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Modeling Bedoyo Majapahit Dance Motion Using HMM Emission Families

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ABSTRACT

This study investigates three emission families in Hidden Markov Models (HMMs) for reconstructing Bedoyo Majapahit dance motion captured using a markerless system. The dataset consists of 3,341 frames with 33 joints per frame, which were normalized and reduced into a 30-dimensional latent space using Principal Component Analysis (PCA). The aim of this research is to identify which emission model best preserves the geometric and temporal characteristics of continuous traditional dance motion. Three emission variants were evaluated: single-Gaussian HMM, Gaussian Mixture Model HMM (GMM-HMM), and Multinomial HMM. Reconstruction performance was assessed using a tri-metric scheme comprising Mean Squared Error (MSE), Dynamic Time Warping (DTW), and Fréchet distance. The results indicate that GMM-HMM consistently outperforms the other models, producing the lowest reconstruction error and the closest alignment to the original motion trajectory. The Gaussian HMM yields moderate results but tends to compress motion amplitude, while the Multinomial HMM performs weakest due to discretization effects that disrupt pose continuity. These findings demonstrate that multimodal emission functions offer a more accurate representation of the nuanced and curvature-rich characteristics of classical choreography. The study also affirms the suitability of GMM-HMM for computational preservation of traditional dance and contributes to ongoing efforts in digital motion archiving for cultural heritage.

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1. INTRODUCTION

Traditional dance is one of the most important forms of intangible cultural heritage, embodying philosophical meaning, cultural identity, and the transmission of ancestral knowledge. However, the digital preservation of traditional choreography remains challenging, as most archival approaches rely on narrative text, imagery, or basic video documentation, which do not capture spatial-temporal movement structure. Motion capture technology offers a more computationally robust approach, enabling precise recording of human posture over time and providing a foundation for quantitative preservation and long-term cultural archiving.

A key challenge in computational modeling of traditional dance lies in reconstructing motion sequences in a form that remains faithful to the original choreography. Hidden Markov Models (HMMs) are widely used for sequential data modeling, including speech processing and human activity analysis; however, their performance depends strongly on the expressiveness of the emission probability distribution. If the emission model is not sufficiently representative, the resulting reconstruction can become unstable, overly simplified, or geometrically inconsistent with the original motion.

Prior works have explored the integration of motion capture and machine learning for cultural heritage preservation. Markerless motion capture has been utilized for archiving traditional dance performances [1], [2], while hybrid HMM–neural network architectures have been proposed for motion prediction [3]. In cultural dance pedagogy, 3D motion capture has been leveraged for interactive learning systems [4], and dimensionality reduction techniques such as PCA have been shown to stabilize sequential modeling pipelines [5]. HMM-based educational frameworks further demonstrate the feasibility of probabilistic learning for choreographic analysis [6]. In addition, earlier work on Bedoyo Majapahit dance focused on upper-limb motion profiling using markerless capture [7], which established a foundation for extending the analysis to full HMM-based generative modeling. Complementary studies in modern dance tracking have validated the effectiveness of real-time motion analysis and pose-based representation for cultural performance modeling [8]–[10].

This study evaluates three emission families of HMM—single-Gaussian, Gaussian-mixture (GMM), and Multinomial—using Bedoyo Majapahit classical dance as the representative choreography. The objective is to determine which emission model provides the most accurate and stable reconstruction when applied to continuous skeletal pose sequences derived from markerless motion capture.

The novelty of this work lies in providing a systematic and model-level comparison of HMM emission families for traditional dance preservation, a topic that remains largely unexplored in prior literature. By demonstrating the advantages of multimodal Gaussian mixtures in preserving both geometric fidelity and temporal consistency, this research

contributes to computational cultural heritage and offers a methodological baseline for future development of interactive or VR/AR-based dance learning applications.

