

Listen, Denoise, Action!

Audio-Driven Motion Synthesis with Diffusion Models

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Fig. 1. Listen, denoise, action! Audio-driven Jazz dance synthesised from our proposed model. The 3D avatar is © Motorica AB.

Diffusion models have experienced a surge of interest as highly expressive yet efficiently trainable probabilistic models. We show that these models are an excellent fit for synthesising human motion that co-occurs with audio, e.g., dancing and co-speech gesticulation, since motion is complex and highly ambiguous given audio, calling for a probabilistic description. Specifically, we adapt the DiffWave architecture to model 3D pose sequences, putting Conformers in place of dilated convolutions for improved modelling power. We also demonstrate control over motion style, using classifier-free guidance to adjust the strength of the stylistic expression. Experiments on gesture and dance generation confirm that the proposed method achieves top-of-the-line motion quality, with distinctive styles whose expression can be made more or less pronounced. We also synthesise path-driven locomotion using the same model architecture. Finally, we generalise the guidance procedure to obtain product-of-expert ensembles of diffusion models and demonstrate how these may be used for, e.g., style interpolation, a contribution we believe is of independent interest.

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1 INTRODUCTION

Automated generation of human motion holds great promise for a wide array of applications such as films and special effects, computer games, crowd simulation, architecture and urban planning, and virtual agents and social robots. Typically, motion occurs in context of other modalities such as audio and vision, and moving appropriately requires taking contextual information into account. Two motion-generation problems where audio information plays an important role for human behaviour are dancing and co-speech gestures. *Co-speech gesticulation* – that is, hand, arm, and body motion that co-occur with speaking – is an integral part of embodied human communication, and can enhance both human-computer interaction (e.g., avatars and social robots) and human-human digital communication (e.g., in VR and telepresence). Dancing is a social and deeply human activity that transcends cultural barriers, with some of the most watched content on platforms like YouTube and TikTok specifically involving dance.

However, generating audio-driven motion has proved to be a difficult problem. Central to the challenge is the fact that such motion is not well predicted by the associated audio: gestures are highly individual, nondeterministic, and generally not well-determined by the speech. The same is true for dancing, which typically synchronises with music structure such as beats and measures, but otherwise can take a vast array of forms even for a single piece of music and genre of performance. Machine-learning has struggled to cope with this ambiguity and great variability, which can only be accurately captured by a very strong probabilistic model. In the absence of convincing and controllable motion synthesis models, applications remain reliant on manual labour in the form of expensive motion capture or even more expensive hand animation.

Fortunately, the recent emergence of diffusion models [Ho et al. 2020; Sohl-Dickstein et al. 2015; Song and Ermon 2019] offers a general and principled way to learn arbitrary probability distributions using the entire arsenal of deep learning architectures, without issues such as network restrictions (as required for invertibility in normalising flows) or difficult minimax optimisation problems (as required for GANs). In this paper, we demonstrate the advantages of diffusion probabilistic models for generating high-quality, audio-driven 3D human motion. Our concrete contributions are:

- We pioneer diffusion models for audio-driven human motion generation, specifically gestures and dance, using Conformers (Sec. 3).
- We demonstrate style control with the proposed approach, using classifier-free guidance to adjust the strength of the stylistic expression (Sec. 4).
- We make available a new dataset with audio and high-quality 3D motion capture from diverse genres of dance (Sec. 4.4).
- We describe and demonstrate how to leverage product-of-experts ensembles of diffusion models for tasks such as interpolation (Sec. 5).

Experiments confirm that the proposed approach outperforms leading baseline systems on multiple datasets in gesture generation and dance, and furthermore is capable of distinctive and adjustable expression of different motion styles. For code, data, and pre-trained systems, please see speech.kth.se/research/listen-denoise-action/.

2 BACKGROUND AND PRIOR WORK

We now review data-driven gesture generation and dance synthesis, as well as the use of diffusion models for the same. For a review of human motion generation with deep learning more broadly, please see Ye et al. [2021].

2.1 Gesture generation

Automatic gesture generation makes for more lifelike and engaging artificial agents [Salem et al. 2012]. It can also aid learning [Novack and Goldin-Meadow 2015] and can communicate social information such as personality [Durupinar et al. 2016; Neff et al. 2010; Smith and Neff 2017], and emotion [Castillo and Neff 2019; Fourati and Pelachaud 2016; Normoyle et al. 2013]. Early work in gesture generation focussed on rule-based approaches [Cassell et al. 2001; Kopp et al. 2003; Lee and Marsella 2006; Lhommet et al. 2015] that typically would play pre-recorded gesture clips (or “lexemes”), at

timings selected by hand-crafted rules; see Wagner et al. [2014] for a review. Alternatively, machine learning can be used to learn when to trigger gestures [Kucherenko et al. 2022], even if the gestures themselves still are rendered using pre-determined clips, e.g., Chiu et al. [2015]; Levine et al. [2010]; Sadoughi and Busso [2019]; Zhou et al. [2022], or via motion matching [Habibie et al. 2022] (where clips only consist of a single frame each [Clavet 2016]). However, designing a rule-based system requires much manual labour and expert knowledge. Clip-based models are furthermore fundamentally limited in that they may struggle to synthesise previously unseen motion. Many of these systems are driven by text rather than audio.

