

LiveGesture: Streamable Co-Speech Gesture Generation Model

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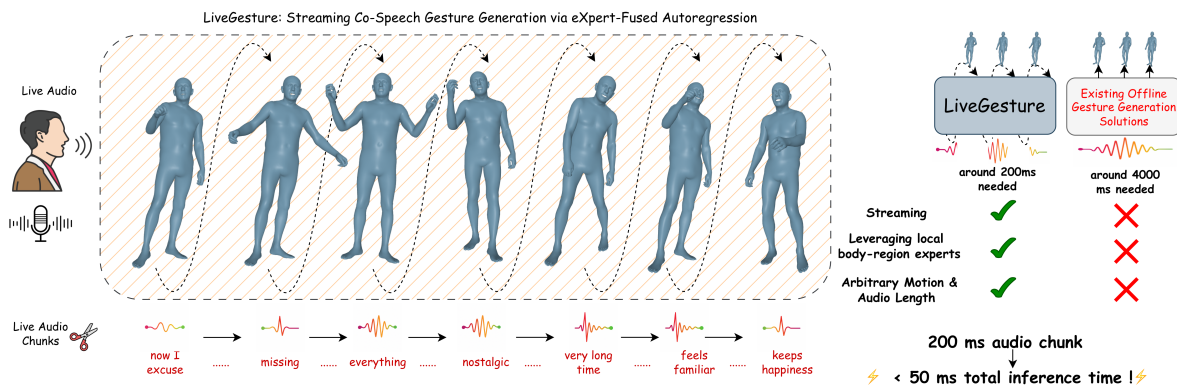


Figure 1. LiveGesture overview. Given live audio chunks, our framework generates full-body SMPL-X motion online with zero look-ahead. A streamable SVQ motion tokenizer and a hierarchical eXpert-fused autoregressive model (region-wise AR eXperts plus causal spatial-temporal fusion) enable low-latency (< 50 ms per 200 ms chunk) generation of diverse, beat-synchronous gestures over arbitrary-length speech, in contrast to prior offline gesture methods that require full utterances and incur much higher latency.

Abstract

We propose *LiveGesture*, the first fully streamable, speech-driven full-body gesture generation framework that operates with zero look-ahead and supports arbitrary sequence length. Unlike existing co-speech gesture methods—which are designed for offline generation and either treat body regions independently or entangle all joints within a single model—*LiveGesture* is built from the ground up for causal, region-coordinated motion generation. *LiveGesture* consists of two main modules: the *Streamable Vector-Quantized Motion Tokenizer (SVQ)* and the *Hierarchical Autoregressive Transformer (HAR)*. The *SVQ* tokenizer converts the motion sequence of each body region into causal, discrete motion tokens, enabling real-time, streamable token decoding. On top of *SVQ*, *HAR* employs region-eXpert autoregressive (*xAR*) transformers to model expressive, fine-grained motion dynamics for each body region. A causal spatio-temporal fusion module (*xAR-Fusion*) then captures and integrates correlated motion dynamics across regions. Both *xAR* and

xAR-Fusion are conditioned on live, continuously arriving audio signals encoded by a streamable causal audio encoder. To enhance robustness under streaming noise and prediction errors, we introduce autoregressive masking training, which leverages uncertainty-guided token masking and random region masking to expose the model to imperfect, partially erroneous histories during training. Experiments on the *BEAT2* dataset demonstrate that *LiveGesture* produces coherent, diverse, and beat-synchronous full-body gestures in real time, matching or surpassing state-of-the-art offline methods under true zero-look-ahead conditions. Project website: <https://m-usamasaleem.github.io/publication/LiveGesture/LiveGesture.html>.

1. Introduction

Gestures naturally emerge alongside speech, emphasizing key ideas, conveying intent, and grounding abstract concepts in physical space. Far from being cosmetic, these non-verbal behaviors are central to how humans communicate

and strongly influence perceived engagement and conversational naturalness. As virtual humans and embodied AI agents become more common in assistants, VR/AR avatars, telepresence, and content creation [12, 32, 34–36, 38], generating believable, real-time co-speech gestures is becoming a core requirement.

Recent co-speech gesture models [18, 23, 44, 45] synthesize full-body motion using either continuous trajectories [11] or discrete motion tokens [18, 45]. While they produce locally plausible movements, their decoupled region representations often fail to capture fine-grained interdependencies across body parts, leading to gestures that lack holistic full-body coordination. Most systems rely on *offline* diffusion-based [3, 4] or autoregressive [18, 45] architectures that assume access to complete utterances or long audio/text contexts, incurring high latency and preventing truly interactive use. GestureLSM [22] moves toward fast inference with a lightweight architecture, but remains *non-streamable*, requiring full speech segments and preventing incremental updates as audio arrives.

