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Creative Insights into Motion: Enhancing Human Activity Understanding with 3D Data Visualization and Annotation

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MoViAn for 3D Human Motion Visualization and Annotation

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This paper presents a novel 3D system for human motion analysis - Motion Data Visualization and Annotation (MoViAn). Designed to provide a comprehensive visual representation of 3D human motion data, MoViAn incorporates detailed visualization of gaze direction, hand movements, and object interactions, alongside an interactive interface for efficient data annotation. A user study involving eight participants indicates that MoViAn enables users to thoroughly explore and annotate human motion data, with System Usability Scale (SUS) results demonstrating a satisfactory usability level. The contribution of this paper lies in the development of an interactive and usable data analytics tool aimed at deepening the understanding of human behaviors and intentions in various creative, cognitive, and physical activities that ultimately can facilitate the design and creation of innovative tools that enhance human life in multiple domains.

CCS CONCEPTS • Human-centered computing – Visualization systems and tools • Computing methodologies – Graphics systems and interfaces • Computing methodologies – Animation • Human-centered computing – Usability testing

Additional Keywords and Phrases: Human motion analysis, 3D visualization, Data exploration, Data annotation, User interface, Usability evaluation

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1 INTRODUCTION

Human activity recognition and analysis are integral to endeavors centered around human experiences. Human motion analysis, such as data visualization and annotation, is crucial in understanding human behaviors and intentions during various activities, which can support the design and development of innovative tools to assist human life across different fields, including creative product design [2], building and community planning [16], child development [14], and physical therapy [13].

Traditional tools for video-based data annotation [5,17,19] enable high-definition video-based visualization of human movements but are limited to a 2D perspective, missing out on the rich context of 3D spatial movements. The emergence of wearable motion-sensing technology [12] has facilitated the tracking of human activities by offering high-quality motion capture without the need for an unobstructed field of view, which is a common requirement for vision-based tracking systems. Nonetheless, these motion sensors often result in large and complex human motion data comprising 3D spatiotemporal trajectories of multiple tracking points, presenting significant challenges in visualization and comprehension due to their multidimensional nature, which often require specialized skills or additional tools for effective analysis.

Researchers have explored various visualization techniques for human motion tracking data, with early work [1,7,8] utilizing a simplified 2D human skeleton to visualize full-body postures. While subsequent studies [10,11] have employed 3D skeleton representations to demonstrate human movements, they primarily concentrate on static posture recognition and clustering rather than capturing the dynamics of human motion and interaction within a 3D space. While recent advancements have leveraged immersive technologies like virtual reality (VR) [4,9] and augmented reality (AR) [15] for the 3D visualization and animation of complex movements through virtual avatars, they often lack the support to display intricate details of gaze and hand movements, which are crucial for a comprehensive understanding of human behavior [13]. Furthermore, little research has focused on the effective visualization of complex motion data in forms comprehensible to humans and the development of tools that facilitate data annotation with relevant tags for identifying significant human activities, which are essential for developing machine learning algorithms for human activity recognition.

This work aims to fill this gap by developing a novel 3D data analysis system for human motion analysis - Motion Data Visualization and Annotation (MoViAn). MoViAn is designed to offer an enriched visual representation of 3D human motion data, encompassing features such as the visualization of gaze, hand movements, and interactions with objects, coupled with an interactive interface for data annotation. We have also conducted a user study to assess the system’s usability, contributing further to this field of study.

2 MOVIAN - A MOTION DATA VISUALIZATION AND ANNOTATION SYSTEM

MoViAn is an analysis tool designed to visualize and annotate input 3D human motion datasets. The system consists of **three major modules** (see Figure 1): 1) data processing, 2) data visualization, and 3) data annotation. MoViAn is a unified system that combines the capabilities of Python-based data analytics packages with dynamic visualization and interactive features of a 3D game engine. Specifically, the visualization and annotation modules are built based on a 3D Game Engine - Unity [21], to make use of its rendering capabilities and robust interaction system, while the data processing module incorporates powerful data analyzing packages to ensure efficient processing and analysis of complex human motion data.