The rise of deep learning has brought increased attention to the problem of audio-driven 3D gesture generation, as a more scalable and generalisable approach to gesture-system creation. Several relatively early deep-learning systems used recurrent neural networks [Ferstl and McDonnell 2018; Hasegawa et al. 2018; Takeuchi et al. 2017] or convolutional approaches [Kucherenko et al. 2019, 2021a]. These were generally based on 3D joint positions in Cartesian coordinates, whereas the field nowadays tends to favour pose representations in terms of joint rotations, since the latter can more easily drive skinned and textured characters in 3D graphics. They were also limited by treating gesture generation as a regression problem, with one single output, typically leading to underarticulated, averaged output and/or other artefacts.

For a more general approach, research has looked to probabilistic models. These approaches hold substantial promise, since they can describe an entire range of motion from which distinct realisations can be sampled and furthermore have the potential to generalise much better beyond the available data. Example approaches have leveraged hidden semi-Markov models [Bozkurt et al. 2020], combinations of adversarial learning and regression losses [Ferstl et al. 2019; Habibie et al. 2021; Liu et al. 2022b], normalising flows [Alexanderson et al. 2020a], VAEs [Ghorbani et al. 2023], VQ-VAEs [Yazdian et al. 2022], combinations of flows and VAEs [Taylor et al. 2021], and different GAN techniques [Wu et al. 2021a,b]. For more in-depth reviews see Liu et al. [2021]; Nyatsanga et al. [2023].

2.2 Gesture style control

Embodied human communication is not merely about what and when we gesture, but also how we do it. Adding control over style such as identity and mood/emotion to synthetic gestures is thus an important tool for enhanced communication. Perhaps the dominant approach for style control today, used by, e.g., Ahuja et al. [2020b]; Fares et al. [2022]; Ghorbani et al. [2022, 2023]; Yoon et al. [2020], involves learning an encoder that maps a motion clip to a space of different gesturing styles, often a latent space in a VAE framework. This setup can be used for one-shot style transfer/adaptation, by feeding examples of novel gestures styles into the encoder to obtain a latent representation of their style. The method in Alexanderson et al. [2020a] differs in its style control, by instead proposing to define styles in terms of continuous-valued kinematic properties such as average hand height, in order to be able to generate different kinds of gesticulation even from a dataset where differences in style had neither been annotated nor deliberately elicited.

This paper uses a different type of style control from all of the above works, which both allows controlling style intensity independently of style identity, and unlocks a new and probabilistically principled way to combine and interpolate between styles.

2.3 Data-driven dance generation

Dance generation is perhaps a less explored topic than gesture generation, and will be reviewed more briefly. The field has seen a similar trajectory as gesture generation in terms of modelling approaches, trying new machine-learning methods as they become available. Perhaps reflecting the complexity of the probability distribution of dance motion, many approaches generate output by stitching together discrete units, such as concatenating motion segments [Chen et al. 2021a; Fukayama and Goto 2015], dance figures [Ofli et al. 2011], or the choreographic action units in ChoroNet [Ye et al. 2020]. Motion matching has also been used [Fan et al. 2011]. Deep-learning techniques used for directly generating dance pose sequences include recurrent neural networks and autoencoders [Crnkovic-Friis and Crnkovic-Friis 2016; Papillon et al. 2023; Tang et al. 2018], GANs [Hu et al. 2022], combinations of GANs and VAEs [Lee et al. 2019b], dilated convolutions and gated activation units [Zhuang et al. 2022], Transformer architectures [Li et al. 2022, 2020, 2021; Valle-Pérez et al. 2021], VQ-VAEs and Transformers with reinforcement learning [Siyao et al. 2022], and Conformers [Zhang et al. 2022b].

The most straightforward application of style control in deep-learning dance synthesis is to use discrete labels representing different dance genres as an additional model input. GANs and Transformers have also been used for dance style transfer [Yin et al. 2023], where style is defined by a motion example rather than a simple label. Oftentimes, published systems use a large set of audio features together with their style control, which might impact the ability to generalise across different-sounding music pieces and genres, in the sense that it risks creating models that chose their style of dance based on the music rather than the style label supplied by the user. A goal of our approach is to be able to generate any style of dance to any music.

The prior publications most similar to our work might be Zhang et al. [2022b] since it integrates Conformers [Gulati et al. 2020] in the architecture, but with adversarial learning in a non-probabilistic setting, or Valle-Pérez et al. [2021], which leverages Transformers and probabilistic deep generative modelling, albeit in the form of normalising flows.

2.4 Diffusion models for motion and audio

Diffusion models [Ho et al. 2020; Sohl-Dickstein et al. 2015; Song and Ermon 2019] are a new paradigm in deep generative modeling that is setting new standards in terms of perceptual quality scores [Dhariwal and Nichol 2021] and also demonstrating very competitive log-likelihood numbers [Kingma et al. 2021]. Central to this success is that diffusion models combine two very powerful properties: the ability to describe highly general probability distributions (only limited by the expressivity of arbitrary deep-learning architectures) with the ability to efficiently learn these distributions

from data by minimising a simple squared-error loss on a carefully designed denoising task.