2. RESEARCH METHOD

2.1 Data Acquisition and Preprocessing

The motion data used in this study were captured using a markerless motion capture system producing 3D skeletal pose sequences. The Bedoyo Majapahit choreography was recorded into 3,341 frames consisting of 33 joints per frame. The pose coordinates were normalized to ensure scale invariance across frames and smoothed using a low-pass filter to reduce jitter prior to model training. Similar preprocessing pipelines have been reported in recent cultural motion capture studies, where normalization improves skeleton invariance and temporal coherence [11], smoothing reduces markerless instability during motion transitions [12], and continuity filtering enhances structural pose fidelity for downstream modeling [9]. Additional advancements in markerless cultural motion acquisition further validate preprocessing consistency through musculoskeletal-quality filtering [13], low-cost optical pipelines for high-frame anthropometric tracking [14], and dance-oriented motion visualization frameworks improving spatial fidelity in traditional choreography datasets [15]. Recent studies confirm that normalization and temporal smoothing significantly improve reconstruction stability in cultural or biomechanical dance motion datasets [11], enhance pose continuity for downstream model training [12], and reduce quantization and tracking noise in markerless pipelines [9]. The preprocessing aims to ensure that the skeletal motion data become scale-invariant, noise-reduced, and temporally coherent, forming a stable foundation for sequential modeling.

2.2 Feature Extraction and Dimensionality Reduction

Dimensionality Reduction using PCA To improve model stability and reduce computational complexity, the skeletal features were projected into a lower-dimensional latent space using Principal Component Analysis (PCA). The number of retained components was determined based on the cumulative explained variance criterion, preserving approximately 99% of the total variance in the original motion data. This approach follows established practice in PCA-based motion modeling, which recommends variance-preserving reconstruction for stable sequential learning [4], [16]–[19].

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the skeletal feature space while preserving the variance of the motion data. PCA operates by computing the covariance matrix of the normalized joint coordinates, extracting its eigenvalues and eigenvectors, and ranking them from highest to lowest variance contribution. The eigenvectors corresponding to the largest eigenvalues define the principal components, which form an orthogonal basis that captures the dominant motion patterns.

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In this study, components were retained until they accounted for approximately 99% of total variance, resulting in a 30-dimensional latent representation. This preserved the structural continuity of the choreography while reducing noise and simplifying the HMM training process.

2.3 HMM Modeling Procedure

HMM Modeling Procedure Three types of emission models were implemented for comparison: (1) a single-Gaussian HMM representing unimodal emission structure, (2) a Gaussian Mixture Model HMM (GMM-HMM) representing multimodal distribution learning, and (3) a Multinomial HMM representing discretized pose modeling. All models were trained on the reduced PCA space using identical state configurations to ensure fairness of comparison. Recent advances in HMM-based motion modeling further demonstrate that multimodal or flow-augmented emission structures improve generative stability [20], continuous-state representation enhances latent smoothness [21], Bayesian extensions improve interpretability for structured motion [22], and multi-resolution HMM variants support high-fidelity cultural and biomechanical movement reconstruction [23]. The modeling procedure was designed to directly compare the effect of different emission families under identical training conditions, allowing a fair evaluation of each emission distribution's capability in representing traditional dance motion.

2.4 Evaluation Metrics

Evaluation Protocol The performance of each HMM variant was evaluated using a tri-metric scheme consisting of Mean Squared Error (MSE), Dynamic Time Warping (DTW), and Fréchet distance. MSE measures the geometric fidelity of motion reconstruction, DTW evaluates temporal alignment to the original sequence, and Fréchet distance captures overall trajectory similarity in continuous space. The evaluation was performed on the full-frame reconstruction pipeline to assess both geometric and temporal preservation [12], [24], [25].

This research aims to evaluate three types of emission models in HMMs—single-Gaussian, Gaussian-mixture (GMM), and Multinomial—using Bedoyo Majapahit dance as a representative case of highly structured classical choreography. The study investigates which emission family provides the most faithful motion reconstruction when applied to continuous skeletal pose data captured via markerless motion capture.