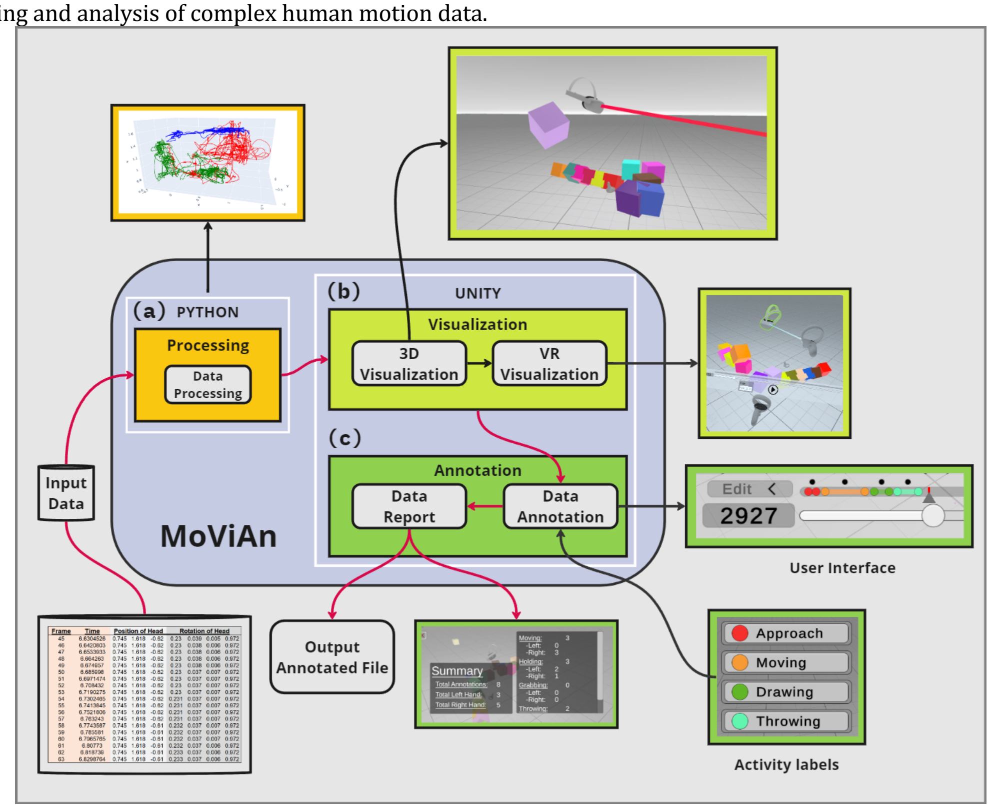

Figure 1: Overview of the MoViAn system with three major modules: (a) data processing, which cleans and processes input complex, multi-dimensional human motion dataset, (b) data visualization, which provides an enriched visual representation of 3D human motion data, such as gaze, hand movements, and object interactions, in both desktop and VR, and (c) data annotation, which offers an interactive user interface for data annotation and analysis. Arrows in red indicate the data flow within the system.

2.1 Data Processing

To allow the user to import a human motion dataset into MoViAn for data visualization and annotation, we implement the data processing module using Python-based data analytics packages, including Scikit-Learn [22], Plotly [23], Pandas [20], and Numpy [24], allowing for denoising and down-sampling the data based on the desired resolution. Our system facilitates the import of motion data, accommodating both 3D positions and orientations for each body-mounted motion tracker. This data format is widely adopted across numerous motion-sensing devices. We extract and restore the motion tracking for different body parts (e.g., head, eye-tracking) depending on their availability in the dataset for virtual avatar visualization in the next step. In addition to processing human data, this module can also process the motion tracking of any objects available in the dataset in order to reconstruct the environment where the human interacts during the activity. This feature can further enhance the interpretation of human movement in the presence of the environment. Furthermore, the data processor module presents a simple user interface for file system management, see Figure 2. This is accomplished through the use of a Python-based package Custom Tkinter [18].