In this work, we introduce *LiveGesture*, to our knowledge the first *fully streamable*, zero-look-ahead co-speech full-body gesture generation framework. *LiveGesture* comprises two core components: the Streamable Vector-Quantized Motion Tokenizer (SVQ) and the Hierarchical Autoregressive Transformer (HAR). The SVQ tokenizer encodes each body region’s motion sequence into causal, discrete motion tokens, enabling real-time, low-latency decoding. Built on top of SVQ, HAR employs region-eXpert autoregressive (xAR) transformers to model expressive and fine-grained motion dynamics for individual regions. A causal spatiotemporal fusion module (xAR-Fusion) further integrates inter-region dependencies, capturing coherent, whole-body coordination. Both xAR and xAR-Fusion operate under strict causality, conditioned on continuously arriving audio features extracted by a streamable causal audio encoder. To improve robustness against streaming noise and prediction drift, we introduce autoregressive masking training, which applies uncertainty-guided token masking and random region masking to expose the model to imperfect and partially corrupted histories. Evaluated on the BEAT dataset, *LiveGesture* generates coherent, diverse, and beat-synchronous full-body SMPL-X gestures in real time—achieving state-of-the-art performance under true zero-look-ahead conditions. Our contributions are summarized as follows:

- We propose *LiveGesture*, the first zero-look-ahead, fully streamable speech-driven full-body gesture generation framework supporting arbitrary sequence lengths, designed for real-time human–AI interaction.
- We introduce a streamable motion tokenizer that converts continuous SMPL-X regional motion sequences into discrete latent motion tokens through an asymmetric archi-

ture of bidirectional encoding, causal decoding, and token quantization, trained via a two-stage pretraining and quantization strategy to ensure strict causality, low latency, and stable representation learning.

- We design a Hierarchical Autoregressive Transformer that consists of region-eXpert autoregressive (xAR) transformers that model expressive, fine-grained motion dynamics for each body region, a causal spatiotemporal fusion module (xAR-Fusion) that captures and integrates correlated motion dynamics across regions, and a streamable causal audio encoder that processes continuously arriving audio signals for live gesture generation.
- Experiments on the **BEAT** dataset demonstrate that *LiveGesture* produces coherent, diverse, and beat-synchronous SMPL-X gestures in real time, matching or surpassing state-of-the-art offline methods under true zero-look-ahead conditions.

2. Related Works

Autoregressive Motion Generation. Autoregressive models have shown remarkable success in language and image generation, as demonstrated by GPT [1], DALL-E [31], and VQ-GAN [7, 41, 47]. Following this, Masked Motion Models [10, 30] have adopted discrete motion token sequences from pretrained codebooks in human motion generation by decoding them in parallel. However, these models require generating all sequences at once and require a predefined motion length. In contrast, methods such as T2M-GPT [48], AttT2M [50], and BAMB [29] also rely on codebook tokens but train their models autoregressively to predict motion token sequences token by token. Similarly, MotionGPT [13] generates motion tokens autoregressively, but integrates both language and motion tokens into a unified encoder, enabling a broader range of motion-related tasks. However, these approaches cannot achieve streamable generation because their motion-token decoders rely on a bidirectional decoder, future tokens influence the decoding of current ones.

Co-speech Gesture Generation. Early work by [9] employs an adversarial model to predict hand and arm poses directly from audio and uses conditional video generation techniques based on pix2pixHD [40] and EverybodyDanceNow [2]. More recent studies [5, 19–21, 23, 24, 33, 43, 49] explore generative models to derive audio-conditioned gesture generations. For example, HA2G [24] constructs both high-level and low-level audio–motion embeddings to guide gesture synthesis. TalkShow [45] models joint body and hand motion dynamics for talk-show videos. CaMN [17] and EMAGE [18] leverage GPT-like decoders for unified face and body modeling. Several methods focus on improving generation quality or efficiency. MambaTalk [44] accelerates gesture synthesis through the state space model architecture. DiffSHEG [4], SynTalker [3],

and GestureLSM [22] adopt diffusion-based pipelines for co-speech gesture synthesis. However, none of the aforementioned methods support live streamable gesture generation because they require access to the complete text and speech input before generating gestures.

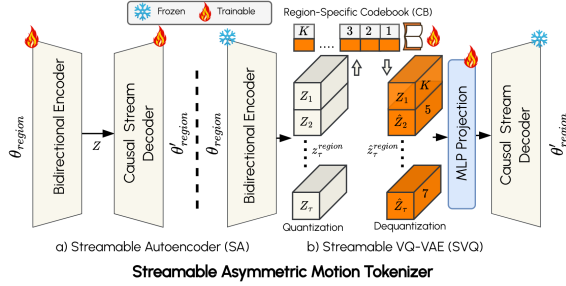


Figure 2. Overview of the Streamable Asymmetric Motion Tokenizer. (a) For each body region, a bidirectional encoder and causal stream decoder learn low-rate latent sequences. (b) Freezing this autoencoder, the Streamable VQ-VAE (SVQ) adds a region-specific codebook and projection head to quantize latents into discrete, time-synchronous motion tokens that remain compatible with strictly causal decoding for streaming.

3. Proposed Method: LiveGesture

Problem Formulation. We study *streaming* co-speech full-body gesture generation with *zero look-ahead*. At time t , the model receives only the recent motion history $\mathbf{S}_t = [\mathbf{q}_{t-H+1}, \dots, \mathbf{q}_{t-1}]$, the current audio token a_t , and optional online transcript tokens w_t , and must predict the next full-body pose gesture \mathbf{q}_t . Formally, the gesture generation f_{Θ} is strictly causal, $\hat{\mathbf{q}}_t = f_{\Theta}(\mathbf{S}_t, a_t, w_t)$. Unlike offline formulations that access future audio or motion, this setup enforces real-time multimodal conditioning and requires region-coordinated, temporally smooth motion aligned with speech rhythm and content under strict latency constraints.