Diffusion models have recently produced blockbuster results in text-conditioned generation of images [Ramesh et al. 2022; Rombach et al. 2022; Saharia et al. 2022] and video [Ho et al. 2022a,b; Höppe et al. 2022; Voleti et al. 2022]. Whilst text-conditioned 3D motion generation has been demonstrated without diffusion models [Ghosh et al. 2021a; Guo et al. 2022; Petrovich et al. 2022], diffusion models have quickly been adopted for that task [Kim et al. 2022; Tevet et al. 2023; Zhang et al. 2022a]. These models have been trained on short clips paired with written descriptions of the motion performed and use Transformer architectures [Vaswani et al. 2017] under the hood. Speech audio is not considered as a model input, nor are text transcriptions of speech. Style control is possible by specifying desired gesture properties as part of the text prompt, assuming these properties can be adequately captured and articulated in words.

In a parallel development, diffusion models have been applied to generate audio waveforms from acoustic information (a.k.a. neural vocoding) [Chen et al. 2021b; Kong et al. 2021]. However, prior models with audio-derived input (i.e., acoustic features) do not generate motion as the output. This is the contribution of this paper, with speech-driven gesture generation and music-driven dance synthesis as example applications.

We note that, in the time span between our initial arXiv preprint and the camera-ready version of our paper, several concurrent works on audio-driven motion synthesis have been made public. These consider either gesture generation [Ao et al. 2023; Zhang et al. 2023] or dance synthesis [Dabral et al. 2022; Ma et al. 2022; Tseng et al. 2023], but never both. It has not been possible to include these works in our empirical comparison, but videos of their motion are available with their respective papers for informal comparison to our results.

3 METHOD

The task in this paper is to generate a sequence of human poses $\mathbf{x}_{1:T}$ given a sequence of audio features $\mathbf{a}_{1:T}$ for the same time instances, and optionally a style vector \mathbf{s} . This section presents the mathematical properties of diffusion models, the new diffusion-model architecture we demonstrate for audio-based motion generation, and how we include style into the models. Our proposal for style interpolation using products of experts is presented separately in Sec. 5. In the exposition, bold type signifies vectors and non-bold type scalars. Limits of summation are written in upper case (e.g., T), with lower case denoting indexing operations and colons delimiting ranges of indexing for sequences.

3.1 Diffusion models

Let \mathbf{x} be distributed according to an unknown density $q(\mathbf{x})$. To construct a diffusion model of \mathbf{x} , we first define a *diffusion process*, a Markov chain $q(\mathbf{x}_n | \mathbf{x}_{n-1})$ for $n \in \{1, \dots, N\}$ that progressively adds noise to an observation \mathbf{x}_0 ($n = 0$), eventually erasing all traces of the original observation, so that $q(\mathbf{x}_N | \mathbf{x}_0)$ has a standard normal distribution. The idea is then to train a network to reverse the q -process and “undo” the diffusion steps, creating observations out of noise. This produces the so-called *reverse* or *denoising process*, p .

We assume that the noise added by each step of the diffusion process q is zero-mean Gaussian, so that

$$q(\mathbf{x}_n | \mathbf{x}_{n-1}) = \mathcal{N}(\mathbf{x}_n; \alpha_n \mathbf{x}_{n-1}, \beta_n \mathbf{I}) \quad (1)$$

for some $\{\alpha_n, \beta_n\}_{n=1}^N$, where \mathcal{N} denotes a multivariate Gaussian density function evaluated at \mathbf{x}_n . In this paper we also set $\alpha_n = \sqrt{1 - \beta_n}$ [Ho et al. 2020; Sohl-Dickstein et al. 2015], in which case $\{\beta_n\}_{n=1}^N$ completely defines the diffusion process.

If the noise added in step n is small relative to \mathbf{x}_n , the reverse distribution is also Gaussian [Sohl-Dickstein et al. 2015]. A Gaussian approximation

$$p(\mathbf{x}_N) = \mathcal{N}(\mathbf{x}_N; \mathbf{0}, \mathbf{I}) \quad (2)$$

$$p(\mathbf{x}_{n-1} | \mathbf{x}_n) = \mathcal{N}(\mathbf{x}_{n-1}; \boldsymbol{\mu}(\mathbf{x}_n, n), \boldsymbol{\Sigma}(\mathbf{x}_n, n)), \quad (3)$$

where \mathcal{N} denotes a multivariate Gaussian density function evaluated at \mathbf{x}_{n-1} , is therefore likely to be accurate. In practice, good results have been achieved by setting $\boldsymbol{\Sigma}$ equal to a scaled identity matrix [Ho et al. 2020]. The learnt distribution is then completely specified by the mean $\boldsymbol{\mu}(\mathbf{x}_n, n)$, which is predicted by a neural network.

Diffusion models are usually trained through so-called score-matching [Hyvärinen and Dayan 2005], which (similar to energy-based models) does not require knowing the normalisation constant of a distribution. With a diffusion model, score-matching leads [Ho et al. 2020] to minimising a loss of the form

$$\mathcal{L}(\theta | \mathcal{D}) = \mathbb{E}_{\mathbf{x}_0, n, \boldsymbol{\epsilon}} [\kappa_n \|\boldsymbol{\epsilon} - \widehat{\boldsymbol{\epsilon}}(\tilde{\alpha}_n \mathbf{x}_0 + \tilde{\beta}_n \boldsymbol{\epsilon}, n)\|_2^2], \quad (4)$$