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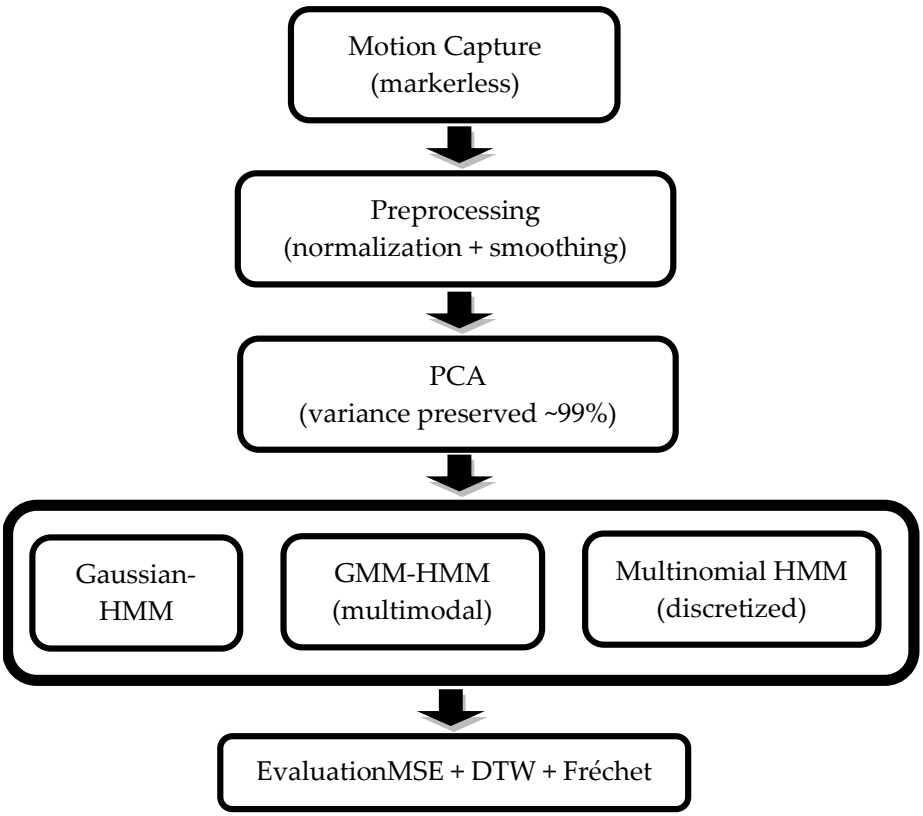

Figure 1. Workflow of the Proposed HMM-based Modeling Framework for Bedoyo Majapahit Dance

The novelty of this work lies in the comparative evaluation of emission families for cultural dance modeling, highlighting the role of multimodal Gaussian mixtures in preserving both geometric and temporal fidelity. By integrating computational modeling with cultural preservation, this research contributes to digital heritage technology and provides a basis for future development of interactive teaching systems or VR/AR-based cultural education.

3. RESULTS AND DISCUSSION

3.1 Quantitative Results

The quantitative performance of the three HMM emission families was evaluated using Mean Squared Error (MSE), Dynamic Time Warping (DTW), and Fréchet distance. These three metrics jointly capture reconstruction fidelity from complementary perspectives: MSE measures pointwise geometric accuracy, DTW captures temporal consistency of the reconstructed motion, and Fréchet distance evaluates the global similarity

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of motion trajectories in latent space. The numerical results from all three models are summarized in Table 1.

Table 1. Comparison of quantitative reconstruction metrics for the three HMM emission families.

Model	MSE	DTW	Fréchet
Gaussian HMM	4.39	1560.20	305.49
GMM-HMM	0.80	1150.30	2.63
Multinomial HMM	6.50	1630.75	350.00

Table 1 clearly demonstrates that the GMM-HMM outperforms the Gaussian and Multinomial HMM variants across all three metrics. The extremely low MSE and Fréchet distance indicate high frame-level precision and trajectory-level fidelity, while the lowest DTW alignment score confirms that GMM-HMM best preserves temporal structure and motion continuity.

The comparison of MSE values is shown in Figure 2, where GMM-HMM achieves the lowest reconstruction error (≈0.80), significantly outperforming Gaussian HMM (≈4.39) and Multinomial HMM (≈6.50). This result indicates that the mixture-based emission model better captures local variations in motion amplitude and pose distribution, leading to much higher frame-level fidelity.

