Interactive Visualization and Dexterity Analysis of Human Movement: AIMove Platform

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Abstract— **This paper introduces an innovative web-based platform for visualizing, analyzing, and generating human movement, leveraging explainable artificial intelligence (AI). It addresses the challenge of limited data by offering one-shot and data-intensive training approaches, facilitates data augmentation, and provides insights into human dexterity through user interaction with the learned movement models. The paper outlines the prototype's implementation, highlighting its tools for analyzing and visualizing complex movements, and discusses its application in analyzing professional movements within the heritage crafts and manufacturing industry. Future work aims to expand its motion capture technology compatibility and improve analytical functionalities. This enhancement seeks to extend the platform's reach, making it a valuable tool for researchers and professionals across various disciplines.**

I. INTRODUCTION

The expertise demonstrated by artisans in their crafts and industrial operators in their tasks reflects a fusion of skill, precision, and tradition cultivated through years of experience and knowledge. Despite technological advancements, comprehending the dexterity of both artisans and industrial operators remains a challenge, primarily due to the intricate interplay of full-body coordination required for task execution. Dexterity can be defined as the skill to perform a given movement or task using the hands or other body parts. This paper introduces an innovative web-based platform designed to address this challenge by analyzing Motion Capture (MoCap) data through explainable artificial intelligence (AI). In contrast to typical AI models, explainable human motion models offer interpretable mappings between input data and generated movements, providing insights into the mechanics behind the model's predictions. In other words, the parameters of the train models can give information about how a person moves in order to achieve a specific goal, such as assembling a TV or making a specific piece of glass. This information helps experts comprehend the underlying patterns in motion data, impacting various domains such as human learning applications, rehabilitation, sports science, and robotics. Beyond mere visualization, the proposed platform offers diverse tools for analyzing human movements, allowing users to manipulate parameters influencing posture prediction. The platform has integrated not only data-intensive approaches but also a one-shot training approach for movement representation and generation. Given the challenges posed by the dependency on extensive labeled datasets and significant computational resources, the platform's one-shot training capabilities offer a viable solution for industries and domains where labeled data are scarce.

The paper commences with an overview of the current challenges in capturing and analyzing professional movements in Section II, followed by an elaborate description of the platform's design and implementation (Section III). Here, the integration of explainable AI methods for analyzing and generating human movements is detailed, categorizing the integrated approaches into those utilizing data-intensive training and those employing one-shot training for movement representation and generation. Subsequently, the interactive visualization of motion descriptors and model's coefficients is shown in Section III-B. In Section IV, two case studies are presented to illustrate the platform's utility in potential real-world applications. Finally, the paper concludes with a discussion in Section V, where limitations and future directions of the work are reflected upon.

II. RELATED WORK

The analysis of human movement patterns is crucial across various domains, such as sports science, healthcare, rehabilitation, and biomechanical research. Such patterns, defined by identifiable sequences and behaviors in individual motions and postures, are essential for comprehending the intricacies of body joint coordination, movement timing, and spatial interrelations among different body parts. MoCap technologies permit the recording of these intricate patterns with precision, offering a basis for analyzing human kinetics and kinematics [17].

Explainable AI has emerged as a valuable strategy for understanding complex human movements, offering the capability not only to predict motions as traditional deep learning approaches but also to comprehend the underlying processes driving them. For instance, Lee et al. [8] showcase an innovative approach for recognizing human interactions through an attention mechanism focused on interacting body parts, highlighting critical body segments. Similarly, the Kinematic and Dynamic coupled Transformer (KD-Former) network utilizes attention maps to clarify kinematic and dynamic elements, pinpointing crucial joints for different movements [5]. There are also non-attribution-based explainable AI methods, which shift their focus away from evaluating the impact of individual input features. Instead, they aim to provide

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interpretations of AI decisions at a conceptual level that is understandable by humans. A notable method in this category is the Testing with Concept Activation Vector (TCAV), which determines the importance of semantic concepts, such as human postures, in classification outcomes by comparing concept activations with those of random instances within the same layer [7]. In alignment with these explainable AI paradigms, previous studies have introduced novel attribution techniques based on parametrizing interpretable mathematical models for human movement analysis [13].

