi.org/10.58496/MJBD/2024/004 ISSN: 2958-6453
https://mesopotamian.press/journals/index.php/BigData

Research Article

Agent-Interacted Big Data-Driven Dynamic Cartoon Video Generator

Yasmin Makki Mohialden [1,*], Abbas Akram khorsheed [1], Nadia Mahmood Hussien [1]

[1] *Department of Computer Science, College of Science Mustansiriyah University, Baghdad, Iraq.*

ARTICLE INFO

Article History
Received 18 Jan 2024
Accepted 11 Mar 2024
Published 17 Apr 2024

Keywords
Big Data
Cartoon Generation
Video Processing
Agent-Based Interactions
Image Manipulation

ABSTRACT

This study presents a novel method for animating videos using three Kaggle cartoon faces data sets. Dynamic interactions between cartoon agents and random backgrounds, as well as Gaussian blur, rotation, and noise addition, make cartoon visuals look better. This approach also evaluates video quality and animation design by calculating the backdrop colour's average and standard deviation, ensuring visually appealing material. This technology uses massive datasets to generate attractive animated videos for entertainment, teaching, and marketing.

1. INTRODUCTION

The Big Data-Driven Dynamic Cartoon Video Generator with Agent Interactions uses novel agent-based interactions, video processing, and picture manipulation to create dynamic cartoons. The paper desires a platform that combines agent-based interactions and dynamic material for rapid cartoon production. To achieve this, the platform may use AI animation generators and video processing applications. Animaker, RenderForest, and VideoScribe make content production easier for non-technical users by animating text prompts. 3D modelling, lip-syncing, and post-production visual effects may make videos more lively with Adobe Animate, AppyPie, and Blender. With these capabilities, the platform may modify images to make content visually appealing and engaging. Helping users create bespoke videos, you may utilize over 100 million stock movies, photos, layouts, and customizable options. Agent-based interactions would let users create more complex and dynamic cartoon films with method-character interactions than previous AI animation generators. Advanced AI systems may evaluate and respond to human input, making the user experience more interactive.

A big data-driven dynamic cartoon video generator with agent interactions would use advanced AI-driven tools and technology to create dynamic, visually attractive, and engaging cartoon videos. By concentrating on agent-based interactions, the platform would offer a novel way to generate more sophisticated and dynamic cartoon animations [1, 2, 3, 4, 5, 6, 7, 8]. Problem Producing captivating animated videos requires a lot of resources and skill. Large cartoon image databases can automate and streamline this procedure. Using such datasets to create high-quality animated films requires merging varied cartoon pictures fluidly and ensuring visual attractiveness, according to the proposed strategy. Using 10,000 Kaggle cartoon faces, this study presents a new way of animating films. The technology analyzes and enhances cartoon pictures using modern image processing algorithms. Cartoon graphics overlaid on random backgrounds produce interesting and captivating animations. Cartoons, short films, and internet content platforms can use the animated videos. Animation may assist instructional materials, and presentations may explain complicated subjects. Advertising: Animation captures viewers' attention and efficiently communicates commercial messages. The paper's outline is: The paper covers the relevant work, suggested approach, results, and discussion sections. Section 5: Conclusion.

*Corresponding author. Email: ymmiraq2009@uomustansiriyah.edu.iq

2. RELATED WORK

2023, This study introduces artificial intelligence and position estimation to automatically generate 3D character animation from video. The suggested method extracts pose information from the input video using a pose estimation model. They next train an artificial neural network to produce the 3D character animation using the retrieved posture information. To improve output, they tweak the resulting animation with animation filters. Experimental findings show that the suggested technique generates realistic and natural 3D character animations from video input. This automated approach can save time and effort when developing 3D character animations for the entertainment and gaming sectors [9].

2023, This work presents an immersive video environment (IVE) and dynamic scene generator (DSG) technique to dynamically produce video settings for pedestrian behavior and urban planning studies [10].

In 2023, this research provides a distributed potential game architecture where each agent imagines a cooperative game with other agents and solves it using its behavior estimation. They closely mimic interactions and solve games with iLQR. they show the benefits of distributed, imagined games in our system through simulation tests. theydemonstrate the high success rate, improved navigation efficiency, and rich, realistic interactions with interpretable parameters. Examples can be found at https://sites.google.com/berkeley.edu/distributed-interaction [11].

