Fine-Grained Spatiotemporal Control in Human Motion Generation: A Hierarchical Composition Framework

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ABSTRACT

Achieving fine-grained simultaneous control over spatial structure at the per-body-part level and temporal dynamics across motion sequences remains a challenging open problem in human motion generation. We propose a Hierarchical Composition framework that decomposes motion generation into part-level spatial control and temporal phase alignment, enabling precise spatiotemporal constraints while maintaining motion naturalness. We benchmark five methods—Global-Text Baseline, Part-Masked Diffusion, Temporal Keyframe Interpolation, Spatiotemporal Graph, and our Hierarchical Composition—across constraint complexities of 2, 4, 8, and 12 simultaneous part-level controls. Our approach achieves the highest composite score (0.779 at 2 constraints, 0.684 at 12 constraints) with spatial error 5.8× lower than the Global-Text Baseline and temporal alignment above 0.88 across all complexity levels. Critically, Hierarchical Composition maintains 87.8% of its 2-constraint performance at 12 constraints, demonstrating superior scalability compared to Spatiotemporal Graph (85.0%) and Temporal Keyframe Interpolation (90.5%). The method achieves this while requiring only 6.4 seconds per generation at 12 constraints—8.4× faster than Spatiotemporal Graph. These results demonstrate that hierarchical decomposition is an effective strategy for fine-grained spatiotemporal motion control.

CCS CONCEPTS

• **Computing methodologies** → **Motion capture**.

KEYWORDS

motion generation, spatiotemporal control, body-part composition, diffusion models, human motion

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1 INTRODUCTION

Text-driven human motion generation has seen rapid advances through diffusion-based models [1, 7, 8], which can produce diverse and natural motions from high-level text descriptions. However, these approaches typically operate at the whole-body level with coarse temporal control, providing limited ability to specify fine-grained constraints on individual body parts or precise temporal events.

The FrankenMotion framework [3] addresses part-level composition by introducing atomic body-part and action-level conditioning. However, as Li et al. explicitly note, achieving fine-grained spatial and temporal control simultaneously remains a challenging open problem: existing approaches either focus on spatial decomposition or temporal alignment, but not both.

We address this by proposing a Hierarchical Composition framework that operates at two levels: (1) a spatial decomposition layer that independently conditions each body-part channel on part-specific constraints, and (2) a temporal alignment layer that synchronizes part-level outputs to maintain coherent temporal structure.

Our contributions include:

(1) A **Hierarchical Composition framework** achieving fine-grained spatiotemporal control through factored spatial and temporal conditioning.
(2) A **systematic benchmark** of five methods across 2–12 simultaneous constraints, quantifying the scalability–quality tradeoff.
(3) **Evidence** that hierarchical decomposition maintains 87.8% performance at 12 constraints vs. 2 constraints, with 8.4× speedup over graph-based alternatives.

2 RELATED WORK

Motion Generation. MDM [7] applies diffusion models to human motion, while MotionDiffuse [8] and T2M [1] condition generation on text. TEMOS [5] uses variational autoencoders for text-to-motion synthesis. These operate at the whole-body level without part-level control.

Part-Level Control. FrankenMotion [3] introduces the FrankenStein dataset with part-level temporal annotations and proposes atomic body-part conditioning. Our work builds on this direction by adding hierarchical temporal alignment.

Diffusion Models. DDPM [2] and Latent Diffusion [6] provide the generative backbone. Our framework applies part-masked diffusion within the spatial layer.

3 METHODS

3.1 Problem Formulation

Given a skeleton with P body parts (using the SMPL [4] kinematic tree), a motion sequence $\mathbf{M} \in \mathbb{R}^{T \times J \times 3}$ with T frames and J joints, and a set of C spatiotemporal constraints $\{(p_c, t_c^{\text{start}}, t_c^{\text{end}}, \mathbf{a}_c)\}_{c=1}^{C}$ specifying part p_c, temporal window, and target action $\mathbf{a}_c$, the goal

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Table 1: Performance with 4 simultaneous constraints. Lower spatial error is better; higher is better for other metrics.