Although these deep learning methods excel in accurately modeling and generating human movements across various classes of movements, their dependency on extensive labeled datasets and considerable computational resources poses significant challenges. These data-intensive approaches might not be viable or applicable in industries or domains where obtaining labeled data is scarce or problematic. Consequently, a critical need emerges for developing AI techniques or tools capable of analyzing human movements through one-shot training. Additionally, there is an equally important need for tools or methods that support data augmentation, which can facilitate training data-intensive deep learning models. In this context, Cabrera et al. [3] have developed a method for creating lifelike movement samples from the features extracted from a single gesture, presenting a promising direction toward minimizing data requirements. Eyobu et al. [15] enhanced classification performance in datasets of imbalanced human activities through a synergy of data augmentation techniques like the synthetic minority oversampling technique (SMOTE) and Random Oversampling (ROS) with ensemble learning. Another study improved action classification in stroke patients with hemiparesis by employing data augmentation methods such as rotation, permutation, and time warping on inertial MoCap data [10]. Other approaches that address the problem of having a small number of samples of human movements for analysis are the ones proposed in [6] and [9]. The first introduces a few-shot motion prediction model using graph neural networks. This model treats the network of sensors as a graph, allowing for task generalization across various tasks that use heterogeneous sensors. In another work by Mahalakshmi et al. [9], the integration of few-shot learning with behavior recognition algorithms is explored through the use of a Siamese network architecture complemented by an attention-focused Memory module. The architecture leverages the Siamese network design to process pairs of input data independently, enabling effective few-shot learning by transferring knowledge from closely related tasks.

In response to these outlined challenges, this paper introduces the prototype of a web-based platform that enables the analysis of movements through models trained via either one-shot or data-intensive approaches. The platform features the visualization of the learned interpretable motion models that users can interact with to generate varied versions of the learned movements; the artificial movements can then be downloaded by users for data augmentation purposes or further external analyses.

Recent advancements in application interfaces for human movement analysis include OpenCap [16], which performs motion analysis through synchronized smartphone videos; PhysioU's Gait Movement Analysis Application, offering insights into walking patterns and gait analysis for various health conditions [4]; Kemtai, leveraging computer vision to transform any camera into a personal exercise guide [2]; and the Mova platform, providing a suite of tools for comprehensive movement visualization and analysis [1]. Although these platforms offer improved movement visualization and fundamental analysis, they do not feature the approaches such as explainable AI for motion analysis and data augmentation capabilities highlighted in the proposed web-based platform. This distinction positions our platform as an innovative tool and a notable advancement in the field.

III. PLATFORM DESIGN AND IMPLEMENTATION

The architecture of the web-based platform is designed to facilitate users in the visualization and analytical examination of MoCap recordings through diverse interactive tools. Developed as a web-based application, it incorporates open-source Python libraries, including Panel, Bokeh, and Plotly, alongside JavaScript libraries to construct a dynamic graphical user interface. This paper presents the current prototype, accessible at https://github.com/olivas-bre/AImove.git, aiming for its eventual integration into the AIMove Moodle website (https://aimove.minesparis.psl.eu/) to facilitate interactive courses on traditional crafts and professional movement analysis from diverse sectors.

Upon accessing the platform, the user interface features a sidebar filled with widgets that assist in navigating through various visualization and analysis options. The primary display area presents the skeleton animation of an initial MoCap recording, as illustrated in Fig. 1. Although currently the platform can only use MoCap data captured with the inertial Biomed MoCap suit from Nansense Inc.(Baranger Studios, Los Angeles, CA, USA) [12], plans are in place to broaden the scope to include multiple forms of movement data. The platform leverages 3D local angles from Biovision BVH files, which contain the recorded joints' hierarchical structure, frame rate, and local joint angles for every frame.

Initially, users can load a MoCap file from the AIMove human motion capture repository via the *'Load MoCap Recording'* option, enabling them to choose a recording for visualization or analysis. The *'Visualization controls'* section allows for selecting and highlighting specific joints on the skeleton animation. Users can choose between 2D or 3D plots of the joint's angle trajectory and adjust the frame viewed with a slider, as shown in Fig. 2.

In the *'Analysis'* section, users can initiate a dexterity analysis window for the current movement and another to showcase kinematic features. Based on the selected recording, there is also the option to add confidence bounds or tolerance intervals on the 2D and 3D plots. These intervals represent the variability in movement performance across time frames, calculated from standard deviations when multiple repetitions of the same movement have been recorded