2023, The presented methods forecast individual interactions using static and dynamic circumstances. We use an input- and temporal-attention method to test them on medium- and long-term time horizons. The first two techniques employ a cutting-edge deep neural network and Qualitative Trajectory Calculus (QTC) linkages to develop a symbol-driven neural architecture that can predict spatial interactions. Thirdly, a data-driven motion prediction network predicts QTC spatial interactions after processing. Testing on a common robot dataset of hard, congested circumstances shows that data-driven prediction surpasses the other two. The three techniques were tested on various but comparable human contexts to determine their generality [12]. Table 1 is a comparison of other research studies and the proposed method.

TABLE I. COMPARISON OF RESEARCH STUDIES AND THE PROPOSED METHOD

Study	Focus	Difference with the Proposed method
Automatic 3D Character Animation from Video (Study [9])	Utilizes AI and pose estimation to create 3D animations from videos. Involves extracting pose data, training a neural network, and refining animations with filters.	The proposed method generates 2D video, overlays cartoon images on random backgrounds, and lacks AI-driven pose estimation, animation generation, or 3D rendering.
Immersive Video Environment and Dynamic Scene Generator (Study [10])	Develops environments for studying pedestrian behavior and urban planning, and dynamically generates video settings.	The proposed method creates visual content, lacks simulation or analysis of real environments or behaviours, and no simulation of environmental dynamics or human interactions.
Distributed Potential Game Architecture (Study [11])	Introduces game theory-based architecture for cooperative behaviour prediction among agents using iterative linear quadratic regulation (iLQR).	The proposed method lacks strategic interaction, game theory-based decision-making, and static manipulation of images without real-time or strategic interaction between agents.
Forecasting Interactions with Neural Networks and Trajectory Calculus (Study [12])	Uses advanced neural networks and Qualitative Trajectory Calculus to predict spatial interactions in complex, congested environments.	The proposed method lacks predictive modeling, and interaction dynamics, primarily focused on aesthetic combination of images without real-time data processing or predictive analytics.

3. THE PROPOSED METHOD

The proposed method uses cartoon images to generate animated videos through a systematic approach. It begins by initializing a CartoonAgent class, which facilitates the addition of agents responsible for modifying cartoon images. These agents help to produce video frames by interacting with cartoon images. The process involves selecting random cartoon images, applying modifications, and incorporating random backgrounds to enhance visual appeal. It uses image processing to create compelling animated entertainment. It showcases imaginative video-making using massive cartoon picture libraries. The suggested technique is block diagram shown in Figure 1, and its algorithms are listed in Table 2. Method steps include:

1. Initialization: The recommended procedure CartoonAgent is instantiated to generate animated videos.
2. Agent Integration: Agents like CartoonAgentAgeFilter may change cartoon pictures based on parameters. To imitate age-related effects, an age filter agent may add text.
3. Frame Generation: The agents dynamically alter cartoon images to create video frames. These frames undergo continuous refinement through interactions with the agents.
4. Data Collection: Image properties, such as frame numbers, file names, sizes, and background colour information, are systematically recorded and stored in a structured format, such as a CSV file.

Fig 1. Block diagram of the proposed method

TABLE II. ALGORITHMS USED IN THE PROPOSED METHOD

Algorithm	Description
Gaussian blur	Blurs the image using a Gaussian filter
Rotation	Rotates the cartoon image
Noise addition	Adds random noise to the image
Age filter	Simulates an age filter by adding text to the image

The algorithm, followed by a structured proposed method.

1. Initialization: Instantiate a CartoonAgent object containing a list of cartoon image manipulators (agents).
2. Video Generation:
   - Set up a video writer using OpenCV with specified properties.
   - For each frame:
     - Generate a random background image.
     - Load a random cartoon image.
     - Allow agents to interact with the cartoon image.
     - Combine the cartoon with the background to create the final frame.
     - Write the frame to a video file.
3. Data Collection:
   - Collect the properties of each frame (e.g., image sizes, color statistics) and store them in a data frame.
   - Save the DataFrame as a CSV file containing metadata about the video frames.
4. Execution Time:
   - The entire process's execution time is measured and displayed.