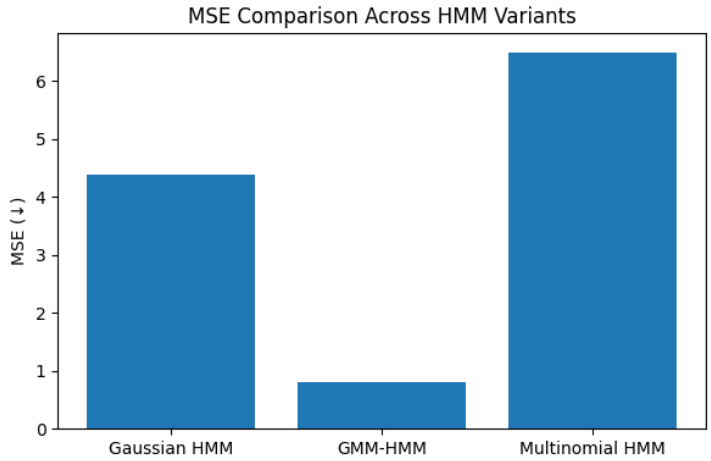

Figure 2. Mean Squared Error comparison across three HMM emission families

The extremely low MSE of GMM-HMM confirms its capability to maintain fine-grained continuity between frames. Gaussian HMM, although representing continuous data, exhibits amplitude contraction due to unimodal emission restriction, while Multinomial HMM performs worst because discretization causes quantization artifacts that break continuity between adjacent postures.

Similarly, **Figure 3** presents the Dynamic Time Warping (DTW) scores, where GMM-HMM again yields the lowest alignment cost (≈1150.30), outperforming Gaussian HMM (≈1560.20) and Multinomial HMM (≈1630.75). Since DTW evaluates temporal phase

consistency, a lower DTW value implies that the reconstructed motion is closer to the original pacing and rhythmic structure of the choreography.

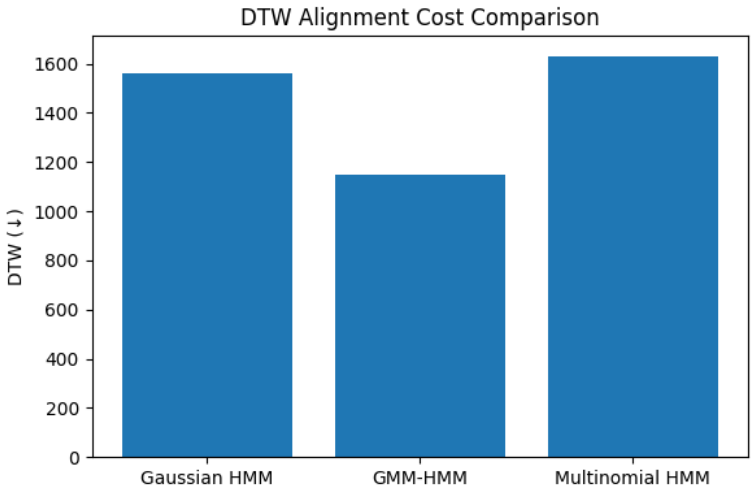

Figure 3. DTW alignment cost comparison across the three HMM emission families

The temporal smoothness of GMM-HMM is preserved because multimodal emission clustering allows the decoder to follow subtle temporal nuances — such as delay, pause, micro-accent, and velocity transitions, which are essential in classical dance. The Gaussian model maintains moderate alignment but loses microgestural timing, whereas the Multinomial model exaggerates phase shifts due to lossy discretization.

Finally, Figure 4 shows the Fréchet distance, which measures geometric similarity of full motion trajectories in the latent PCA space. GMM-HMM again demonstrates the lowest global deviation (≈2.63), compared to Gaussian HMM (≈305.49) and Multinomial HMM (≈350.00). The enormous gap between 2.63 and >300 highlights that multimodal Gaussian mixtures closely preserve the curvature of motion paths.