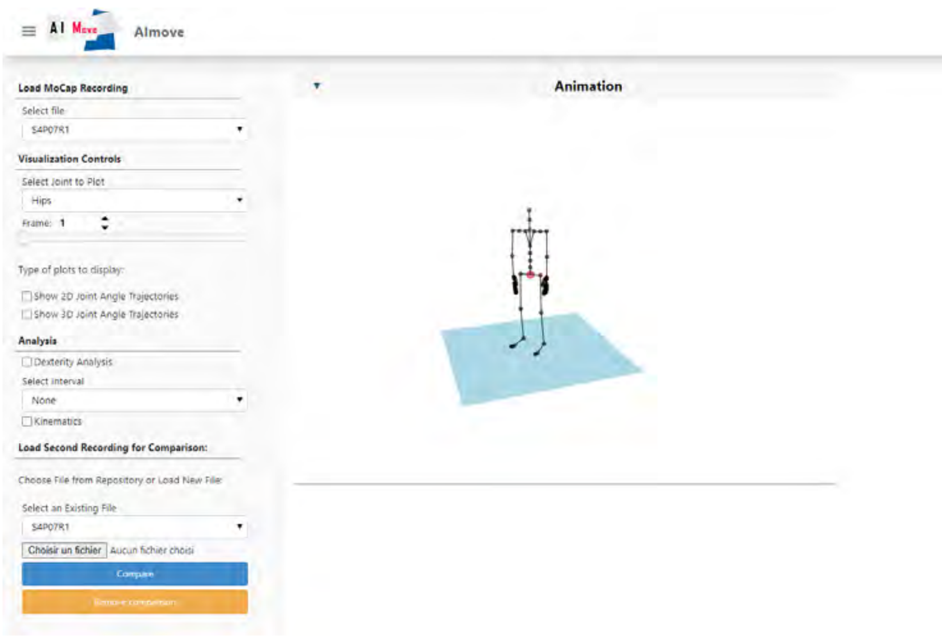

Fig. 1. Interface overview with sidebar navigation and MoCap recording animation, with the selected joint highlighted.

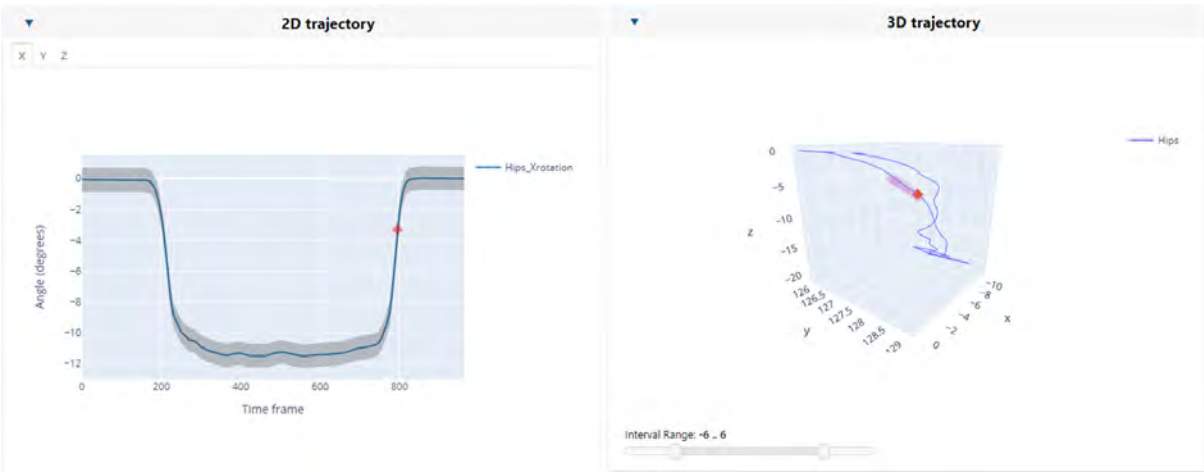

Fig. 2. 2D and 3D plots of joint angle trajectories from the selected MoCap recordings. The red dot represents the current frame that is visualized in the skeleton animation.

and analyzed to establish the intervals.

Finally, the *'Load Second Recording for Comparison'* section offers the capability for users to load a second MoCap recording for a side-by-side comparison with the first. This feature accommodates both selections from the repository and uploads of new MoCap files. All user-specified visualizations will be applied to both recordings, enabling a comprehensive comparison, as shown in Fig. 3.

The following subsection delves deeper into the full-body dexterity analysis of the recorded movement through explainable AI. It also illustrates the uses of the developed widgets for interacting with the results.

A. Dexterity Analysis

Leveraging the explainable AI algorithms proposed in [13], this subsection explains how the platform harnesses these algorithms to analyze and interpret the intricate dynamics of human movement, as well as generate artificial movements. Through state-space modeling, the platform offers insights into the joints' mediations, coordination, and fluidity of movements, providing a quantitative assessment of an individual's dexterity.

The upcoming section will detail the Gesture Operational Model (GOM), which corresponds to the state-space mathematical representation of human movements, and how its time-varying coefficients can be used for dexterity analysis. The second subsection will introduce the various training methods available on the platform for training GOM, either using data-intensive training with neural networks or one-shot training with Kalman filters.

1) Gesture Operational Model: GOM fuses biomechanical insights and stochastic models to formulate an un-