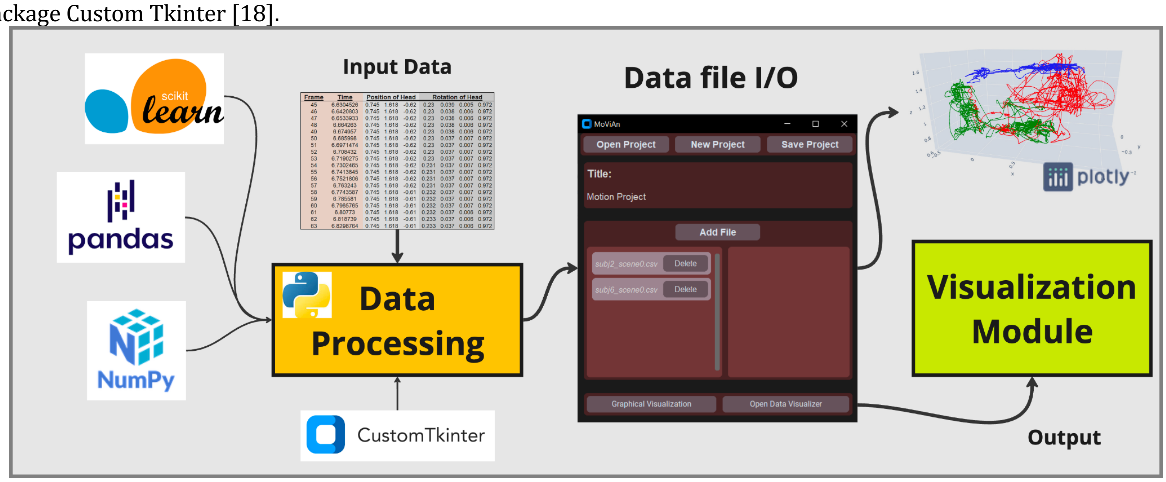

Figure 2: The MoViAn's data processing module is implemented based on several Python-based data analytics packages (extensible) and provides the user an interface to import and process the data, preparing for visualization in the next step.

2.2 Data Visualization

The main goal of the data visualization module is to generate 3D visualization of human motion data and animate their interactions with the 3D environment. As a proof of concept, this paper focuses on visualizing human motion data captured in a VR environment, where only the head and hand motion are captured and displayed using a VR headset and two hand controllers in our system. A standout visual layer, denoted object-tracing, uses colored trails to map the head, hand, and object movements over time, effectively illustrating motion trajectories (see Figure 3 (a)). Additionally, eye-tracking data, when available, triggers the display of another visual layer, namely eye-tracking, a red laser projecting from the headset to indicate gaze direction (refer to Figure 3 (b)). While environmental objects are initially shown as colored blocks positioned and oriented as per the data, their scale can be adjusted by the user within the module for a more accurate scene representation (see Figure 3 (b)).

The module further integrates video playback functionalities, allowing the user to view the motion data in the form of 3D video, just like how they would view a 2D video. We further offer functionalities, including play/pause buttons, a progress bar, and speed adjustment options (see Figure 3 (d)). When the user plays the 3D video, all the scene objects, including the human avatar and environmental objects, are animated according to the recorded motion in the dataset. The user can also drag the knob on the progress bar to adjust which frame of the data they would like to view. Keyboard shortcuts, such as arrow keys for video navigation and the spacebar for toggling playback, enhance the tool's user-friendly nature. Given the possibility of motion obscuring from certain perspectives, our visualization module allows the user to adjust the camera position and orientation in the 3D space to optimize the view. We also include VR implementation of this module, which offers an immersive experience, enabling the user to observe the motion data unfold in a virtual environment, see Figure 3 (c).

