Generative AI, Decision-Making, and Collaborative Choreography: How LSTM Networks Mirror Human Creativity

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Abstract

This study explores the potential of generative AI, specifically Long Short-Term Memory (LSTM) networks, to advance collaborative choreographic composition within the framework of the Body Logic (BL) Method—a choreographic approach grounded in cognitive science designed to challenge inherited habits and practices in contemporary dance. Through five cognitive tasks that emphasize different movement types and their qualities, we investigate how LSTM networks recognize established movement patterns and innovate by combining them in novel ways, mirroring the processes of human creativity. Furthermore, we examine how LSTM-generated sequences, derived from learned data, convey expressive qualities through a variety of movements. The AI-generated movements closely follow the original movement trajectory but exhibit minor deviations attributable to the LSTM model's inherent prediction uncertainty. These variations illustrate the model's capability to introduce fresh elements while maintaining learned patterns, akin to human creativity. This research contributes novel perspectives on how technology can enrich artistic expression and challenge habitual decision-making in dance.

Keywords

Generative AI, Contemporary Dance, Creativity, Decision-Making, Habit

1. Body Logic (BL) Dance Method: Generating Creative Movements

The Body Logic (BL) Method is a choreographic approach designed to challenge entrenched habits in contemporary collaborative dance (Rijmer, 2022). It encourages dancers to engage more deliberately by using movement research grounded in cognitive science to inspire new ways of thinking and dance-making. This practice-led research method challenges dancers' choices of movement patterns, conceptually inherited from various dance traditions and embodied in their unique bodies, reflecting their own Body Logic. A dancer's Body Logic is an individualized framework of cognitive responses and embodied practices that shape their interpretation, selection, and execution of movements, influenced by personal experiences and cultural background (Bourdieu, 1977).

The BL Method promotes exploring new movement patterns, informed choice-making, and creativity through improvisation and self-exploration. It adopts a dual perspective on movement change causation: Dodging and Scanning modes. Dodging involves reacting to external stimuli or other dancers' movements, emphasizing interaction and collaboration. Scanning focuses on movements originating from specific body parts (Prime Movers, or PMs), focusing on detailed exploration of movement initiation and execution. The BL Method uses a typology of movement change generation and the qualities these new movements produce, studying alternatives to habitual movement patterns. Through specific exercises and cognitive tasks, like those described in this study, dancers explore these alternatives, examining types of images movements create and what this means for their own dance-making.

2. Gen AI Body Logic Dancer: Bridging AI and Choreography

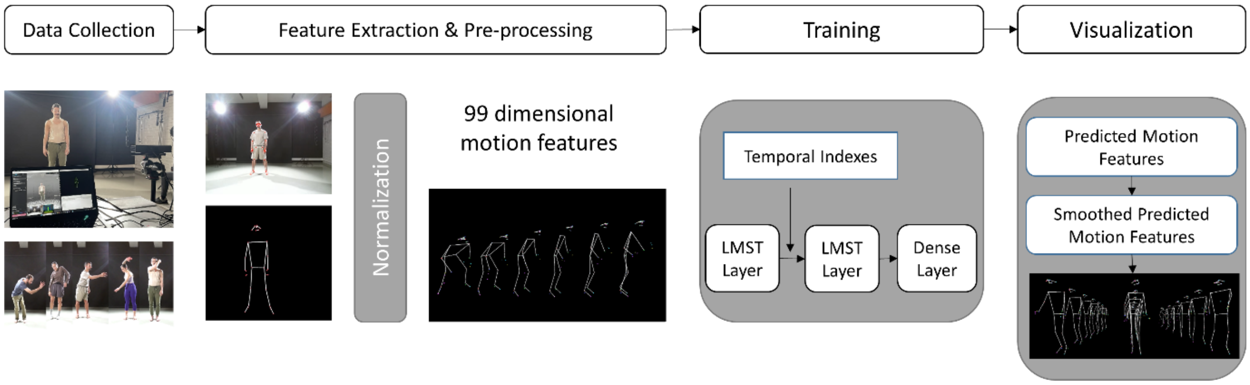

Figure 1: Workflow diagram illustrating the Generative AI Body Logic (BL) Dancer framework, showcasing the steps from data collection and feature extraction to model training and movement generation.