Method Overview. As illustrated in Figure 2 and Figure 3, *LiveGesture* comprises two main modules, *Streamable Vector-Quantized Motion Tokenizer (SVQ)* and the *Hierarchical Autoregressive Transformer (HAR)*, for strictly causal, zero-look-ahead inference. First, the motion tokenizer converts the motion sequence of each body region into causal and discrete motion tokens to support real-time streamable token decoding. On top of SVQ, HAR first employs region-eXpert autoregressive (xAR) transformers to learn expressive and fine-grained motion dynamics of each body region. Then, the causal spatial-temporal fusion (xAR-fusion) model captures and fuses correlated motion dynamics among different body regions. Both xAR and xAR-fusion models are conditioned on the live-continuously arriving audio signals encoded by a streamable audio encoder.

3.1. Streamable Vector-Quantized Motion Tokenizer

We propose a per-region streamable motion tokenizer that converts the continuous motion sequence of each SMPL-X body region (lower body, upper body, hands, and head) [28] into discrete latent motion tokens while preserving strict causality and low latency. The tokenizer adopts an asymmetric architecture comprising three key components: (1) a bidirectional encoder that projects raw motion sequence into a latent space capturing rich bidirectional dependencies; (2) a causal decoder that reconstructs motion in a strictly streamable and causal manner from the latent representation; and (3) a token quantizer that discretizes continuous motion embeddings into compact latent tokens, enabling autoregressive motion generation through cross-entropy training. Previous research shows that simultaneous training of encoder and quantizer can cause token and embedding collapses, leading to degradation in the quality of learned representations. To mitigate this problem, we adopt a two-stage training strategy: Asymmetric Autoencoder Pretraining and Quantization Learning.

Asymmetric Autoencoder Pretraining. In the first stage, we train separate *Streamable Autoencoders (SA)* for each region’s SMPL-X parameters. Let $\theta_t^{\text{SMPL-X}} \in \mathbb{R}^D$ denote the full SMPL-X vector at original motion frame time $t \in \{1, \dots, T_f\}$, partitioned into region-specific subsets $\theta_t^{\text{region}} \in \mathbb{R}^{d_{\text{region}}}$. For each region, the input sequence $\{\theta_t^{\text{region}}\}_{t=1}^{T_f}$ is encoded by a 1D convolutional encoder E into a downsampled latent sequence

$$z^{\text{region}} = \{z_{\tau}\}_{\tau=1}^T = E(\{\theta_t^{\text{region}}\}_{t=1}^{T_f}), \quad T = T_f/4,$$

using strided convolutions to reduce the frame rate by a factor of 4 and obtain a compact representation for fast streaming inference. The encoder is bidirectional, aggregating past and future context, while the corresponding *Causal Stream Decoder* D_{CS} is strictly causal and reconstructs $\hat{\theta}_t^{\text{region}}$ from the latent sequence z^{region} . This asymmetric design yields a globally coherent latent space while enforcing the causal decoding required for streaming. Each SA is trained with a reconstruction loss

$$\mathcal{L}_{\text{AE}} = \lambda_{\text{AE}} \mathcal{L}_{\text{recon}}.$$

Quantization Learning. In the second stage, we convert the continuous latents $z^{\text{region}} = \{z_{\tau}\}_{\tau=1}^T$ into discrete tokens, while keeping the encoder E and decoder D_{CS} frozen so that the temporal geometry and streamability learned in Stage 1 are preserved. For each region, we introduce a region-specific codebook

$$C^{\text{region}} = \{c_k\}_{k=1}^K,$$

and vector-quantize z^{region} via nearest-neighbor assignment, obtaining dequantized embeddings