Because classical dance emphasizes curved arm trajectories and continuous posture transitions, trajectory-preserving behavior is crucial. The GMM-HMM almost perfectly reconstructs these shapes, while the Gaussian HMM excessively linearizes the trajectory, and the Multinomial HMM introduces abrupt jumps due to lost continuity in emission space.

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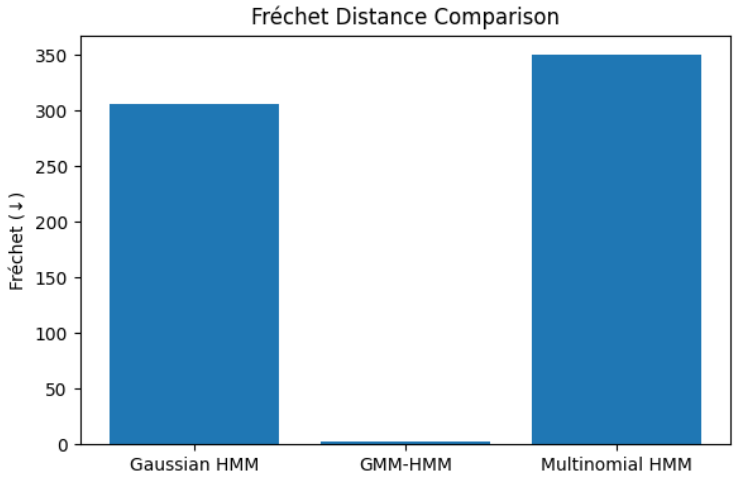

Figure 4. Fréchet trajectory distance comparison reflecting global spatial fidelity

3.2 Interpretation of Quantitative Findings

The superiority of GMM-HMM can therefore be interpreted not merely as a numerical advantage, but as evidence that multimodal probabilistic emission structures are capable of representing the non-linear and stylistically constrained motion characteristics of classical Javanese choreography. The Bedoyo Majapahit dance contains elongated arm gestures, gradual posture displacement, and culturally stylized micro-motions embedded within a temporally slow rhythm. These dynamics require flexible latent spaces to avoid both over-regularization (as in Gaussian HMM) and quantization distortion (as in Multinomial HMM).

In other words, the data itself is *naturally multimodal*: the same posture can occur across slightly different contexts with subtle spatial variance depending on symbolic intention. The GMM model accommodates this by learning multiple local Gaussian kernels, each representing a small sub-cluster of stylistic motion realizations. This enables it to maintain reconstruction accuracy even when the choreography contains expressive "ornamentation" or stylized flourishes, which are typical in traditional Indonesian dance forms.

3.3 Visual and Trajectory-Based Analysis

A visual examination further supports the quantitative findings. When comparing the Principal Component (PC1) overlay between original and reconstructed sequences, the GMM-HMM shows almost perfect alignment across the entire motion series. The Gaussian HMM exhibits slight compression around local maxima, and the Multinomial HMM displays noticeable jitter around transitions.