2.1. Data Collection and Feature Extraction

. Original dance data was collected using the BL Method, focusing on five motion image types classified by the shapes and qualities their movements create: Echo, Glitch, Suspend, Freeze, and Repeat. Five professional dancers performed task-based improvisations in a controlled setting, executing each BL Method movement quality in two rounds of sequences.

We captured RGB and depth data using a Microsoft Kinect V2, prioritizing high-quality, low-noise captures to preserve detailed movement information. Despite Kinect V2's challenges with occlusions and swift motions, we enhanced data quality using BlazePose (Bazarevsky et al., 2020) for feature extraction (see Fig. 2). This pose estimation model, which was notably superior in our tests, captures 33 key points and estimates depth, which is critical for analyzing complex dance movements with precision.

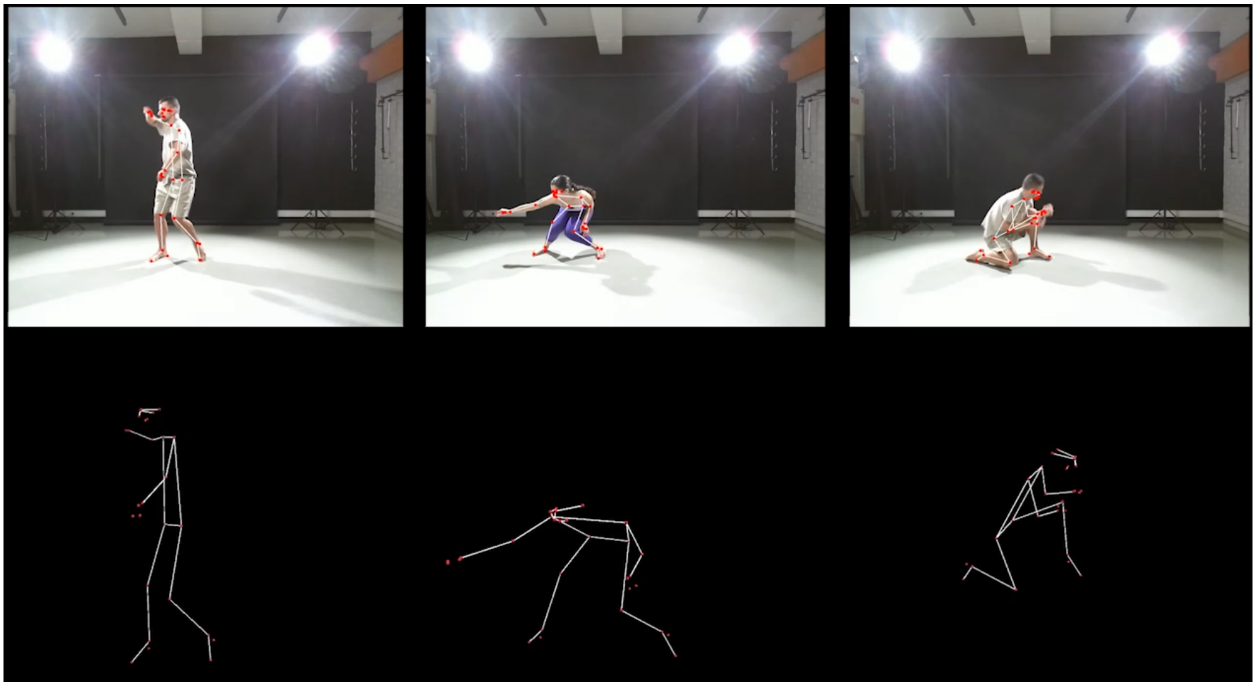

Figure 2: Illustration of the BlazePose model's feature extraction process, demonstrating both 2D (above) and 3D (below) key point detection used for analyzing complex dance movements.

2.2. Model Training and Visualization

.The features extracted for each dancer were aggregated by Body Logic (BL) motion image type. These aggregated features were used to form sequences, which were labeled accordingly and used to train a Long Short-Term Memory (LSTM) model (Hochreiter et al., 1997). Through this training process (see Fig. 1), labeled sequences were generated to encapsulate the temporal dynamics and distinctive attributes of each BL movement type.