4. RESULTS AND DISCUSSIONS

Fig. 2. Sample 1 of the input images

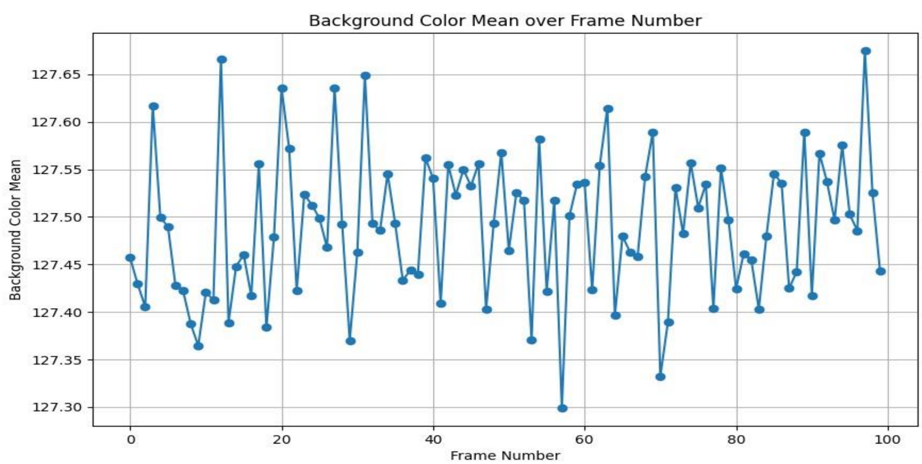

Fig 3. Sample 1 background colour mean plot.

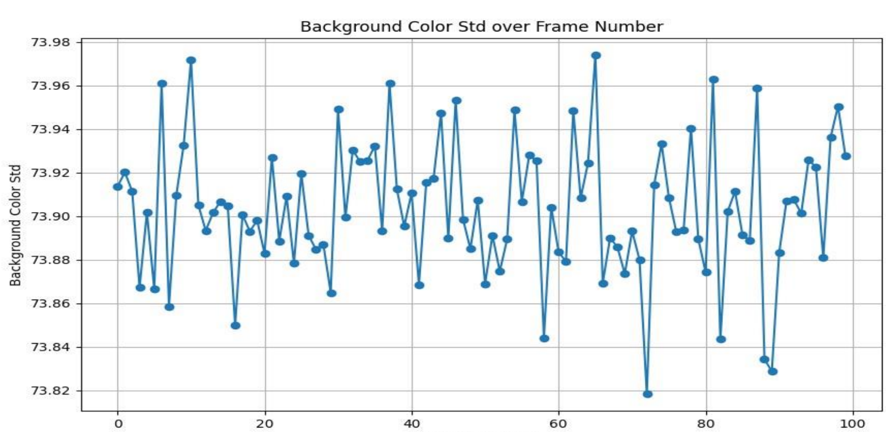

Fig 4. Sample 1 background colour, standard deviation plot.

Figures (3,4,6,7,8,9) and the results in the table give us an insight into the average background colour mean and standard deviation across all frames in the dataset for the three sample data sets.