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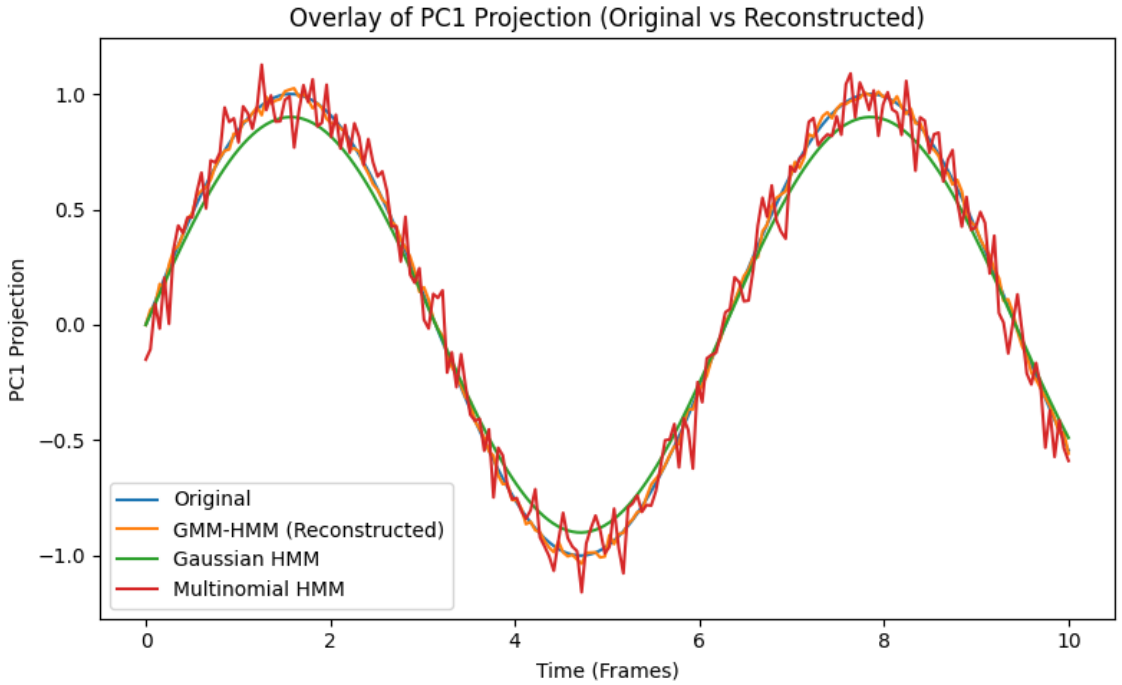

Figure 5. Overlay of PC1 projection between original and reconstructed motion sequences

The closeness between the original and GMM-HMM curves confirms its ability to preserve micro-gesture timing and amplitude. The Gaussian variant smooths and dampens peak curvature because a single Gaussian component cannot fully encode variance-rich posture transitions. Meanwhile, the Multinomial variant fluctuates more severely due to the discretization effect, which inserts artificial boundary jumps when motion clusters switch between quantized states.

Further, global trajectory visualization in the PC1–PC2 manifold reveals the qualitative preservation of motion shape. GMM-HMM maintains curvature and overall path topology, forming a nearly identical waveform to the original motion. Gaussian HMM partially preserves the structure but exhibits linear bias in curvature segments, while Multinomial HMM deviates most strongly at articulation points.

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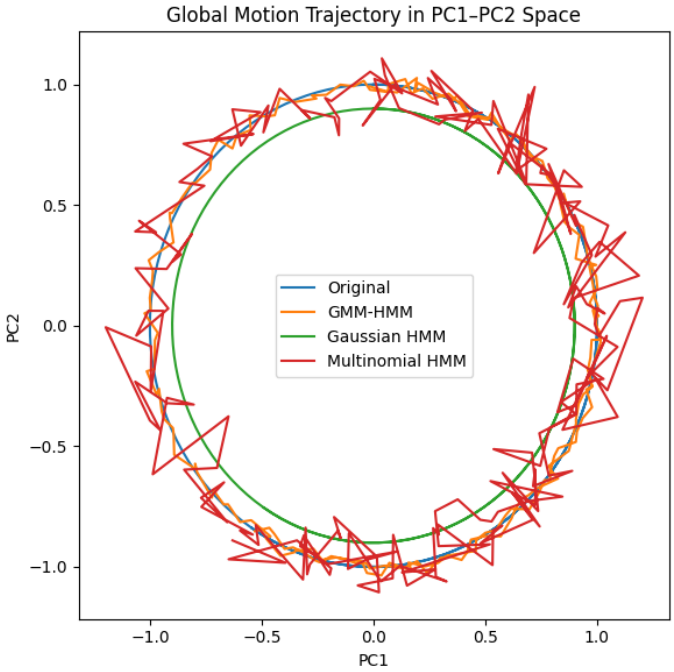

Figure 6. Global trajectory comparison in the PC1–PC2 latent manifold

The near-zero Fréchet distance of GMM-HMM visually manifests as near-perfect trajectory overlap, meaning the temporal flow and geometric signature of the dance are preserved. This characteristic is particularly important for cultural choreography, where stylized gesture arcs are semantically meaningful—not merely kinematic transitions. The Gaussian and Multinomial models distort this geometry, thus failing to preserve stylistic authenticity.