To optimize the LSTM model's performance, we used Keras Tuner and a grid search method to explore various hyperparameters, including the number of LSTM units, layers, epochs, learning rate, and batch size. This systematic adjustment identified the optimal configuration for accurate prediction and generation of new movement sequences.

3. Empirical Evaluation and Results

Sequential models depend on temporal dependencies within data sequences to predict future states based on preceding sequences. Consequently, the efficacy of these models in learning is critically influenced by how training sequences are constructed and the correlations between sequential data and target predictions. On one hand, it was imperative to capture a smooth sequence of movements that encapsulates the essence of the BL movement type and its quality. Equally important was ensuring sufficient overlap to include variability in newly generated sequences.

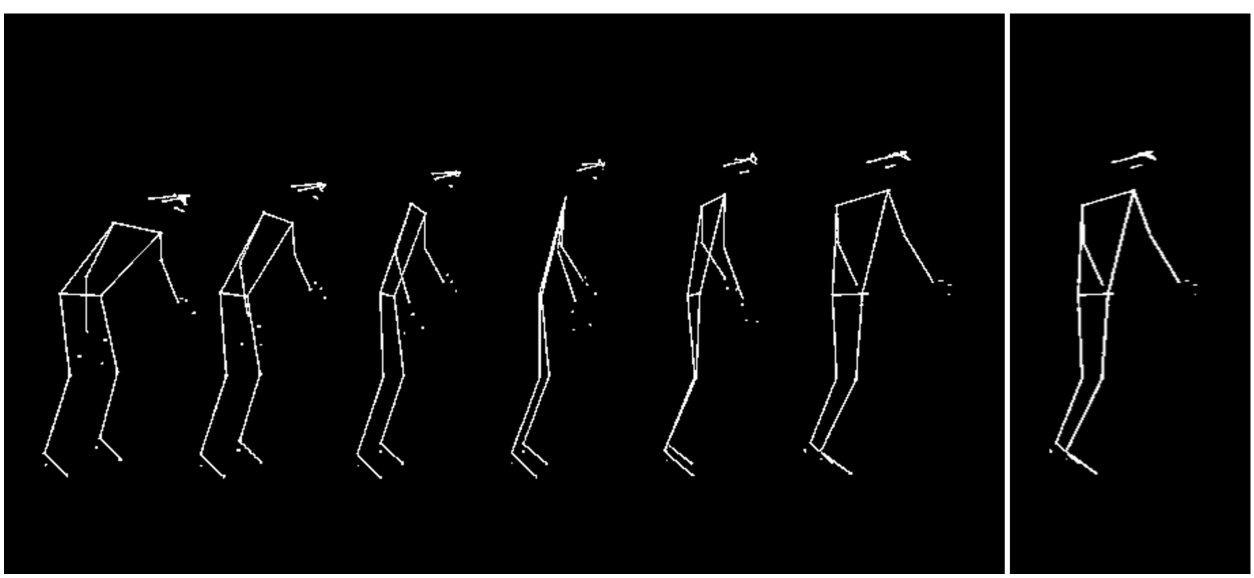

Figure 3: Illustration of a training sequence depicting the generation of a predictive frame (far right) based on a previous sequence used for generating new dance movements using the Body Logic Method with LSTM models.

Determining the optimal balance between sequence length and overlap can only be achieved empirically, as it depends heavily on the specific task and perspective. In other words, the choreographer's final decision hinges on their choreographic aim. To achieve this, we conducted a series of experiments varying sequence length, overlap step, and number of predicted frames (see Fig. 3).

With this approach, we generated multiple proposals for each of the five BL movement types. The data was analyzed using dimensionality reduction techniques, such as Principal Component Analysis (PCA) (Abdi et al., 2010).