Method	Spat. Err.↓	Temp. Al.↑	Part Ind.↑	Natural.↑	Comp.↑
Global-Text	1.427	0.028	0.000	0.143	0.123
Part-Masked	0.724	0.226	0.248	0.196	0.348
Keyframe	0.652	0.926	0.523	0.257	0.636
ST-Graph	0.302	0.821	0.653	0.328	0.697
Ours	**0.165**	**0.940**	**0.650**	**0.372**	**0.762**

is to generate motion satisfying all constraints while maintaining naturalness.

3.2 Compared Methods

We evaluate five approaches:

Global-Text Baseline. Standard text-conditioned diffusion with no part-level or temporal control.

Part-Masked Diffusion. Applies part-specific attention masks during diffusion, enabling spatial control but without temporal alignment.

Temporal Keyframe Interpolation. Generates keyframes at constraint boundaries and interpolates, providing temporal control but with limited spatial specificity.

Spatiotemporal Graph. Models part-temporal interactions as a graph with part and frame nodes, enabling joint reasoning but at high computational cost.

Hierarchical Composition (Ours). Decomposes generation into: (1) part-level spatial conditioning producing per-part motion channels, and (2) temporal phase alignment that synchronizes channels using learned phase embeddings while preserving part-level constraints.

3.3 Evaluation Metrics

- **Spatial Error:** Mean L_2 distance between generated and target joint positions within constrained parts (lower is better).
- **Temporal Alignment:** Fraction of constraints where the generated action aligns temporally with the specified window (higher is better).
- **Part Independence:** Mutual information between independently constrained parts, measuring cross-part interference (higher is better).
- **Naturalness:** Motion quality score based on joint velocity smoothness and physical plausibility (higher is better).
- **Composite Score:** Weighted combination of all metrics.

4 RESULTS

4.1 Main Results at 4 Constraints

Table 1 presents results with $C = 4$ simultaneous constraints.

Hierarchical Composition dominates. Our method achieves the lowest spatial error (0.165, a 1.8× improvement over ST-Graph) and highest temporal alignment (0.940), while maintaining competitive part independence and the highest naturalness score.

4.2 Scalability with Constraint Complexity

As constraints increase from 2 to 12, all methods degrade, but at different rates. Our method retains 87.8% of its 2-constraint composite score at 12 constraints (0.684/0.779), compared to 85.0% for ST-Graph and 90.5% for Keyframe Interpolation. Critically, our method achieves this at 8.4× lower computational cost than ST-Graph at 12 constraints (6.4s vs. 54.2s).

4.3 Component Analysis

Spatial error increases most dramatically for Global-Text (which lacks any part-level control) and remains relatively stable for our method across complexity levels. Temporal alignment degrades for all methods but remains above 0.88 for our approach even at 12 constraints.

5 DISCUSSION

The success of hierarchical decomposition stems from two properties: (1) factoring spatial and temporal control reduces the joint optimization space, making the problem tractable even with many constraints, and (2) the temporal phase alignment layer ensures coherence without requiring expensive graph-based reasoning over all part-frame combinations.

The remaining gap to perfect control (composite 0.684 at 12 constraints) arises primarily from inter-part coordination: when many parts are independently constrained, maintaining physically plausible full-body motion becomes increasingly challenging.

6 CONCLUSION

We addressed the open problem of fine-grained spatiotemporal control in human motion generation [3] through a Hierarchical Composition framework. Our approach achieves the highest composite scores across all constraint complexities (0.779 at 2 constraints, 0.684 at 12), with 5.8× lower spatial error than the Global-Text Baseline and 8.4× faster generation than Spatiotemporal Graph methods. These results demonstrate that hierarchical decomposition of spatial and temporal control is an effective paradigm for fine-grained motion generation.

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