in addition to a minor loss term based on the negative log likelihood $-\ln p(\mathbf{x}_0 | \mathbf{x}_1)$. In Eq. (4), \mathbf{x}_0 is uniformly drawn from the training data \mathcal{D} , n is uniform on $\{1, \dots, N\}$, $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, and – critically – $\widehat{\boldsymbol{\epsilon}}(\mathbf{x}, n)$ is a neural network that predicts the noise $\boldsymbol{\epsilon}$ that was added to \mathbf{x}_0 . This is the neural network that defines the denoising process, and thus also the learnt probability density $p(\mathbf{x}_0)$. $\tilde{\alpha}_n$ and $\tilde{\beta}_n$ are constants that depend on $\{\beta_n\}_{n=1}^N$, while κ_n are weights. However, a differently-weighted version of the loss, which sets $\kappa_n = 1$ as proposed by [Ho et al. 2020], is widely used in practice, since it tends to achieve better subjective results [Kingma et al. 2021]. For a conditional probability model conditioned on some variable \mathbf{c} , one simply trains a network $\widehat{\boldsymbol{\epsilon}}(\mathbf{x}, \mathbf{c}, n)$ with \mathbf{c} as an additional input.

It is interesting to note that the training objective in Eq. (4) contains a simple squared-error minimisation. Under normal circumstances, the squared-error loss is minimised by the (conditional) expected value, which would regress towards the mean pose and give unnatural motion. However, the presence of the random variable $\boldsymbol{\epsilon}$ distinguishes the setup from classic minimum mean-squared error, and one can show that score-matching as in Eq. (4) in fact corresponds to maximising a variational lower bound on the data log-likelihood [Kingma et al. 2021]. This means that diffusion models actually learn an entire probability distribution. The variational bound gets tighter as the number of diffusion steps N grows large, obtaining a stochastic differential equation (SDE) in the limit $N \rightarrow \infty$ [Song et al. 2021].

Sampling from a diffusion model starts from $\mathbf{x}_N \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ and works backwards through the N steps of the reverse process p , which may be time-consuming. Accelerated sampling from trained diffusion models is currently a focus of intense research, e.g., Dhariwal and Nichol [2021]; Lam et al. [2022]; Meng et al. [2022]; Nichol

and Dhariwal [2021]; Salimans and Ho [2022]. As our aim in this paper is to advance the state of the art in audio-driven motion generation, exploring faster synthesis is left as future work.

3.2 Model architecture

To generate motion conditioned on audio information, we build on the DiffWave architecture [Kong et al. 2021] from conditional audio synthesis. This model takes acoustic feature vectors as input (usually sampled at 80 Hz) and uses a conditional diffusion model to generate a scalar-valued audio waveform at 22.5 kHz as output. The model generates all output in parallel, without autoregression or recurrent connections. Internally, it uses a residual stack of dilated convolutions with skip connections, similar to the trendsetting WaveNet model [van den Oord et al. 2016] for audio synthesis, except that the model (unlike WaveNet) is parallel rather than autoregressive and therefore can use non-causal convolutions.

Denote the sequence of input acoustic feature vectors by $\mathbf{a}_{1:T}$, where T is the number of frames. We adapt DiffWave to generate output at the same frame rate as the input (i.e., remove the up-sampling), and change to vector-valued rather than scalar output. In other words, we learn a distribution of the form $p(\mathbf{x}_{1:T} | \mathbf{a}_{1:T})$, where $\mathbf{x}_{1:T} = \mathbf{x}_{1:T, 0}$ is the output of a diffusion process (0 indicates the last denoising step) and \mathbf{x}_t is a representation of the pose at time t . In the experiments of this paper, the acoustic features \mathbf{a} are standard audio features such as mel-frequency cepstrum coefficients (MFCCs) [Davis and Mermelstein 1980], while the output poses are skeletal joint rotations parameterised using an exponential map representation [Grassia 1998] relative to a T-pose like in [Alexanderson et al. [2020a]], but this setup is not dictated by our model and other design choices are likely to work similarly well.

The dilated convolutions and skip connections in the original WaveNet together integrate information across many time scales [Hua 2018] and allow for an exceptionally wide receptive field that can reach several thousand samples [van den Oord et al. 2016]. In DiffWave, dilated convolutions (one per residual block l) have kernel size 3 and cycle between different dilations $d(l) = 2^{l \bmod \bar{l}}$ with $\bar{l} = 9$. Each block also uses a gating mechanism when integrating the conditioning information $\mathbf{c}_{1:T}$ (here the acoustics $\mathbf{a}_{1:T}$) on the output. This can be considered a generalisation of FiLM conditioning [Perez et al. 2018].

Another highly successful mechanism for effectively integrating information over long time scales is multi-head neural self-attention (e.g., Cheng et al. [2016]), especially as used in Transformer architectures [Vaswani et al. 2017]. That said, convolutional networks (CNNs) still retain an advantage over Transformers in computing kinematically important properties such as finite differences between time frames to represent motion speed and acceleration (force). Fortunately, the two approaches can be combined by replacing the feedforward networks (convolutions with kernel size 1) inside Transformers with CNNs with kernel sizes larger than one. This architecture is known as a *Conformer* and outperforms both Transformers and CNNs on tasks like speech recognition [Gulati et al. 2020]. To harness these mechanisms, we replace the dilated convolution in the residual blocks of DiffWave with a stack of Transformers or Conformers. In our experiments, we stack 4 of these in