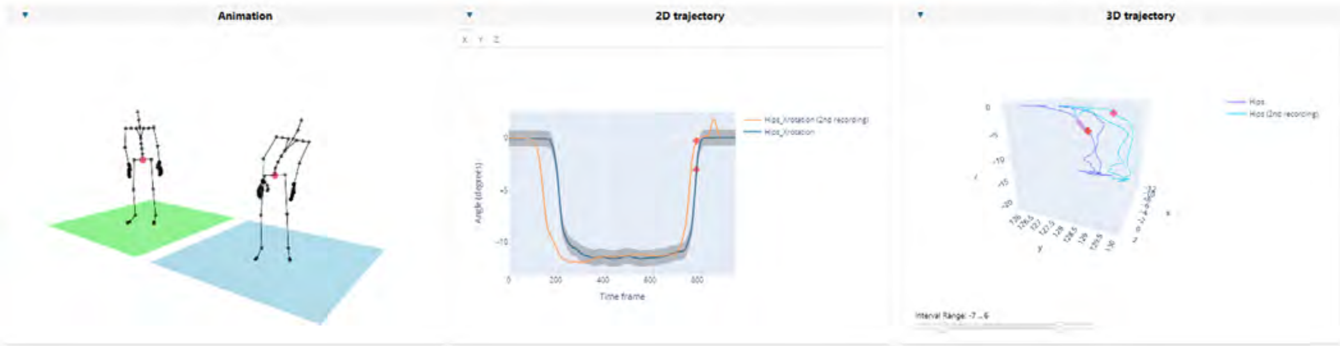

Fig. 3. Comparative visualization feature showcasing side-by-side analysis of two MoCap recordings. The selected joint is highlighted in the skeleton animation, and the red dot on the plots corresponds to the current frame visualized in the skeleton animation.

derstandable mathematical representation of human motion, emphasizing kinematic elements. Each motion representation corresponds to an autoregressive model capturing specific patterns of a motion descriptor, such as local joint angles. In the context of full-body movements, an equation system comprising autoregressive models is established, with each model modeling one of the measured motion descriptors. This equation system forms the foundation of GOM.

Imagine a human movement depicted as a sequence of postures $P_t = [P_1, P_2, ..., P_T] \in \mathbb{R}^{T \times N}$, where T signifies the sequence length. The dimensionality of motion descriptors is contingent upon the number of measured joints (J) multiplied by the dimensions associated with each joint's motion descriptor (D), resulting in $N = J \times D$. The equation system is composed of N models, which each incorporates four different assumptions that account for the dynamic relationships among body joints and their temporal dependencies:

- **H1 Transitioning**: Velocity of movement.
- **H2 Intra-joint association**: Movement of body joints in 3D space.
- **H3 Inter-limb synergies**: Coordination and synchronization between body limbs.
- **H4.1 Serial and H4.2 Non-serial intra-limb mediations**: Cooperation between sequentially and non-sequentially linked body joints.

Each assumption in GOM encapsulates specific variables (e.g., local joint angles) parameterized to represent particular relationships between body joints or temporal dependencies. These interactions are captured through state-space modeling with second-order models. Let's consider modeling the Euler angle trajectory of a body joint P_t along the X-axis, denoted as Px_t. This representation decomposes the movement into *XYZ* axes (Px_t, Py_t, and Pz_t) and is linked with j body parts. The mathematical expression for this motion descriptor is formulated as follows:

$$Px_{1,t} = \underbrace{\alpha_{t,1}Px_{1,t-1} - \alpha_{t,2}Px_{1,t-2}}_{\text{H1}} + \underbrace{\beta_{t,1}Py_{1,t-1} + \beta_{t,2}Pz_{1,t-1}}_{\text{H2}} + \underbrace{\beta_{t,3}Px_{2,t-1} + \cdots + \beta_{t,n}Px_{j,t-1}}_{\text{H3 or H4}} \quad (1)$$

In this equation, the motion representation is characterized by time-varying coefficients $A_t \in \mathbb{R}^{1\times 2}$ and $B_t \in \mathbb{R}^{1\times N}$, but they can also be constant $A \in \mathbb{R}^{1\times 2}$ and $B \in \mathbb{R}^{1\times N}$. Examining these learned coefficients enables the assessment of their significance in the modeling and generation. Resolving the equation system of GOM enables the generation of full-body human movements. These models can find utility across diverse applications, including the development of human learning applications that contrast expert motion models with those of novices. Additionally, integrating the artificially generated movements can boost the efficacy of other AI frameworks during their training procedures. The next section details three distinct approaches integrated into the platform for training GOM representations.

2) Training: This platform integrates data-intensive and one-shot approaches for training GOM. These were previously presented and detailed in [13] for the data-intensive approaches and at [14] for the one-shot approach. A comprehensive summary of each approach is given next:

a) Data-intensive: The platform integrates three data-intensive approaches to derive the GOM representation from the selected recording. These approaches utilize autoencoders, with the decoder in each framework determining time-varying coefficients. However, the role of the encoder varies across approaches, leveraging their distinct encoder-decoder architectures. The first approach, VAE-RGOM, employs a Variational Autoencoder (VAE) architecture with the Recurrent Neural Network (RNN) encoder serving as an inference network. The second approach, ATT-RGOM, utilizes a Long Short-Term Memory (LSTM) autoencoder with a Luong attention mechanism (global). The third approach, T-RGOM, adopts a Transformer architecture with self-attention. In both the ATT-RGOM and T-RGOM approaches, attentional hidden states are used to generate the time-varying coefficients through the decoder, emphasizing prediction loss during training. It is important to note that all networks were trained using the entire MoCap data from the AIMove repository [12]. Therefore, when the recording file and training approach are selected, the MoCap data extracted from the file undergoes preprocessing via sliding windows and standardization, then is fed into the corresponding trained network. Subsequently, the network provides the appropriate time-varying coefficients for its GOM representation, which are visualized in the platform (Next in Section III-B).