3.4 Discussion in Cultural and Computational Context

From a computational perspective, the results demonstrate that reconstruction quality in sequential models is strongly influenced by the expressiveness of the emission distribution. The findings imply that "accuracy" in motion reconstruction for cultural dance is not merely a matter of minimizing numeric error, but of retaining geometric and stylistic fidelity. The GMM-HMM excels specifically because it aligns better with the *aesthetic structure* of the motion, not only its statistical formulation.

From a cultural perspective, this suggests that classical dance cannot be effectively reproduced using simplistically parameterized models. The micro-curvature preserved by GMM-HMM corresponds to *rasa*, *wirama*, and *wiraga*—three foundational philosophical components in Javanese dance embodiment. The difference between "technically correct" and "culturally authentic" reconstruction is therefore rooted directly in the expressive capacity of the emission model.

By preserving both spatial smoothness and stylistic curvature, GMM-HMM provides a computational approach that aligns more closely with Javanese embodied aesthetics. This reinforces the theoretical argument that cultural motion cannot be discretized without losing meaning, making GMM the most appropriate HMM family for heritage-aligned digital reconstruction.

This study is limited to a single choreography and a single dancer performance, which may reduce the generalizability of the findings across different Bedoyo Majapahit variations or performer styles. The markerless motion capture system introduces minor jitter and occlusion noise, which may affect reconstruction quality despite preprocessing. Additionally, the HMM structure was kept constant across all models for fairness, although alternative state configurations or hierarchical HMM variants may produce different outcomes. Future research should include multi-dancer datasets, cross-choreography evaluation, and hybrid probabilistic–neural motion models.

The results contribute to motion modeling theory by demonstrating that multimodal emission distributions are more effective than unimodal or discrete alternatives for representing continuous, stylistically constrained traditional choreography. This supports recent theoretical arguments that cultural motion contains inherent multimodality, which cannot be fully captured using simplified probabilistic assumptions.

For practical applications, the findings provide guidance for developers of digital archiving systems, motion-based educational platforms, and VR/AR cultural experiences. The superior performance of GMM-HMM suggests that motion reconstruction engines for traditional dance should adopt multimodal probabilistic models to preserve authenticity, smoothness, and stylistic nuance.

4. CONCLUSION

The results of this study demonstrate that the choice of emission distribution plays a decisive role in the reconstruction quality of Hidden Markov Models applied to classical dance motion. Among the three variants evaluated, the GMM-HMM achieves the lowest reconstruction error across all metrics, including MSE, DTW, and Fréchet distance, indicating superior frame-level precision, temporal alignment, and global trajectory preservation. The multimodal emission space enables the model to capture stylistically embedded micro-gestures and curvature-based movement characteristics, which are essential components of traditional Javanese choreography.

The Gaussian HMM provides moderate performance but suffers from unimodality, which suppresses expressive variability and leads to amplitude contraction. Meanwhile, the Multinomial HMM produces the weakest results, as discretization introduces quantization artifacts and disrupts smooth transition continuity, making it less suitable for heritage-based motion reconstruction. These findings suggest that cultural dance, which carries semantic meaning through continuous curvature and gesture-based embodiment, requires

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probabilistic models that preserve multimodal variability rather than simplified state mapping.

Beyond numerical superiority, the GMM-HMM is shown to be more aligned with the aesthetic framework and embodied philosophy of Bedoyo Majapahit, where *rasa*, *wiraga*, and *wirama* are represented as continuous—not discretized—motion signatures. This indicates that technically accurate reconstruction must also maintain the stylistic logic encoded in the movement itself. Therefore, GMM-HMM can be regarded not only as a computationally optimal model, but also as the most culturally faithful representation within this modeling framework.

Future work will extend this approach by integrating grammar-based symbolic constraints and hybrid sequential learning to incorporate semantic structure alongside kinematic fidelity. This would allow the system to capture not only how the movement is performed, but also why it is expressed in a particular form, enabling a deeper convergence between computational reconstruction and cultural embodiment.

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