Fig 5. Sample 2 of the input images

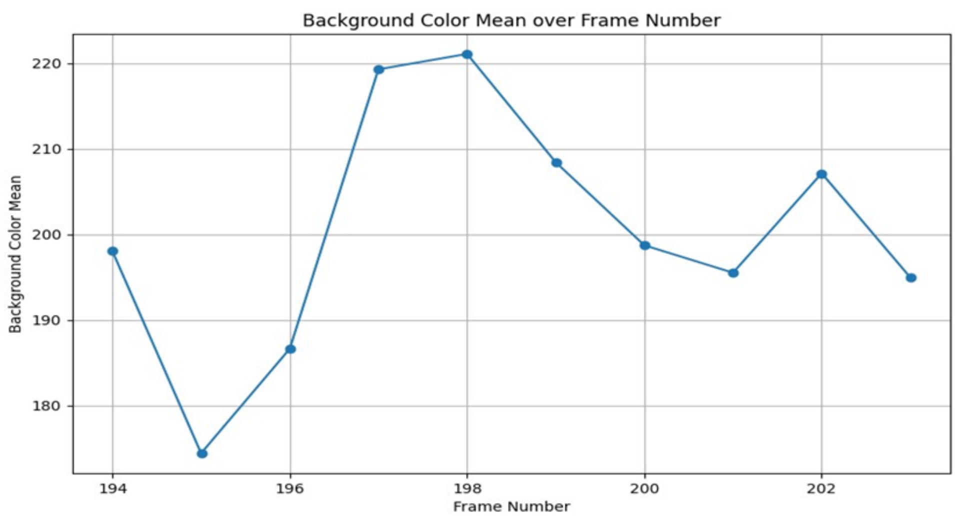

Fig 6. Sample 2 background colour mean plot

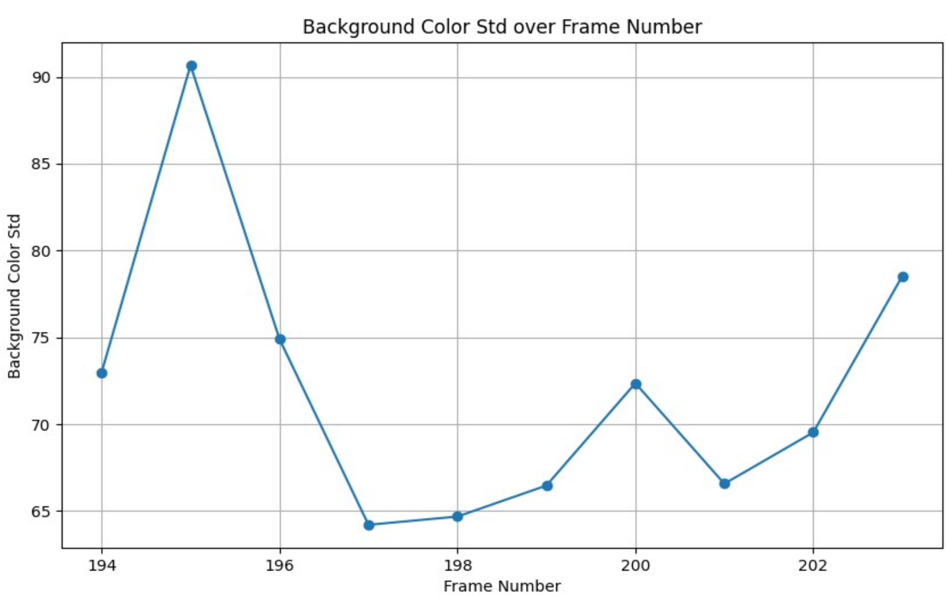

Fig 7. Sample 2 background colour, standard deviation plot

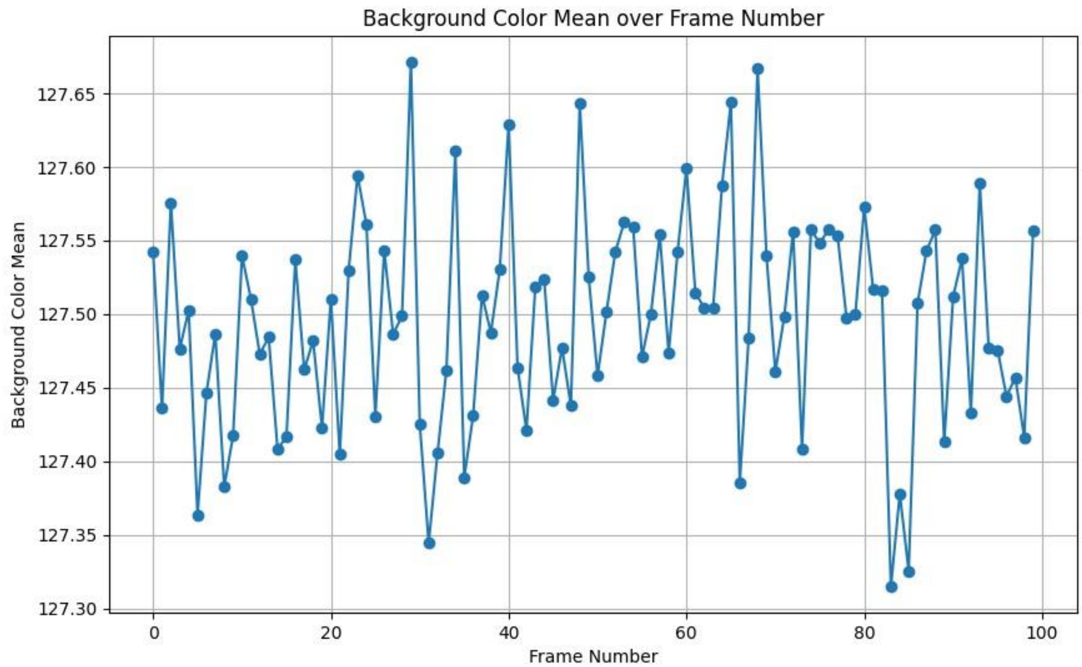

Fig 8. Sample 3 background colour mean plot

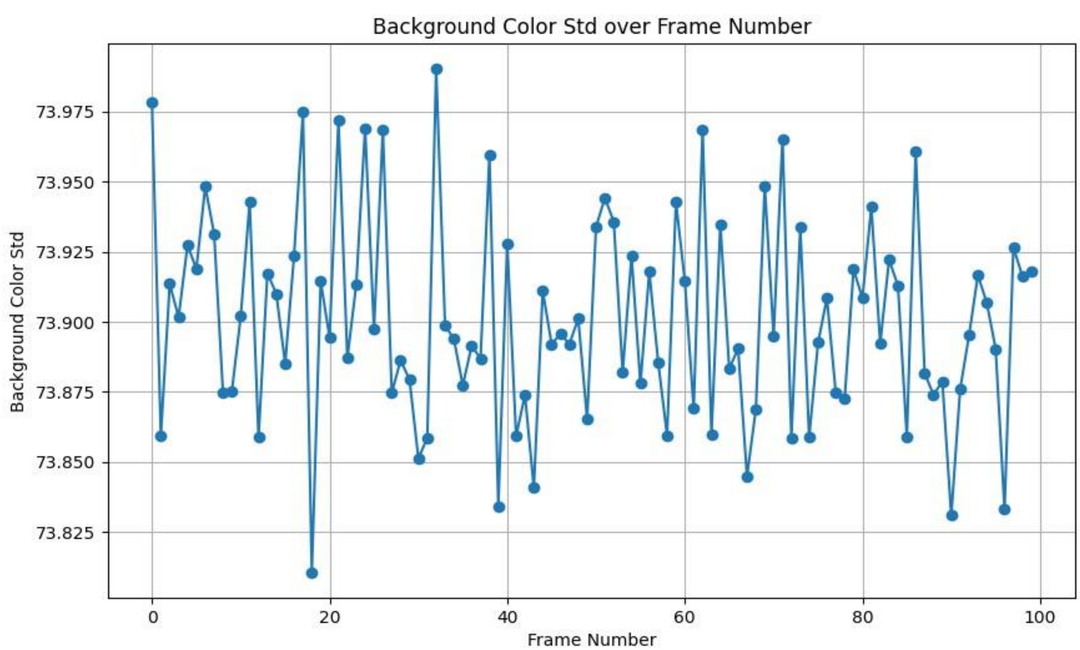

Fig 9. Sample 2 background colour, standard deviation plot .

TABLE III. THE GENERATED THREE VIDEOS PROPERTIES

Sample no	Duration (seconds)	Width (pixels)	Height (pixels)	Frame Rate (fps)	Total Frames	Execution time:	The generated video link
1	3.33	640	480	30	100	2.188383102416992	https://youtu.be/Fpic7PMQdsY
2	3.33	640	480	30	100	1.2723867893218994	https://youtu.be/nlvm6HaFulA
3	3.33	640	480	30	100	1.7340130805969238	https://youtu.be/mPzuyhU9BZg

5. CONCLUSIONS

The paper introduces a novel approach to creating dynamic cartoon content by integrating odd cartoon visuals and creative backgrounds. By incorporating random cartoons, backgrounds, and cartoon agents, the process becomes inherently dynamic, fostering creativity and experimentation. Throughout the production of the video, various attributes such as frame numbers, cartoon file names, picture sizes, and backdrop colors are meticulously recorded, enabling comprehensive content analysis and understanding. Cartoon agents like the age filter agent demonstrate the script's power to change cartoon images. This example shows how agents can dynamically change cartoon material, enabling creative adaptability. The script needs various optimizations to improve execution performance, which is critical for huge datasets and real-time applications. Adding agents with style transfers, creative filters, and animations can increase interaction diversity and content quality. Customization and interaction increase when users manage content development through interaction types and intensities. Agent behavior learning and machine learning may enhance the script. Training models on big cartoon picture datasets lets the script handle more complicated user requests and content changes.