b) One-shot: The platform integrates a one-shot training approach utilizing Kalman Filters to derive constant coefficients for GOM. This method, KF-GOM, is fully described in [14]. In this approach, the mathematical representation of each motion descriptor is individually trained using only the selected recording. In the iterative process of the Kalman filter, the log-likelihood of the observed motion descriptor is calculated based on a specified set of GOM coefficients. The GOM representation containing the constant coefficients maximizing the log-likelihood of the observed motion descriptor is then visualized within the platform.

B. Interactive Visualization

The platform introduces an innovative interface for visualizing and interacting with the resulting parameters (shown in Fig. 4). The interface is organized within a window titled *'Gesture Operational Model'*, which is divided into three main tabs:

1) **Joint Angles**: This tab shows the interactive plots of the joint angles employed during training, enabling users to examine and manipulate the raw data inputs by dragging them with the cursor.
2) **Model**: Divided into *'Training Approach'*, *'Prediction'*, and *'Assumptions'* sections:
    - *Training Approach*: Here, toggle buttons are provided for each training approach (VAE-RGOM, ATT-RGOM, T-RGOM, or KF-GOM), enabling users to select their preferred method for estimating time-varying or constant coefficients.
    - *Prediction*: Offers a drop-down list for the axes (X, Y, Z) selection to specify which angle axis is modeled in accordance to the selected joint, influencing the visualization in the *'Assumptions'* section.
    - *Assumptions*: The platform presents interactive plots showcasing either time-varying coefficients or sliders for constant coefficients for each of the variables comprising the GOM assumptions. The coefficients are arranged inside tabs according to their respective assumption in the selected joint angle model. To explore the impact of parameter adjustments on the movement model, users can directly manipulate the coefficients by dragging their data points within the plots, as demonstrated in Fig. 5a, when dealing with time-varying coefficients. Alternatively, for constant coefficients obtained through the KF-GOM training approach, users can utilize sliders to adjust these coefficients, as depicted in Fig. 5b. The effects of these modifications are illustrated in a dedicated *'Generated Movement'* tab, featuring a plot of the selected generated joint angle alongside an animation displaying the resulting skeleton poses. An additional tab in this section called *'All Assumptions Statistics'* presents standard statistics obtained from the calculated coefficients (mean, standard deviation, quartiles, max, and min values).
3) **Generated Movement**: The final tab showcases a plot of the predicted joint angle and the full-body postures generated based on the training data and adjusted coefficients. Upon fine-tuning the coefficients to their satisfaction, users can press the 'Predict Joint Angle' button, prompting the platform to reveal the generated movement through both skeleton animation and trajectory plot visualization. To aid comparison, the GUI includes a reference to the prediction using the original coefficients, ensuring users can gauge the effects of their modifications, and the real trajectory of the motion descriptor.

For those wishing to conduct further analysis or for data augmentation purposes, the platform facilitates downloading the generated movement via the *'Download Generated Movement'* button.

IV. CASE STUDIES

The section explores the practical application of dexterity analysis within two distinct sectors: heritage crafts and the manufacturing industry. In this context, dexterity refers to the skill and proficiency exhibited in executing specific movements or tasks using the hands or other body parts. It begins by demonstrating how the provided tools can be utilized to analyze professional movements, such as those found in heritage crafts. An illustrative example showcases the platform's capability to compare two movements of an expert glassblower, including a comparison of their mathematical representations. Furthermore, it highlights how adjusting the coefficients of a movement's mathematical model generates new movements. This section also analyzes a movement from the manufacturing industry using one-shot training. This involves examining the constant coefficients, their statistical significance to identify meaningful motion descriptors, and their effect on the artificial generation of the movement.

A. Heritage Crafts: Comparative Analysis and Generation using Time-Varying Coefficients

As previously mentioned, the present subsection illustrates how the proposed web-based platform enables the examination of complex professional movements. The analysis of dexterity in heritage crafts offers invaluable insights into preserving the intricate techniques inherent to traditional practices. By dissecting the complex motions of craftsmen, such as glassblowers, this analysis supports the documentation, teaching, and perpetuation of these skills, thereby facilitating knowledge transfer to future artisans. As an example, the results of the body dexterity analysis of a movement from a glassblower are shown. Two repetitions of the same movement are observed, revealing similar patterns in its joint angle trajectory and the time-varying coefficients of their mathematical representation. The significance of the mathematical representation, alongside the visualization of