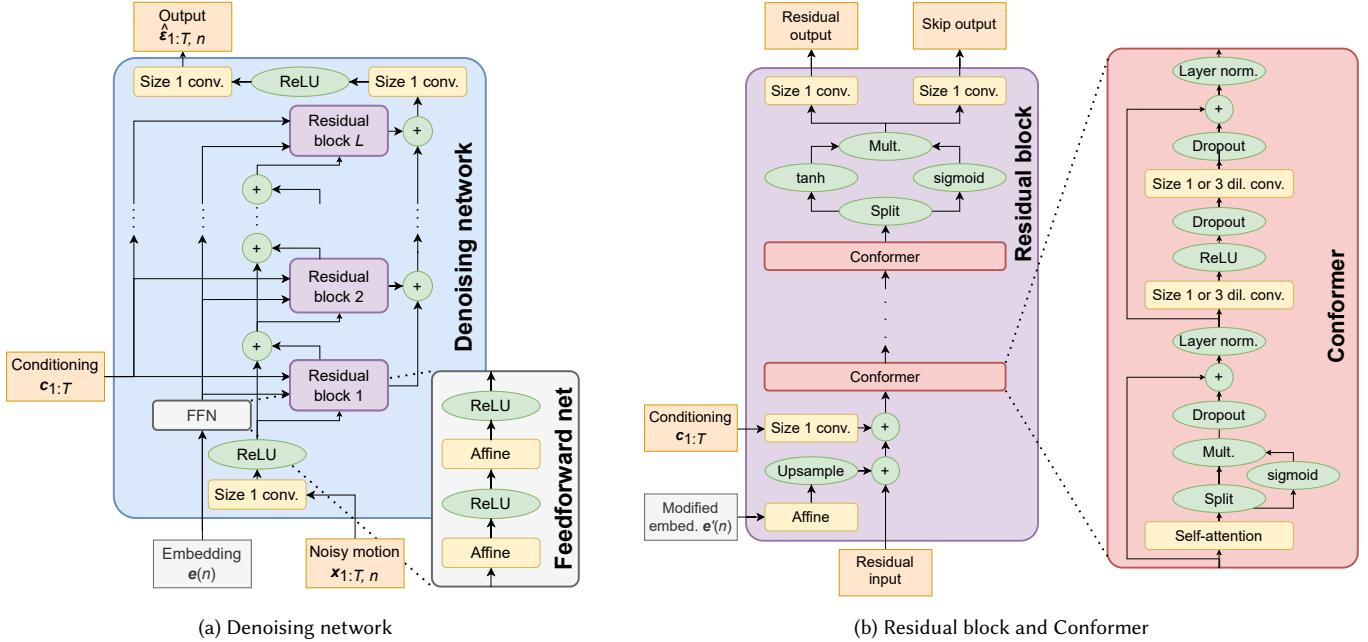


Fig. 2. Architecture diagrams. Each subfigure illustrates a component of the prior subfigure. Rectangular boxes are vectors and scalars, rounded boxes are neural networks or learnt operations, and ovals are fixed mathematical operations.

each residual block, all using the same dilation $d(l) = 2^{(l \bmod \bar{l})-1}$ with $\bar{l} = 3$, where $d(l) < 1$ here means that the residual block uses a Transformer (i.e., CNN kernel size 1) rather than a Conformer (kernel size 3), and compare to a similar DiffWave architecture with conventional dilated convolutions and no Transformer/Conformer stack (henceforth just “Conformers”).

Conformers have no inherent concept of time t , and require a position-encoding mechanism to use time information in the computations. Since we expect motion to be invariant to translation in time, we decided to use a translation-invariant scheme [Raffel et al. 2020; Wennberg and Henter 2021], specifically a version of translation-invariant self-attention (TISA) [Wennberg and Henter 2021], to parameterise the impact of sequence position t on the self-attention activations. This ensures that invariance to temporal translation does not need to be learnt.

Our final architecture is shown in Fig. 2, with the specific Conformer architecture shown in Fig. 2b. Like DiffWave, we use sinusoidal embeddings [Vaswani et al. 2017] passed through a feed-forward net to encode the diffusion step input $e(n)$ to the denoising network. The Conformers in our experiments use ReLU nonlinearities and a gating operation. While Kong et al. [2021] decided to use an L1 loss to train the denoising model in the original DiffWave paper, we only consider the L2 loss, since that is consistent with the theory in Eq. (4) and seemed to give better results.

Beyond the fact that other recent diffusion models for motion [Kim et al. 2022; Tevet et al. 2023; Zhang et al. 2022a] condition on text rather than audio, and focus on generating motion corresponding to simple actions rather than gestures or dancing that align with the timing and rhythm of an audio signal, our proposal also differs

in the architecture of the denoising network. Specifically, the cited works all use a stack of Transformers (with Zhang et al. [2022a] adding cross-modal attention), but none use Conformers nor dilations. Furthermore, none of the models use translation-invariant schemes for incorporating positional information, with Kim et al. [2022]; Tevet et al. [2023] both using sinusoidal position encodings that are known to generalise poorly to sequences longer than those used during training [Press et al. 2022].

3.3 Style control with guided diffusion

For many applications, it is not only important to obtain motion that matches the context – here the audio that co-occurs with the motion – but also to have control over the expression of the motion, e.g., generating motion in different styles. Conditional diffusion models offer a compelling mechanism for controlling not only which style to express (by conditioning \hat{e} on style), but independently also the strength of stylistic expression. The latter is accomplished by a technique called *guided diffusion* [Dhariwal and Nichol 2021], which corresponds to tuning the temperature $\gamma > 0$ of part of the denoising process distribution as

$$p_\gamma(x_{n-1} | x_n, c) \propto p(x_{n-1} | x_n) p(c | x_n)^\gamma, \quad (5)$$

so as to focus synthesis on the most distinctive examples of the given class c [Dhariwal and Nichol 2021; Dieleman 2022].