$$\hat{z}^{\text{region}} = \{\hat{z}_{\tau}\}_{\tau=1}^T,$$

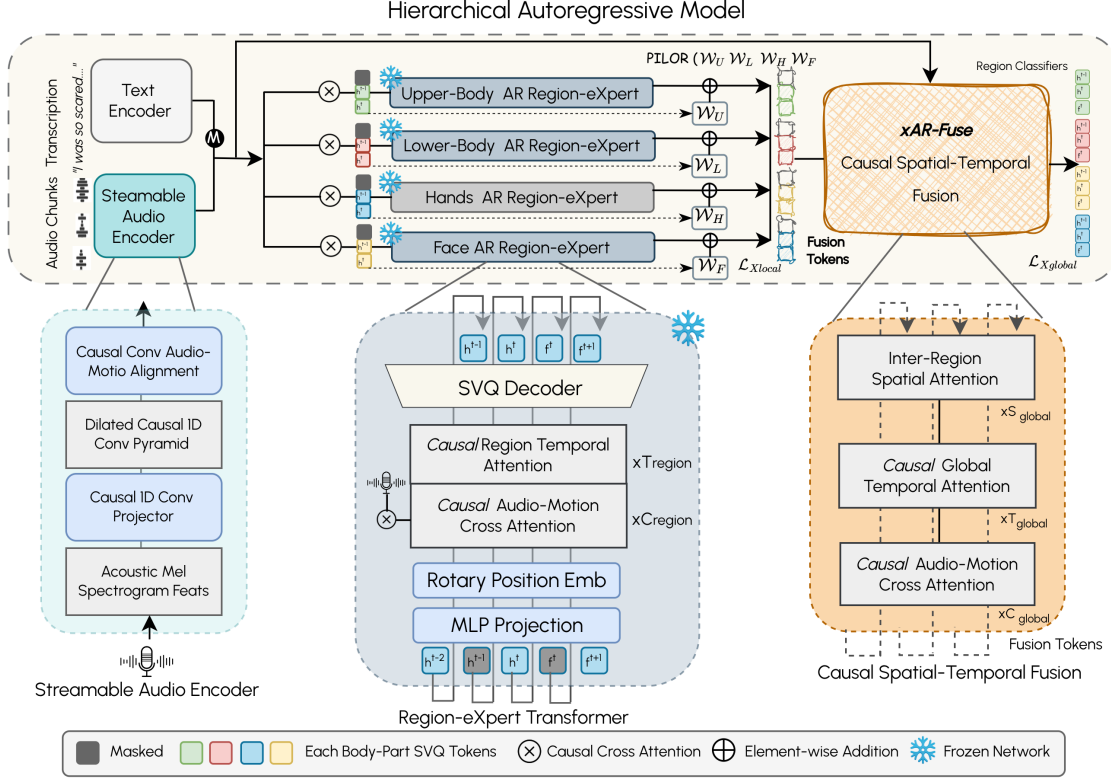


Figure 3. Overview of the Hierarchical Autoregressive Model in *LiveGesture*. A streamable audio encoder and optional text encoder provide causal audio/text tokens to four local AR Region-eXperts (upper body, lower body, hands, face), each modeling its own SVQ motion token stream. Their frozen states are adapted by per-region Pre-Infusion Adapters (PILOR) and fused by xAR-Fuse, a causal spatial-temporal transformer with audio-motion cross-attention, global temporal attention, and inter-region spatial attention that predicts next-step SVQ tokens for zero-look-ahead streaming full-body gesture generation.

whose indices define time-synchronous motion tokens at the downsampled rate. A lightweight projection head W^{region} , implemented as a small MLP, is applied after quantization to map each \hat{z}_τ into the latent space expected by the frozen decoder, yielding $\tilde{z}^{\text{region}} = \{\tilde{z}_\tau\}_{\tau=1}^T$, $\tilde{z}_\tau = W^{\text{region}}(\hat{z}_\tau)$

This projection serves as a learned adapter between the discrete codebook space and the original autoencoder latent space: it allows the codebook to remain compact and region-specific, while the decoder operates in a richer, globally learned space, and it absorbs quantization artifacts so that codebook updates do not disrupt the temporal structure encoded in D_{CS} . The projected sequence $\tilde{z}^{\text{region}}$ is then decoded causally to reconstructed SMPL-X parameters, $\hat{\theta}^{\text{region}} = D_{\text{CS}}(\tilde{z}^{\text{region}})$. During this stage, only the codebook C^{region} and projection head W^{region} are updated. We use an L1 reconstruction term on SMPL-X region parameters and a standard VQ codebook loss $\mathcal{L}_{\text{cb}}(z^{\text{region}}, e^{\text{region}})$ [39], where e^{region} denotes the selected codebook embeddings, leading

to

$$\mathcal{L}_{\text{stage2}} = \lambda_{\text{rec}} \left\| \hat{\theta}^{\text{region}} - D_{\text{CS}}(W^{\text{region}}(\tilde{z}^{\text{region}})) \right\|_1 + \lambda_{\text{cb}} \mathcal{L}_{\text{cb}}(z^{\text{region}}, e^{\text{region}}).$$

EMA-style codebook updates and occasional resets [8] keep the codebook well conditioned, and the resulting SVQ tokens are discrete, time-synchronous, region-wise representations that remain compatible with the strictly causal decoder and are well suited for downstream streaming autoregressive SMPL-X gesture generation.

3.2. Hierarchical Autoregressive Model

The hierarchical autoregressive model consists of (1) region-eXperts, which are temporal causal transformers that learn expressive and fine-grained motion dynamics of each body region, (2) a global fusion model, which is a spatial-temporal causal transformer that captures the coherent and dependent dynamics among different body regions, and (3) a streamable audio encoder, which is a causal convolution network that enables live gesture generation conditioned on continuously arriving audio signals.

3.2.1. Region-eXpert Autoregressive Transformer (xAR)

Local region experts learn audio-driven motion dynamics for individual body parts, as different regions exhibit distinct motion distributions. For example, the upper body often produces large-scale movements, while the hands perform fine-grained, high-frequency gestures. In particular, we divide full-body into four regions $\mathcal{R} = \{\text{upper body, lower body, hands, face}\}$. For each region $r \in \mathcal{R}$, we maintain a stream of motion tokens $\{x_t^r\}_{t=1}^T$ and aligned audio tokens $\{a_t\}_{t=1}^T$, with optional text tokens $\{w_t\}_{t=1}^T$ when available. In this stage, each eXpert is trained independently, but all share the same audio encoder so they learn to respond to a common audio representation. At time step t , the eXpert for region r receives a causal window of past region tokens $\{x_{t-h}^r, \dots, x_{t-1}^r\}$ and audio tokens $\{a_{t-h}, \dots, a_t\}$. Motion tokens are embedded by an MLP projection and augmented with rotary positional embeddings, yielding a continuous sequence that is stable under streaming shifts. This sequence is processed by a small stack of causal Transformer blocks that interleave (i) causal audio–motion cross attention, where region tokens attend only to past and current audio (and text) tokens, which enables rhythm-and-gesture alignment, and (ii) causal temporal self-attention, which captures region-specific inter-token correlations. The output motion embedding h_t^r is fed into a token classifier that models audio-condition categorical motion distribution.