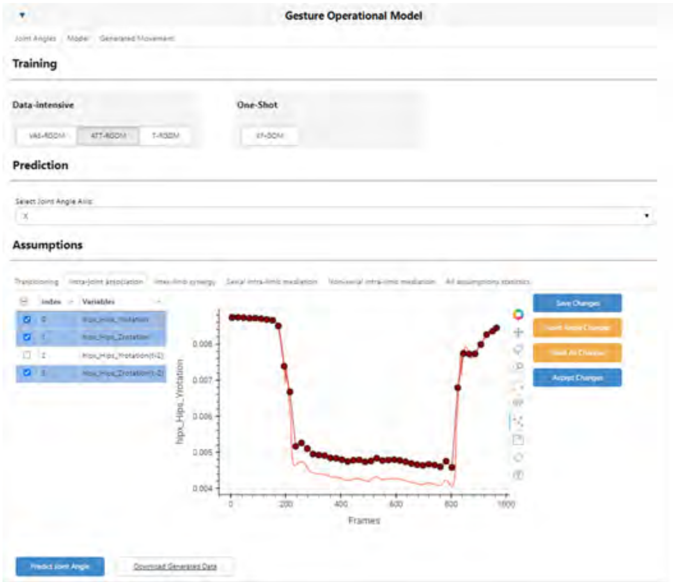

Fig. 4. Interface for the dexterity analysis of human movements using GOM.

Fig. 5. Illustration to interact and modify model's coefficients to examine their effect in human postures: (a) shows how to modify time-varying coefficients by dragging the visualized data points throughout the plot. The user can select a group of dots or change only one dot. (b) illustrates the sliders to modify constant coefficients.

joint angle plots, lies in its ability to directly identify the most relevant motion descriptors for modeling the movement. For instance, visualizing the time-varying coefficients of each motion descriptor allows for discerning their impact on the performance of the movement and their contribution to predicting joint angle trajectories. Motion descriptors with higher coefficients are more influential in prediction, while those closer to zero are less relevant.

In Fig. 6a, the skeletons of two movements performed by the glassblower are visualized, wherein he shapes a glass decanter curves with a wooden block while simultaneously turning the blowpipe with his right hand. Fig. 6b illustrates a joint angle trajectory, with the purple line representing the first recording being analyzed and the black dashed line corresponding to the second repetition. Fig. 6c displays the time-varying coefficients of the spine X variable for predicting the selected joint angle of the left arm (X-axis). By observing figures 6b and 6c, it is noticed similar patterns in both joint angle plots and time-varying coefficients, indicating the glassblower's capability to replicate the same movement. The contribution of spine X to the trajectory of the left arm varies over time (Fig. 6c), becoming smaller during certain periods.

The time-varying coefficients displayed in Fig. 6c can be modified using the tools located to the right of their plot. After adjusting the data points, the user can press the *'Save Changes'* button to preserve modifications. Once all desired modifications to the time-varying coefficients are made, the user can press the *'Accept Changes'* button to save coefficient values. Subsequently, pressing the *'Predict Joint Angle'* button solves the GOM representation to generate new human poses, which are visualized in the *'Generated Movement'* tab, as depicted in Fig. 6d. This tab presents a plot of the generated trajectory of the selected joint angle, its original trajectory, and the modified predicted trajectory obtained with the user's modifications. Additionally, an animation of the generated human poses is provided, along with the 3D trajectory of the predicted joint position and the original trajectory, facilitating comparison.

B. Manufacturing Industry: Analysis and Generation using Constant Coefficients

In the manufacturing sector, dexterity analysis is crucial in optimizing operational efficiency and ensuring worker safety. By closely examining assembly line tasks, it pinpoints