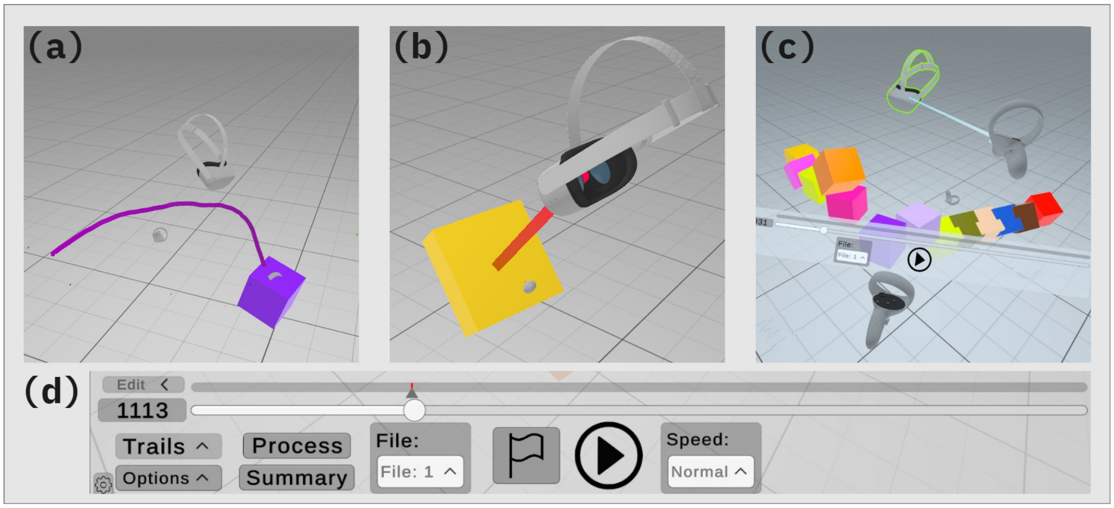

Figure 3: The MoViAn's data visualization module converts the input human motion data into 3D visualization and animation and supports various visual layers such as object-tracking (a) and eye-tracking (b) to enrich the data expressiveness. The user can also visualize and interact with the data in the VR implementation of this module (c). Visualization playback functionalities include a progress bar, play button, speed controls, and other advanced options (d).

2.3 Data Annotation

Built on top of the visualization module is the annotation module, which is a user interface made of a collection of tools to facilitate the user in annotating human activities that occur within the data. The user defines what constitutes an action (e.g., throwing) or an activity (e.g., reading, drawing), with the system supporting various annotation types for diverse action categorization. Utilizing motion playback capabilities from the visualization module, the user can thoroughly navigate and annotate the dataset. The annotation toolkit comprises action markers for denoting start and end points, user-defined action types, and an edit panel focusing on a specific annotation for refined adjustments. As shown in Figure 4 (a), annotated actions and activities represented as colored marks, namely flags, appear above the video playback bar, indicating how long the action lasts (in frames). Opening the editor panel launches a detailed view for precise flag position adjustments, as illustrated in Figure 4 (b). Upon completing annotations, a data summary report panel displays all annotations with their types, as shown at the bottom of Figure 1. The system allows for various export options, including data reports and the fully annotated dataset. These exports can be reimported into the data processor for further analysis.

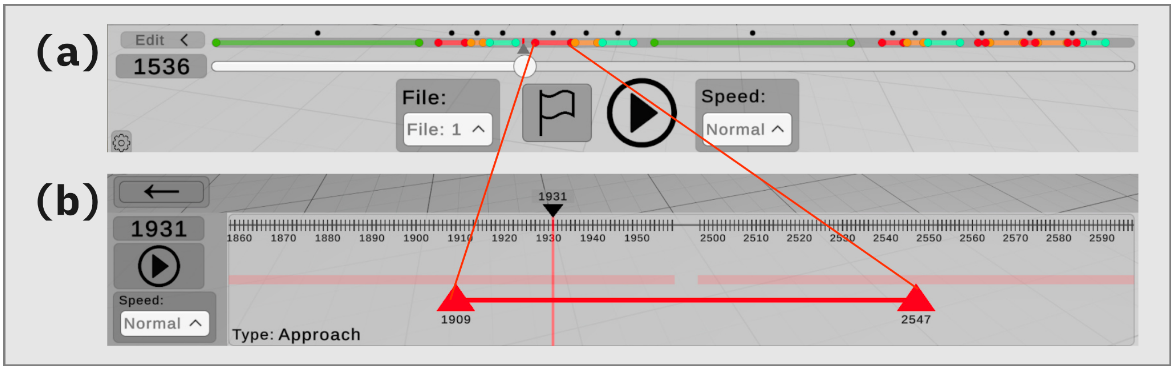

Figure 4: The MoViAn's data annotation module offers an interactive user interface to allow the user to mark down the beginning and end of each action and activity, appearing as colored flags above the scrub bar (a) and fine-tune the timing of a specific annotation in an editor panel with a detailed view (b).