Interestingly, the above effect can be achieved by combining the predictions of a conditional and an unconditional diffusion model, which is called *classifier-free guidance* [Ho and Salimans 2021]. This has been used to great effect in models such as GLIDE [Nichol et al. 2022], DALL-E 2 [Ramesh et al. 2022], and Imagen [Saharia et al.

2022]. If we let $s_{1:T}$ be a vector representing the style input throughout the pose sequence, and define the style-added conditioning $c_{1:T}$ with $c_t = [\mathbf{a}_t^\top, s_t^\top]^\top$, then classifier-free guidance for stylistic expression can be achieved by combining the prediction of a style-conditional model $\hat{\epsilon}(\mathbf{x}_{1:T}, c_{1:T}, n)$ and that of a style-unconditional model $\hat{\epsilon}(\mathbf{x}_{1:T}, \mathbf{a}_{1:T}, n)$ during the reverse diffusion process as

$$\begin{aligned}\hat{\epsilon}_Y(\mathbf{x}_{1:T}, c_{1:T}, n) &= \hat{\epsilon}(\mathbf{x}_{1:T}, \mathbf{a}_{1:T}, n) \\ &+ \gamma(\hat{\epsilon}(\mathbf{x}_{1:T}, c_{1:T}, n) - \hat{\epsilon}(\mathbf{x}_{1:T}, \mathbf{a}_{1:T}, n)).\end{aligned}\quad (6)$$

This de-emphasises the effect of the style input s for $0 \leq \gamma < 1$ and exaggerates the effect for $\gamma > 1$. $\gamma = 0$ recovers the unconditional model. Our experiments study style control both with and without guidance, where s is a one-hot vector that encodes discrete style labels from the data, which do not change with the time t in a sequence. It is possible to train one single network to describe both the style-conditional and style-unconditional models, by randomly dropping out the style information $s_{1:T}$ from some sequences during training, in order to represent the unconditional case, but this is not necessary to apply the method. In our experiments, we instead used separate style-conditional and style-unconditional models, since that led to better-looking results in preliminary tests.

4 EXPERIMENTS

We conducted a number of experiments to demonstrate the capabilities of our proposed approach. After describing the data processing and modelling approach (in Sec. 4.1) and the general evaluation framework (in Sec. 4.2), we begin by comparing our proposal to the best available alternatives on two gesture-generation datasets (Sec. 4.3). We thereafter describe an additional user study that compared our approach to the state of the art in music-driven dance synthesis (Sec. 4.4). Objective metrics are reported in Sec. 4.5 whilst Sec. 4.6 shows that the approach generalises to path-driven locomotion generation. Sec. 4.7 summarises the findings. Please see speech.kth.se/research/listen-denoise-action/ for video clips of generated motion. Demonstrations of our proposal to create product-of-expert diffusion models are reserved for Sec. 5.

4.1 Data and modelling

Our experiments used five different datasets from high-quality 3D motion capture. An overview of these datasets is provided in Table 1, with additional information provided in the section where each dataset is used.

All experiments considered full-body motion only. This is a more challenging problem than only generating upper-body motion (cf. Yoon et al. [2022]), both due to the increased dimensionality of the output space and due to the visual prominence of artefacts such as foot-sliding and ground penetration if highly nonlinear constraints due to foot-ground interactions are not accurately modelled.

All datasets were initially 60 frames per second or more, but were converted to 30 fps for the modelling. We used skeletal joint rotations to represent poses, and parameterised these rotations using an exponential map representation [Grassia 1998] relative to a T-pose. All models except for path-driven locomotion generated three additional outputs (namely instantaneous rotation and forwards and lateral translation, similar to Habibie et al. [2017]; Holden et al.

Table 1. Overview of datasets and hyperparameters. Numbers after a slash are for style-unconditional models.

| Dataset | TSG | Zero-EGGS | Motorica | 100STYLE |
|---------------------|----------|-----------|----------|----------|
| | | Dance | MMA | |
| Motion | Gestures | Gestures | Dancing | Fighting |
| Duration | 244 min | 135 min | 373 min | 60 min |
| Performers | 1 male | 1 female | 3 F, 2 M | 1 male |
| No. styles | 1 | 19 | 8 | 1 |
| \mathbf{c}_t dim. | 20 | 35/16 | 11/3 | 8 |
| Audio | 20 | 16/16 | 3/3 | 0 |
| Other | 0 | 19/ 0 | 8/0 | 8 |
| \mathbf{x}_t dim. | 70 | 70 | 61 | 61 |
| Pose | 67 | 67 | 58 | 58 |
| Root offset | 3 | 3 | 3 | 3 |
| Steps N | 100 | 100 | 150 | 150 |
| No. updates | 112k | 67k | 180k | 52k |
| | | | | 292k |

[2016]) that describe the motion of the root node along the ground plane, to enable the model to move the character around. Because root-node rotation is parameterised using change of heading relative to the previous frame it is not subject to phase-wrapping discontinuities, simplifying the learning task. For path driven locomotion, the root-node motion was used as an input to the synthesis, rather than an output, and was then smoothed across 10 frames to emulate the smooth paths typically used in animation systems.