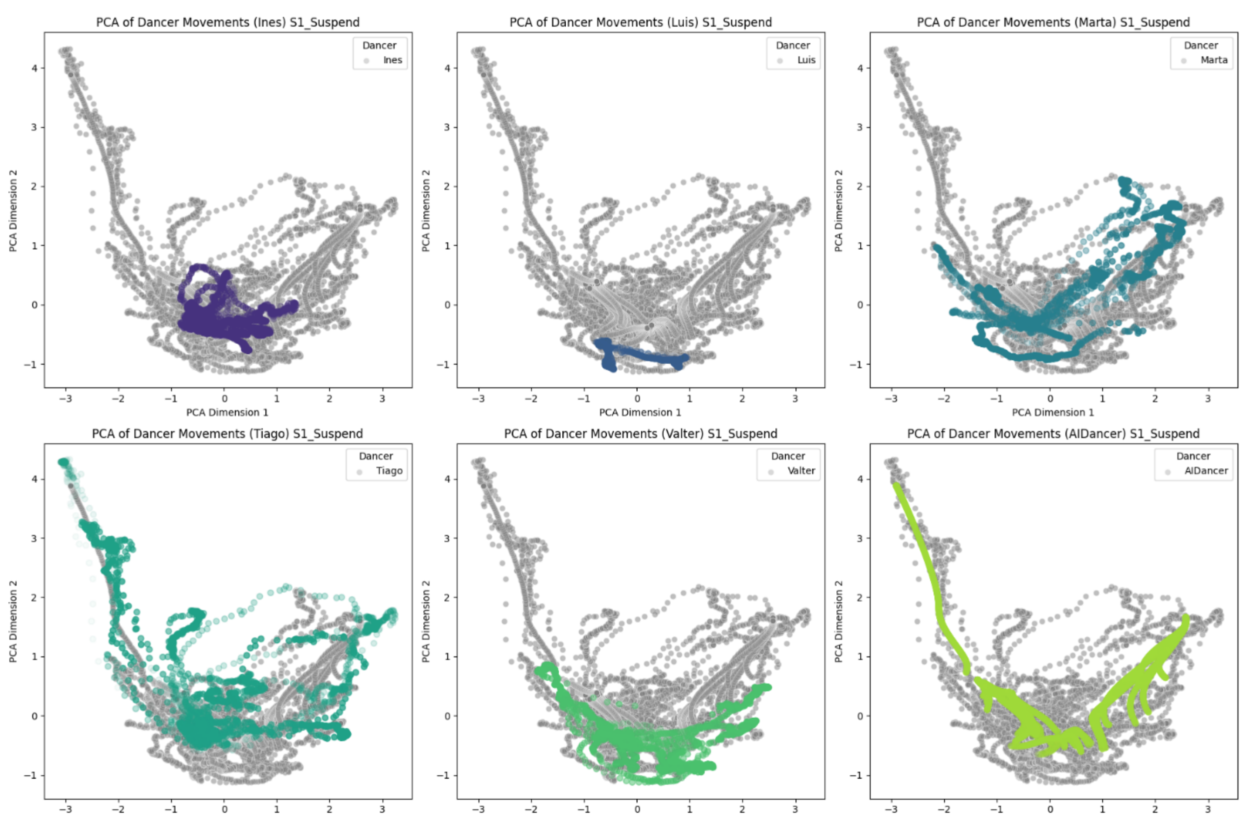

Figure 4: PCA analysis of the BL movement quality ‘Suspend,’ showing the original movements of the dancers (Ines, Luis, Marta, Tiago, Valter) and the generated movements of the AI Dancer (bottom-right plot).

The PCA analysis (Fig. 4) illustrates the principal components of dancer movements for BL movement type and quality ‘Suspend.’ The grey dots represent the original movement data, while the colored trajectories correspond to the movements generated by the LSTM model for each dancer. As observed in the PCA plots, the AI-generated movements (represented by different colors for each dancer) follow the general trajectory of the original movements but exhibit slight variations. These differences arise from the inherent prediction uncertainty of the LSTM model, which introduces subtle yet meaningful deviations. These variations are indicative of the model’s capacity to generate new sequences that, while rooted in learned patterns, introduce novel elements reflective of human creative processes.

4. Conclusions

Through this methodology, we explored how LSTM networks recognize and build upon familiar movement patterns while introducing novel combinations, mirroring the processes of human creativity. Additionally, we investigated how the LSTM’s generated sequences reflect aspects of expressiveness through varied movements. This research offers new insights into how technology can enhance artistic expression and challenge habitual decision-making in dance.

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