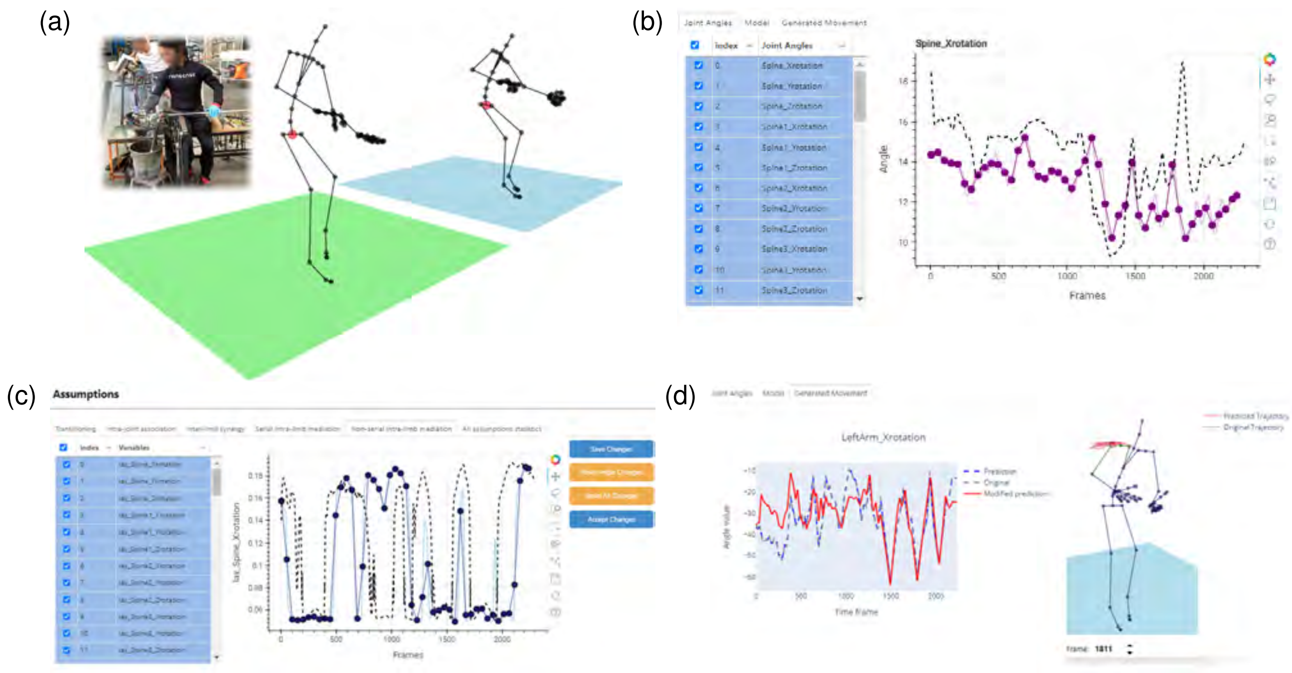

Fig. 6. Visualization and analysis of two movements performed by a glassblower: (a) Skeleton representation of glassblower movements; (b) Joint angles trajectories; (c) Time-varying coefficients of spine X (Non-serial intra-limb mediation): analyzing the contribution of spine X to the trajectory of the left arm, demonstrating variations over time and their impact on predicting joint angle trajectories; (d) Generated movement visualization: Joint angle trajectories and human poses. The animation of the generated poses has its own slider to control the visualization of the skeleton. The red dot highlights the joint angle that is being modeled. Also, its predicted and original position trajectories are displayed on the animation for comparison.

areas for ergonomic enhancements, streamlines production processes, and reduces the risk of injuries. Subsequently, the analysis of an industrial professional task is presented, illustrating how meaningful motion descriptors of specific movements are identified. In this instance, the process of identifying these descriptors is showcased not only by analyzing the models' coefficients but also by assessing their statistical significance. Fig. 7a provides insight into a typical movement observed in airplane assembly, where an operator holds a bucking bar while riveting an airplane float part. By using one-shot training with Kalman filters, the resulting constant coefficients are visualized with sliders (as shown in Fig. 7b), enabling users to adjust the estimated coefficients. Adjusting the coefficient sliders or directly altering the joint angles in the *'Joint Angles'* tab results in creating a new artificial movement, depicted in Fig. 7c. This figure contrasts the original movement, the initial generated movement using learned coefficients, and the modified version.

Further analysis of these coefficients and their time-varying counterparts is detailed in [14] and [11]. However, in this context, the focus is on their visualization within the web-based platform. All coefficients and their respective p-values are accessible in the *'All Assumptions Statistics'* tab, as depicted in Fig. 8. Each coefficient undergoes a hypothesis test, assuming it equals zero, suggesting the corresponding variable lacks influence on the dependent variable. The alternative hypothesis suggests the coefficient significantly differs from zero, indicating substantial influence on the dependent variable. A t-test is utilized to assess the significance of the estimated coefficient relative to its standard error. If the p-value is below 0.05, the null hypothesis is rejected, signifying the variable's significance for the dependent variable. Conversely, if the p-value exceeds 0.05, it is concluded that there is insufficient evidence to support the variable's significant impact on the dependent variable. This analysis facilitates understanding the relationship between motion descriptors and modeled movements. Users can arrange the variables based on the column values by clicking on the column title. Fig. 8 shows the variables arranged in ascending order according to their p-values. This organization enables the identification of the most statistically significant motion descriptors for the motion representation of the selected joint angle. In this particular case, these descriptors correspond to the time-dependent assumptions and serial and non-serial mediations (spine X and right forearm). These findings align with the observed movement, as the operator bends over and raises his arm to reach the point to hold the bucking bar.