3 EVALUATION STUDY

We conducted an IRB-approved user study with 8 individuals (ages 19 - 20, 2 females and 6 males) with backgrounds in Computer Science (50%), Engineering (37.5%), and Graphics Design (12.5%) to get initial feedback on the usability of the data visualization and annotation modules of the proposed MoViAn system. After completing the consent forms, the participants were given instructions on how to use the MoViAn system. The participants were then told what specific actions they needed to annotate and given sufficient time to practice and ask questions. Each participant was given two different human motion data files (see Figure 5 and Figure 6) containing various human actions to annotate using MoViAn running on a laptop computer. These motion data were selected from an open-source VR dataset - OpenNEEDS [6], where human activities with object interactions were collected in VR. At last, the participants were asked to fill out the System Usability Scale (SUS) questionnaire [3] to evaluate the usability of the MoViAn system. SUS is a reliable and widely recognized tool for assessing the usability of various systems, which comprises 8 questions regarding the system's usability aspects, such as ease of use, efficiency, and overall satisfaction.

Data collection and analysis. The responses, scored on a 5-Likert scale, were then analyzed to calculate an overall SUS score, providing a quantitative measure of the system's usability. Specifically, for each of the odd-numbered questions, subtract 1 from the score; for each even-numbered question, subtract their value from 5. The final score (out of 100) can be calculated by adding up all the sub-scores and multiplying by 2.5.

4 RESULTS AND DISCUSSION

Examples of System Use. Figure 5 illustrates the visualization sequences of two actions: throwing (a) and moving (b), which utilize eye-tracking and object-tracing visual layers of MoViAn's data visualization module, respectively. By identifying the actions with the visualization system, the user is able to annotate human activities and actions as they appear in the data. Figure 6 illustrates an example of data annotation results. By showing the corresponding 3D visualizations on top, indicating how the annotations link to the visualized actions.

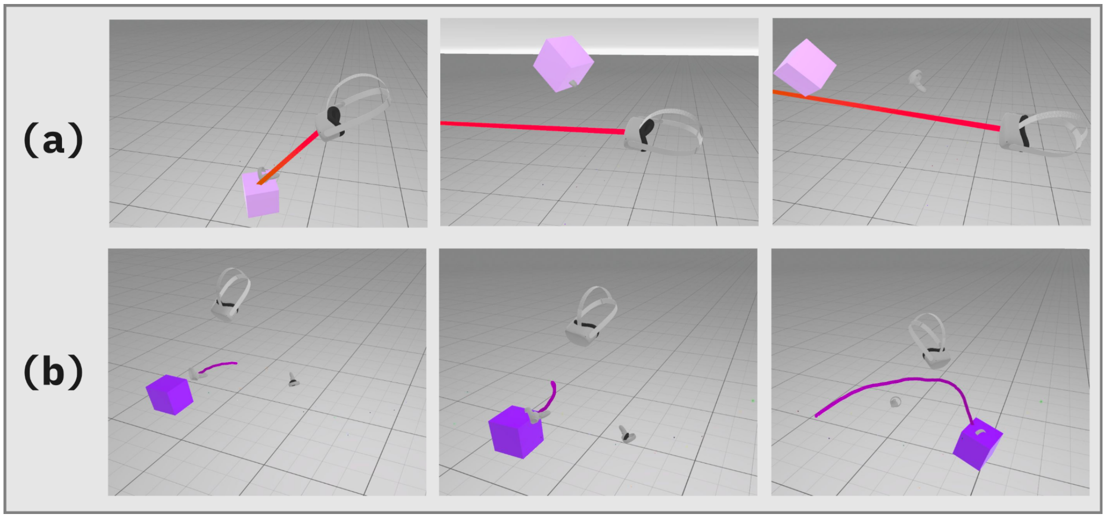

Figure 5: Visualizations of two actions: throwing (a) and moving (b), utilizing two visual layers of the MoViAn system, eye-tracking (a) and object-tracing for hand trajectory visualization (b).