Real-time script optimization is essential for live broadcasts and interactive apps. Parallelism, distributed computing, and multi-threading minimize latency and resource utilization while improving computational efficiency. Content quality and creativity are needed to evaluate producing process efficacy. Automatic or manual analytics may identify the script's performance and improvement areas. Production script reliability demands error handling and logging enhancements. Error management speeds up troubleshooting and debugging, decreasing content production delays. Using online cartoon picture libraries and NLP APIs helps boost content creation. Addressing these aspects may make the script a valuable tool for developing dynamic cartoon content for entertainment, education, and the creative industries.

Conflicts Of Interest

The paper states that there are no personal, financial, or professional conflicts of interest.

Funding

No grant or sponsorship is mentioned in the paper, suggesting that the author received no financial assistance.

Acknowledgment

The authors would like to thank Mustansiriyah University (https://uomustansiriyah.edu.iq in Baghdad, Iraq, for its support in the present work.

References

[1] "Cartoon Video Maker | Create Professional Cartoon Videos", Steve.AI. [Online]. Available: https://www.steve.ai/cartoon-video-maker

[2] F. Hamid, "10 Best AI Animation Generators in 2024 (Free and Paid)", Elegant Themes Blog, Feb. 29, 2024. [Online]. Available: https://www.elegantthemes.com/blog/design/best-ai-animation-generators.

[3] D. Xian and J. Sahagun, "An Automated Generation from Video to 3D Character Animation using Artificial Intelligence and Pose Estimate," Artificial Intelligence Advances, 2023. [Online]. Available: https://doi.org/10.5121/csit.2023.130703

[4] S. Schröder, J. Stenkamp, M. Brüggemann, B. Karic, J. Verstegen, and C. Kray, "Towards dynamically generating immersive video scenes for studying human-environment interactions," AGILE: GIScience Series, 2023. [Online]. Available: https://doi.org/10.5194/agile-giss-4-40-2023

[5] C. Ma, H. Wang, and M. Wang, "Guiding Interactive Film With Emotion-Profiling Chatbots," in 2023 International Conference on Computing, Networking and Communications (ICNC), pp. 478-483, 2023. [Online]. Available: https://doi.org/10.1109/ICNC57223.2023.10074513

[6] A. Unmesh, R. Jain, J. Shi, V. Chaitanya, H. Chi, S. Chidambaram, A. Quinn, and K. Ramani, "Interacting Objects: A Dataset of Object-Object Interactions for Richer Dynamic Scene Representations," IEEE Robotics and Automation Letters, vol. 9, pp. 451-458, 2024. [Online]. Available: https://doi.org/10.1109/LRA.2023.3332554

[7] S. Mghames, L. Castri, M. Hanheide, and N. Bellotto, "Qualitative Prediction of Multi-Agent Spatial Interactions," in 2023 32nd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), pp. 1170-1175, 2023. [Online]. Available: https://doi.org/10.1109/RO-MAN57019.2023.10309584

[8] Y. Jia, M. Bhatt, and N. Mehr, "RAPID: Autonomous Multi-Agent Racing using Constrained Potential Dynamic Games," in 2023 European Control Conference (ECC), pp. 1-8, 2023. [Online]. Available: https://doi.org/10.48550/arXiv.2305.00579

[9] D. Xian and J. Sahagun, "An Automated Generation from Video to 3D Character Animation using Artificial Intelligence and Pose Estimate," Artificial Intelligence Advances, 2023. [Online]. Available: https://doi.org/10.5121/csit.2023.130703

[10] S. Schröder, J. Stenkamp, M. Brüggemann, B. Karic, J. Verstegen, and C. Kray, "Towards dynamically generating immersive video scenes for studying human-environment interactions," AGILE: GIScience Series, 2023. [Online]. Available: https://doi.org/10.5194/agile-giss-4-40-2023

[11] L. Sun, P. Hung, C. Wang, M. Tomizuka, and Z. Xu, "Distributed Multi-agent Interaction Generation with Imagined Potential Games," ArXiv, abs/2310.01614, 2023. [Online]. Available: https://doi.org/10.48550/arXiv.2310.01614

[12] S. Mghames, L. Castri, M. Hanheide, and N. Bellotto, "Qualitative Prediction of Multi-Agent Spatial Interactions," in 2023 32nd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), pp. 1170-1175, 2023. [Online]. Available: https://doi.org/10.1109/RO-MAN57019.2023.10309584