Audio conditioning inputs differed between models and were dependent on domain (speech vs. music). We used one hot-encodings for all style inputs, since we only considered discrete style labels. The fighting model in Sec. 5.3 took binary flags for a set of fighting moves as input. See Table 1 for an overview of the input and output feature dimensionalities of different models. For most systems with style control, we also trained one identical model but without the style input, to enable adjusting the stylistic expression via classifier-free guidance as described in Sec. 3.3. Values for these style-unconditional systems are shown on the right side of the slashes ('/') in the table. Additional details on the data processing are provided in the appendix.

Initial hyperparameter tuning was performed on the dance dataset in Sec. 4.4 using the Optuna framework. We found that the most important aspect to tune was the noise scheduling (the β_n -values), where we could achieve significantly improved motion by increasing the end-value of the linear schedule. This leads to more time spent using high-noise data in the diffusion process.

The proposed models were trained on a single GPU with 80 5-second motion sequences per batch. The number of training updates for each dataset is specified in Table 1. Additional details on model training and hyperparameters are provided in the appendix.

4.2 Evaluation methodology

The gold standard in evaluating motion naturalness, style expression, etc. is to perform subjective evaluation (i.e., user studies), and careful subjective studies are hence the core of the evaluations in this paper. The reason for this is that these fields (unlike core machine

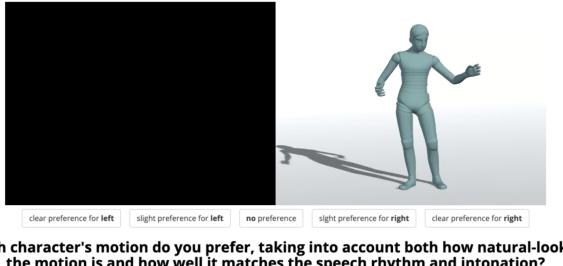


Fig. 3. Screenshot of the user interface used for subjective evaluations.

learning) lack common benchmark datasets and have no widely validated objective metrics. Although we compute and report objective metrics in Sec. 4.5, the core of our evaluation is our user studies, since these directly measure how gestures appear to humans.

For the task of gesture generation, the most successful instances of common benchmarking are the GENEVA challenges [Kucherenko et al. 2021b; Yoon et al. 2022], which compared a large number of contemporary gesture-generation methods under a common setup in several best-practices user studies that are the largest in the field as of yet. These challenges have been held twice thus far, once (in 2020) using data from the Trinity speech-gesture (TSG) dataset [Ferstl and McDonnell 2018], and once (in 2022) using data from Talking With Hands 16.2M [Lee et al. 2019a]. We compared our proposed method to the deep generative model with the highest output quality in each instance of the challenge, as described in Sec. 4.3.1 and Sec. 4.3.2.

Concretely, we performed a total of four user studies to assess both motion quality and the distinctiveness of stylistic expression. Three of the studies considered gesture generation and one considered dance, but all shared the same setup and analysis method. Each study was based on pairwise comparisons, where two 10-second video clips were played consecutively side by side. A number of 20-second long comparison videos were assembled, first showing an animation on the left side, with a black frame on the right, followed by an animation on the right and a black frame on the left (see Fig. 3). The audio driving the animation was always the same for the left and the right clip, and all clips within a study used the same avatar, but each of the two videos in a comparison was from a different system (condition). The main experimental screen consisted of a video with a text question and five response buttons underneath, where the full video had to be played for the response buttons to become active. Participants for the user studies were recruited using the Prolific crowdsourcing platform¹ and filtered using attention checks prior to analysis. Please see the appendix for more details, e.g., regarding the attention checks.

Our main method of analysis for each user study relied on merit scores [Parizet et al. 2005]. In this methodology, responses with a slight preference for a system were encoded numerically as a score of 1, and clear preferences were assigned a 2, whereas ties or a preference for the other system in the comparison gave a score of 0. The data was then analysed by means of a one-way ANOVA and

Table 2. Overview of the design of the different user studies. “No. ordered pairs” is the number of possible pairwise comparisons of distinct conditions, taking presentation order into account. “Ordered pairs seen” refers to how many times each participant was exposed to each ordered condition pair.

| Dataset Evaluation | TSG | ZeroEGGS | Dance |
|------------------------|-------|----------|-------|
| Pref. | Pref. | Style | Pref. |
| No. conditions | 4 | 3 | 3 |
| No. ordered pairs | 12 | 6 | 6 |
| Styles evaluated | 1 | 4 | 4 |
| Videos per condition | 36 | 36 | 36 |
| ...and style | 36 | 9 | 9 |
| Total video stimuli | 432 | 216 | 216 |
| Audio included? | ✓ | ✓ | ✗ |
| Participants recruited | 131 | 40 | 40 |
| Participants included | 129 | 38 | 38 |
| Ordered pairs seen | 3 | 6 | 6 |
| | | | 3 |

a post-hoc Tukey multiple-comparisons test for statistical significance. In addition to reporting the merit scores with 95% confidence intervals for each condition, we also report the win rate (excluding ties) of our main proposed system in every study.