V. CONCLUSIONS AND FUTURE WORKS

This paper introduces a novel web-based platform designed for interactive visualization, dexterity analysis, and data augmentation of human movement. Leveraging the capabilities of explainable AI, the platform provides users with an intuitive interface to explore the dynamics of human movements through interpretable models, trained using either one-shot or data-intensive approaches. Additionally, the interface allows users to interact with the trained models, enabling them to investigate the implications of the model's assumptions on predictions and to create diverse

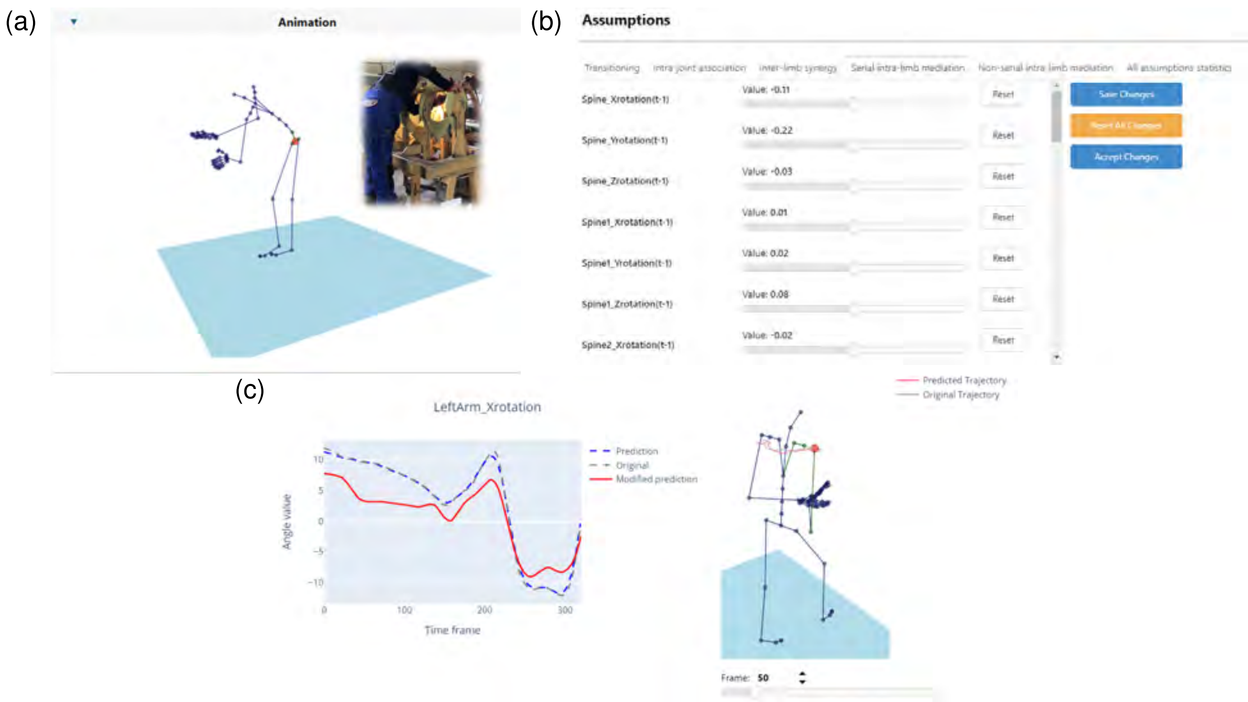

Fig. 7. Illustration to interact and modify model's coefficients to examine their effect in human postures: (a) Visualization of industrial task: depicting an operator holding a bucking bar while riveting an airplane float; (b) Coefficients Representation: Depicting the resulting model's coefficients from one-shot training (Serial intra-limb mediation), adjustable with sliders to modify the estimated constant coefficients; (c) Generated movement: Comparison of original, initially generated, and modified movements in a 2D plot and skeleton animation trajectories.

PLNS02P03R02: Hips X-axis

index	Coefficients	P-values
Hips_Xrotation(t-1)	1.955151	0.0
Hips_Xrotation(t-2)	-0.982473	0.0
Bias	1.708606	0.0
RightForeArm_Yrotation(t-1)	-0.01304	0.0
Spine_Xrotation(t-1)	-0.106171	0.0
LeftUpLeg_Yrotation(t-2)	0.064118	0.0
Spine_Yrotation(t-2)	0.227767	0.0
Spine_Yrotation(t-1)	-0.221112	0.000001
LeftArm_Yrotation(t-1)	0.018614	0.000001
RightForeArm_Yrotation(t-2)	0.011537	0.000002

Fig. 8. Statistical analysis of motion descriptors: Displaying coefficients and corresponding p-values for identifying the most statistically significant motion descriptors in the modeling.

variations of the learned movement. The work details the design and implementation of the platform, emphasizing its ability to load and analyze motion capture data, visualize motion descriptors and model's coefficients, and compare movements through an interactive interface. Case studies presented within the paper illustrate the platform's utility in analyzing complex movements within heritage crafts and the manufacturing industry, showcasing its potential to contribute significantly to both the preservation of traditional crafts and the optimization of industrial processes.

Acknowledging its limitations, future developments will aim to expand the platform's compatibility with various motion capture technologies, integrate kinetic analysis, improve the robustness of its analytical tools, and add extra to aid the dexterity assessment. These proposed enhancements will broaden the platform's applicability and enable more profound insights into the intricate mechanics of diverse professional tasks.

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