3.2.2. Causal Spatial-Temporal Fusion (xAR-Fuse)

Local eXperts learn rich region-specific motion distributions but do not explicitly enforce full-body coordination. The causal fusion transformer operates on top of the frozen eXperts to model inter-region spatiotemporal correlations while preserving strict causality. At each time step t , we collect the hidden embeddings $\{h_t^r\}_{r \in \mathcal{R}}$ from all region eXperts. Since these embeddings are generated by independently trained networks, they are not naturally aligned for joint fusion. To bridge this gap, we introduce a lightweight residual adapter for each region, i.e., $\Delta h_t^r = \mathcal{W}_r h_t^r$, $\tilde{h}_t^r = h_t^r + \Delta h_t^r$. This adapter gently aligns the output embeddings from different eXperts into a shared fusion space with minimal parameters and computational overhead. The adapted embeddings $\{\tilde{h}_t^r\}_{r \in \mathcal{R}}$ are passed through the fusion transformer, implemented as a stack of causal Transformer blocks. Each block is factorized into three attention layers that separately address audio–motion coupling, temporal refinement, and spatial coordination. A causal audio–motion cross-attention layer allows each region to query the current audio (and text) tokens, reinforcing beat and semantic alignment at every step. The inter-region spatial-attention layer, coupled with the causal global temporal-attention layer, explicitly and efficiently captures whole-body spatiotemporal coordination such as arm–torso coupling or mirrored hand gestures. Instead of sharing a single MLP token classifier,

the output embeddings from the fusion transformer are finally fed into region-specific token classifiers to enhance fine-grained regional expressiveness.

3.2.3. Streamable Audio Encoder

To enable live gesture generation conditioned on continuously arriving audio signals, we design a causal audio encoder. First, an acoustic mel-spectrogram feature extraction module converts raw waveforms into log-mel frames using a short analysis window and small hop, chosen to match the latency budget of downstream streaming. These features are processed by a causal 1D convolutional projection module with left-only padding that enforces causality from the first layer. A dilated causal convolutional pyramid then captures multi-scale temporal structures in rhythm and prosody, expanding the receptive field without increasing latency. Finally, a causal audio–motion alignment module aggregates pyramid activations within each motion step using temporal striding, producing audio tokens a_t at the same frame rate as motion tokens. Each audio token depends only on past and current acoustic evidence, yielding multi-scale, low-latency, and temporally aligned representations ideal for zero–look-ahead streaming gesture generation.

3.3. Autoregressive Masked Training

Our model is trained in two stages: first learn audio-driven autoregressive motion dynamics for each region, and then train the fusion transformer with a hybrid masking strategy.

Stage 1: Local autoregressive modeling. For each region $r \in \mathcal{R}$, the local eXpert defines a causal token-level model

$$p_\phi^r(x_{1:T}^r | a_{1:T}, w_{1:T}) = \prod_{t=1}^T p_\phi^r(x_t^r | x_{1:t-1}^r, a_{1:t}, w_{1:t}),$$

where x_t^r is the motion token for region r at time t , a_t is the audio token, and w_t is the optional text token. During training, we teacher-force the ground-truth history and optimize a standard autoregressive cross-entropy loss

$$\mathcal{L}_{\text{local}} = - \sum_{r \in \mathcal{R}} \sum_{t=1}^T \log p_\phi^r(x_t^r | x_{1:t-1}^r, a_{1:t}, w_{1:t}),$$

optionally combined with a small reconstruction loss in pose space. To mitigate *exposure bias*, i.e., the mismatch between teacher-forced training histories and self-generated histories at inference time, we also inject small Gaussian noise into the embedded history tokens with a small probability p_{noise} , so that local eXperts learn to cope with slightly corrupted context rather than relying on perfectly clean ground-truth sequences. This stage yields frozen local eXperts that provide well-calibrated next-token distributions and hidden states h_t^r for each region.

Stage 2: Hybrid Masking for Robust Fusion. To capture the inherent motion dynamics dependency among different

body regions, a certain number of motion tokens from different regions at different time instances are masked out. The fusion transformer is trained to predict the next token based on partially corrupted motion sequence, audio embeddings, and optional text transcript tokens. The reconstruction probability of each motion token under motion corruptions is

$$p_{\theta}(x_t^r \mid \tilde{x}_{1:t}^{1:|\mathcal{R}|}, a_{1:t}, \tilde{w}_{1:t}), \quad r \in \mathcal{M}_t,$$

where $\tilde{x}_{1:t}^{1:|\mathcal{R}|}$ represent corrupted motion sequence up to time t and $\tilde{w}_{1:t}$ are the (possibly masked) text tokens. The training objective is to minimize the negative log-likelihood of the next motion token prediction

$$\mathcal{L}_{\text{fuse}} = - \sum_{t=1}^T \sum_{r \in \mathcal{M}_t} \log p_{\theta}(x_t^r \mid \tilde{x}_{1:t}^{1:|\mathcal{R}|}, a_{1:t}, \tilde{w}_{1:t}).$$