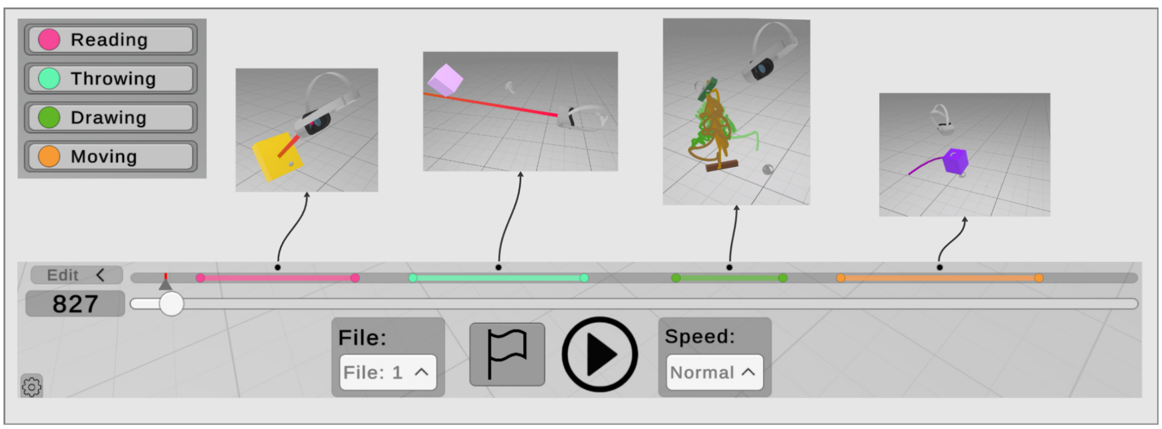

Figure 6: Data annotation results showing the visualized actions are linked to the annotation marks on the progress bar.

System Usability Scale (SUS) results. According to the SUS questionnaire [3], on average, participants agreed that the design of the MoViAn system was "acceptable" (average = 79.06, Figure 7). Specifically, 87.50% of participants gave the MoViAn system a higher-than-acceptable score, and 75% of participants rated the system 80% or higher regarding system usability. This result suggests that the usability of MoViAn is higher than average compared to other systems using the SUS survey.

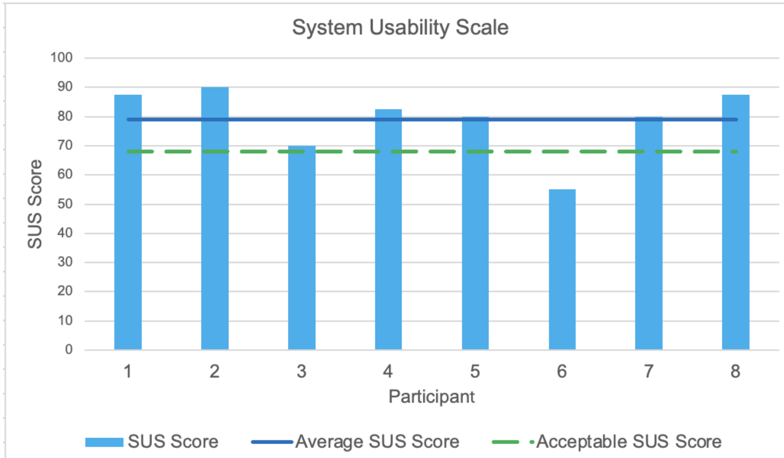

Figure 7: System Usability Scale Results.

5 CONCLUSION AND FUTURE WORK

In this paper, we introduce MoViAn, a novel 3D system designed for the analysis of human motion aimed at enhancing data visualization and annotation. This is essential for gaining insights into human behaviors and intentions across a variety of creative, cognitive, and physical tasks. MoViAn provides a comprehensive visual representation of 3D human motion data alongside an interactive interface for efficient data annotation. Our user study reveals that MoViAn enables users to thoroughly explore and annotate data, with System Usability Scale (SUS) results demonstrating a satisfactory usability level, averaging a score of 79.06. Moving forward, we aim to augment MoViAn's annotation functionalities by integrating machine learning algorithms for improved action recognition, automatically detecting patterns and cluster motion data, thereby assisting users in the annotation process. Moreover, we intend to enhance the current VR visualization aspect of the MoViAn system to support more intuitive 3D interactions in a 3D space. Furthermore, we plan to extend our user study to gather further feedback and implement enhancements to the system.

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