We adopt two types of masking strategies: uncertainty-guided token masking (UGM) and random region masking (RM). Together, they expose the fusion model to the imperfect, partially erroneous histories it will see at inference time, further reducing exposure bias. For token masking, the masking ratio (i.e., the percentage of tokens is masked) is controlled by a cosine scheduler over training steps. Concretely, let $\lambda_{\text{UGR}}(s) \in [0, 1]$ be a cosine-annealed masking ratio at training step s . The $M_{\text{eff}}(s) = \lfloor \lambda_{\text{UGR}}(s) M_{\text{max}} \rfloor$ least confident tokens based on their prediction probabilities are masked out. Early in training, $\lambda_{\text{UGR}}(s) \approx 0$, so masking ratio is low and the fusion transformer learns to intereXpert dependency under mostly clean inputs. As training progresses, $\lambda_{\text{UGR}}(s)$ increases toward 1, and the model is gradually exposed to more aggressively corrupted motion sequences. In addition to token-level masking, we apply a *region masking* scheme: with a small probability p_{drop} per training sequence, we select a region $r_{\text{drop}} \in \mathcal{R}$ and treat its entire token trajectory $\{x_t^{r_{\text{drop}}}\}_{t=1}^T$ as masked, forcing the fusion transformer to reconstruct the masked body region purely from audio and the remaining unmasked regions

Classifier-Free Logits Guidance. To further enhance audio/text–motion alignment, we apply classifier-free guidance to the discrete logits of the token classifiers. During training, audio, text, or both modalities are randomly dropped with a small probability to enable the model to learn an unconditional prior. At inference, the conditional and unconditional logits for each region $r \in \mathcal{R}$ are combined as $\ell_{\text{guided}}^r = \ell_{\text{uncond}}^r + \gamma(\ell_{\text{cond}}^r - \ell_{\text{uncond}}^r)$, where $\gamma \geq 1$ denotes the guidance scale. The resulting guided logits are then passed through a softmax function to produce the token distribution used for sampling during inference.

4. Experiments

Datasets. We train and evaluate LiveGesture on the BEAT2 corpus introduced by EMAGE [18], which con-

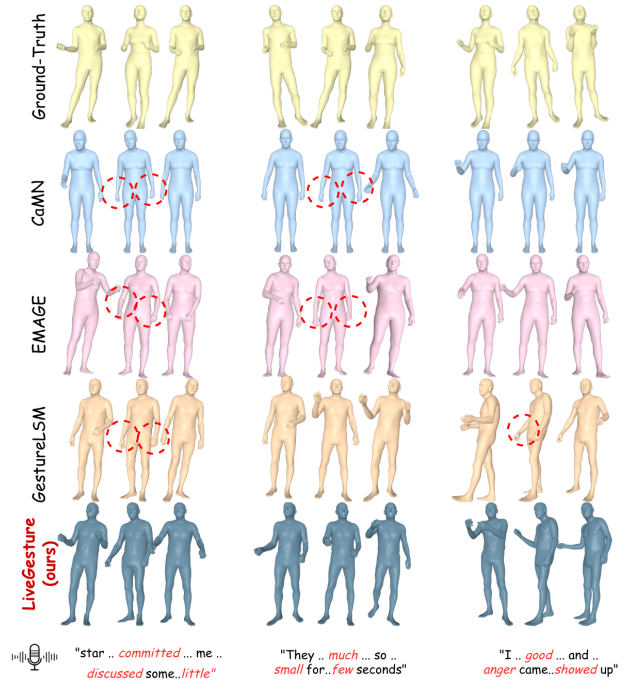


Figure 4. Qualitative comparison with state-of-the-art methods on BEAT. LiveGesture generates more diverse, expressive full-body gestures that better follow speech rhythm, while red circles mark representative failure cases of prior methods.

tains 60 hours of SMPL-X full-body motion aligned with speech from 25 speakers (1,762 conversational clips, average length 65.66 s). The data cover diverse speaking styles and gesture behaviors. All experiments follow the official train/test split of EMAGE [18] for fair comparison.

Evaluation Metrics. We assess gesture quality in terms of realism, diversity, audio–motion alignment, and facial accuracy. Realism is measured by Fréchet Gesture Distance (FGD) [46]; diversity (Div.) [14] is the average L1 distance between generated clips for the same audio; audio–motion synchronization is evaluated by Beat Constancy (BC) [15]; and facial accuracy is measured by vertex MSE between predicted and ground-truth SMPL-X face vertices [42]. For readability, FGD and BC are scaled by 10^{-1} and MSE by 10^{-7} in all tables.

Table 1 compares LiveGesture with recent state-of-the-art co-speech gesture models on BEAT2. Although it is the *only* zero–look-ahead streaming method, LiveGesture remains competitive with or superior to offline systems: it achieves near-best Fréchet Gesture Distance (FGD; 4.57 vs. 4.25 for GestureLSM), the best Beat Constancy (BC = 0.794), the highest Diversity (13.91), and the second-lowest facial MSE (1.241 vs. 1.021), indicating tight rhythm alignment, rich motion variation, and high-fidelity full-body and facial motion under strict streaming constraints. We at-

Table 1. State-of-the-art comparison on BEAT. Best results are shown in **bold** and second best are underlined. The *Streaming* column indicates whether the method supports zero-look-ahead streaming (✓) or is offline-only (✗); Our method is the only streaming model while remaining superior in most of important metrics.

Methods	Venue	Streaming	FGD (↓)	BC (→)	Diversity (↑)	MSE (↓)
Offline Solutions						
HA2G [24]	CVPR'22	✗	12.32	0.677	8.626	–
DisCo [16]	MM'22	✗	9.417	0.643	9.912	–
CaMN [17]	ECCV'22	✗	6.644	0.676	10.86	–
TalkShow [45]	CVPR'23	✗	6.209	0.695	13.47	7.791
DiffSHEG [4]	CVPR'24	✗	7.141	0.743	8.21	9.571
ProbTalk [25]	CVPR'24	✗	5.040	0.771	13.27	8.614
EMAGE [18]	CVPR'24	✗	5.512	0.772	13.06	7.680
MambaTalk [44]	NeurIPS'24	✗	5.366	<u>0.781</u>	13.05	7.680
SynTalker [3]	MM'24	✗	4.687	0.736	12.43	–
RAG-Gesture [27]	CVPR'25	✗	9.110	0.727	12.62	–
RAG-Gesture (w/ Discourse) [27]	CVPR'25	✗	8.790	0.739	12.62	–
GestureLSM [22]	ICCV'25	✗	4.247	0.729	<u>13.76</u>	1.021
Streaming Solution (Ours)						
LiveGesture (ours)	Ours	✓	<u>4.57</u>	0.794	13.91	<u>1.241</u>

tribute this to three factors: (i) the streamable asymmetric motion tokenizer (SVQ), which learns a globally coherent latent space while decoding strictly causally, providing clean low-rate motion tokens; (ii) region-wise AR eXperts plus xAR-Fuse, which align frozen eXpert states and apply causal spatio-temporal attention for coherent whole-body coordination; and (iii) hybrid masked training on top of a strictly causal audio encoder, which exposes the model to realistic corrupted histories and yields robust audio–motion coupling. Together, these choices allow LiveGesture to achieve extremely low First-Token Latency (250 ms), the amount of time a model takes to generate the first motion frame in its response after receiving the first audio token.

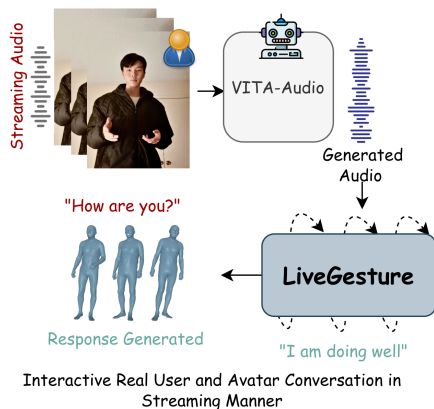


Figure 5. Interactive human–avatar conversation enabled by *LiveGesture*. User speech is converted into a spoken reply by VITA-Audio, while our LiveGesture streaming gesture model simultaneously generates synchronized full-body SMPL-X motions from live audio, allowing the avatar to respond in real time.

4.1. Ablation Studies

We ablate the key components of LiveGesture to understand which design choices allow a strictly causal, zero-look-ahead model to surpass offline methods. We vary (i) fusion architecture and region conditioning, (ii) motion tokenization and audio encoding, and (iii) streaming-aware training objectives and masking strategies. Quantitative results are summarized in Table 2. More

Effectiveness of LiveGesture Components. Table 2a shows that fusion-level temporal attention is essential: removing it causes the largest drop across all metrics (FGD 4.57→15.52, BC 0.794→0.712, Div. 13.97→10.40), confirming the need for causal temporal modeling beyond local eXperts. Spatial attention also clearly improves FGD and diversity (6.64 / 11.56 without it), highlighting the importance of inter-region coordination for full-body coherence. PILOR removal degrades FGD and BC (4.89 / 0.774), indicating that low-rank pre-infusion alignment stabilizes fusion over frozen eXperts. Disabling UGR yields the worst BC (0.723) and higher FGD (4.98), showing that uncertainty-guided refinement mitigates exposure bias under streaming errors. Text removal leaves FGD and diversity almost unchanged and slightly improves BC (0.796), suggesting that audio is the primary driver of rhythm, with text providing modest semantic/style refinements.

Region-eXperts vs. Full xAR-Fuse. Table 2b compares local region-eXperts alone to the full architecture. eXperts alone achieve reasonable quality (FGD 6.458, BC 0.762, Div. 12.844) but underperform LiveGesture. Adding xAR-Fuse on top of frozen eXperts improves all metrics (FGD 4.57, BC 0.794, Div. 13.91), validating our hierarchical design: specialized region-eXperts provide strong local priors,

Table 2. Ablation studies of LiveGesture design choices, including core components, architecture, tokenization, audio encoders, loss weights, and UGR.

Configuration	FGD↓	BC→	Div.↑
w/o PILOR	4.89	0.774	13.41
w/o UGR	4.98	0.723	13.64
w/o spatial attn.	6.64	0.732	11.56
w/o temporal attn.	15.52	0.712	10.40
w/o text cues	4.60	0.796	13.96
LiveGesture (ours)	4.57	0.794	13.97

(a) Effectiveness of LiveGesture components

Architecture	FGD↓	BC→	Div.↑
Local region eXperts only	6.458	0.762	12.844
LiveGesture (ours)	4.57	0.794	13.91

(b) Local experts vs. full LiveGesture

Stage-2 trainable components	FGD↓
1-stage (Enc+Dec+Quant)	4.691
AE + 2-stage (Dec+Quant)	4.633
AE + 2-stage (Dec+Quant+MLP)	4.610
AE + 2-stage (Quant+MLP)	4.557

(c) Effect of which SVQ components are trainable in Stage 2 after autoencoder pre-training on xAR-Fuse performance.

Model Type	FGD↓	BC→	Params (M)↓
Magic-Codec [37]	4.51	0.793	103
FocalCodec [6]	4.95	0.773	88
ours	4.57	0.794	0.5

(d) Streamable audio encoders

λ_{local}	λ_{fuse}	FGD↓	BC→
0.0	1.0	4.89	0.795
0.3	1.0	4.57	0.794
0.5	1.0	4.67	0.781
0.7	1.0	4.74	0.783
1.0	1.0	4.85	0.774

(e) Role of Local Expert Loss in \mathcal{L}_{AR} .

UGM masking schedule	FGD↓	BC→	Div.↑
$\gamma(\tau \in \mathcal{U}(0, 1))$	4.63	0.775	12.95
$\gamma(\tau \in \mathcal{U}(0, 0.3))$	4.84	0.792	13.24
$\gamma(\tau \in \mathcal{U}(0, 0.5))$	4.57	0.794	13.91
$\gamma(\tau \in \mathcal{U}(0, 0.7))$	4.67	0.773	13.60

(f) Effect of masking schedule in uncertainty-guided masking (UGM).

while a dedicated causal fusion stage is needed to turn them into globally coherent streaming motion.

Effect of SVQ on xAR-Fuse. Table 2c examines which SVQ components are trainable in Stage 2. Jointly training encoder, decoder, and quantizer (1-stage) yields the worst FGD (4.691), indicating that learning compression and causal decoding simultaneously is suboptimal. In the two-stage setting, performance improves as we freeze more of the autoencoder, with the best FGD when only the Quantizer+MLP are updated and the decoder is fully frozen (4.557). This supports our SVQ design (Sec. 3.1): first learn a stable, streamable latent space, then adapt a lightweight quantizer and projection on top without altering the decoder.

Streamable Audio Encoder. Table 2d compares our lightweight Streamable Audio Encoder with heavier pre-trained neural codecs. Magic-Codec slightly improves FGD (4.51 vs. 4.57) but uses 103M params, whereas our audio encoder attains near-identical FGD, the best BC (0.794), and only 0.5M parameters; FocalCodec is both larger and less accurate. This shows that a lightweight, task-specific, strictly causal encoder aligned to the motion token rate is sufficient to generalize well and deliver high-quality, low-latency gesture streaming without the overhead of generic codecs.

Role of Local Expert Loss. Table 2e ablates the weights in $\mathcal{L}_{\text{AR}} = \lambda_{\text{local}}\mathcal{L}_{\text{local}} + \lambda_{\text{fuse}}\mathcal{L}_{\text{fuse}}$. Using only fusion loss ($\lambda_{\text{local}} = 0$) yields good BC but worse FGD, so xAR-Fuse alone under-regularizes regional dynamics. A small local weight ($\lambda_{\text{local}} = 0.3$) gives the best FGD while preserving BC, whereas larger values hurt both metrics, indicating that region-eXperts work best as lightly guided priors with xAR-Fuse handling final coordination.

Masking Ratio in Uncertainty-Guided Refinement (UGR). Table 2f evaluates different UGR masking sched-

ules. Very broad or very narrow masking ranges lead to worse FGD or BC, while our default schedule $\gamma(\tau \in \mathcal{U}(0, 0.5))$ achieves the best trade-off (FGD 4.57, BC 0.794, Div. 13.91). This suggests that UGR is most effective when it injects moderate corruption that mimics streaming errors without making refinement unstable.

4.2. Application: Interactive Human–Avatar Conversation

LiveGesture can be plugged into streaming speech agents such as VITA-Audio [26] to enable fully interactive human–avatar conversations. In our prototype, user speech is converted by VITA-Audio into a spoken response whose waveform is streamed into our xAR-based gesture model, driving synchronized full-body SMPL-X motion in real time. The same pipeline can be extended with virtual clothing or character skins over the generated motion, enabling expressive avatars for games, VTubers, and telepresence.

5. Conclusion

We introduce *LiveGesture*, a zero-look-ahead, fully streamable co-speech full-body gesture framework that integrates a streamable asymmetric motion tokenizer with hierarchical region-eXpert autoregression. A per-region SVQ tokenizer first produces causal motion tokens; local audio-conditioned eXperts model region-specific dynamics, while xAR-Fuse performs causal spatio-temporal fusion across regions. Hybrid uncertainty-guided masking, along with random region masking strategies, trains the model to refine low-confidence predictions under realistic streaming noise. Together, these components enable diverse, coherent, and beat-synchronous gesture generation over arbitrarily long sequences, making *LiveGesture* well suited for interactive applications such as live avatars, VTubers, telepresence agents, social robots, and AR/VR characters

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