4.3 Gesture-generation experiments

4.3.1 Experiment on the Trinity speech-gesture dataset. In the first experiment, we compared ourselves to *StyleGestures*² [Alexanderson 2020], an autoregressive normalising-flow model for speech-conditioned gesture synthesis that achieved the best motion quality in the GENEVA Challenge 2020 [Alexanderson et al. 2020a; Kucherenko et al. 2021b]. For this evaluation, we used the TSG dataset (also used as the basis for the GENEVA Challenge 2020), which contains around four hours of full-body motion capture and speech audio from a male actor delivering spontaneous monologues. We used the same train/test split as the 2020 GENEVA Challenge and evaluated only on data from the test set. Motion was visualised using the GENEVA 2022 avatar seen in Fig. 3. The avatar design lacks mouth and gaze, to instead draw attention to the rest of the body.

The TSG data did not deliberately elicit different styles and does not contain any style labels. Although *StyleGestures* described the optional capability to control the motion style, this was demonstrated using kinematically derived style correlates such as hand height, hand speed, and gesticulation radius [Alexanderson 2020]. As *StyleGestures* has not been validated on the discrete style control we consider in this paper, we therefore only compare to *StyleGestures* in terms of motion quality, using only speech audio conditioning for all models in the experiment. To represent the speech acoustics, we used 20-dimensional mel-frequency cepstrum coefficients (MFCCs) [Davis and Mermelstein 1980] for each frame.

For our experiment on the TSG data we performed a preference test to evaluate the quality of the gesture motion. Four conditions were compared: ground-truth motion capture (labelled GT), the proposed system (LDA), an ablation that used the original DiffWave architecture instead of our proposed Conformers (LDA-DW), and a *StyleGestures* system without style input (SG). 36 audio segments

¹<https://www.prolific.co/>

²<https://github.com/simonalexanderson/StyleGestures>

Table 3. Results from user studies. Studies include a proposed system (LDA), a dataset-dependent variant thereof, a baseline, and (where indicated) ground truth (GT). We report merit scores [Parizet et al. 2005] with 95% confidence intervals and the win rate excluding ties of every condition versus LDA.

| Dataset Evaluation Measure | TSG | | ZeroEGGS | | | | Dance | |
|----------------------------|-----------------|-----------|-----------------|-----------|---------------|------------------|-----------------|----------|
| | Preference test | | Preference test | | Style control | | Preference test | |
| | Merit score | Win rate | Merit score | Win rate | Merit score | Win rate | Merit score | Win rate |
| GT | 0.95±0.04 | 67.3% | - | - | - | - | 0.87±0.06 | 61.1% |
| Variants | LDA-DW | 0.50±0.03 | 42.5% | - | - | - | - | - |
| | LDA-G | - | - | 0.41±0.07 | 37.2% | 0.61±0.05 | 62.2% | - |
| | LDA-U | - | - | - | - | - | 0.51±0.05 | 36.7% |
| Baselin. | SG | 0.31±0.03 | 28.0% | - | - | - | - | - |
| | ZE | - | - | 0.43±0.07 | 34.7% | 0.50±0.04 | 56.5% | - |
| | BL | - | - | - | - | - | 0.24±0.06 | 23.5% |

of 10 s from the TSG test set were used to generate animation with each of the three models (LDA, LDA-DW, SG) plus ground truth (GT). These animations were then evaluated in a user study, as described in Sec. 4.2. For each comparison video in the study, participants were asked “Which character’s motion do you prefer, taking into account both how natural-looking the motion is and how well it matches the speech rhythm and intonation?”. Answers were given using a 5-point Likert-style preference response scale, with the response alternatives “clear preference for left”, “slight preference for left”, “no preference”, “slight preference for right”, and “clear preference for right”; see Fig. 3. Additional information about the user study is provided in Table 2.

Table 3 summarises the results of the user study on the TSG dataset. The ground-truth motion capture (GT) achieved the best merit score, followed by LDA, LDA-DW, and SG, in that order. Our statistical analysis found all differences to be significant, with $p < 0.01$ for LDA vs. LDA-DW and $p < 0.001$ for all other differences. Whilst not reaching the same level as human motion capture, our proposed diffusion model thus outperformed StyleGestures. We also found that the proposed architecture with Conformers contributed to this. The difference between LDA and LDA-DW was furthermore larger in pilot studies we performed using different hyperparameters, including a different noise schedule, suggesting that the Conformers also are less sensitive to hyperparameter settings. Since LDA-DW performed less well, it is not considered in subsequent studies.

4.3.2 Experiments on the ZeroEGGS dataset. In the second and third experiments, we compared ourselves to the best-performing deep generative submission to the 2022 GENEVA Challenge [Yoon et al. 2022], namely a model [Ghorbani et al. 2022] later released as ZeroEGGS [Ghorbani et al. 2023]. ZeroEGGS is an autoregressive model consisting of a feedforward speech encoder, a probabilistic style encoder (using a Transformer) with a standard Gaussian prior, and a recurrent gesture-generation module (using gated recurrent units, GRUs).

ZeroEGGS was released alongside a new gesture dataset of the same name [Ghorbani et al. 2023] with two hours of speech and full-body motion capture of a female actor delivering monologues in 19 diverse styles. This data allows us to demonstrate control over a range of style expressions. (The GENEVA 2022 data has no

such styles.) We selected four styles for our evaluation, spanning emotional states (*happy* and *angry*), speaking styles (*public speaking* a.k.a. *oration*), and age (*old*). This experiment used 16-dimensional MFCCs as input, instead of 20 dimensions as used for TSG. This is because the Madmom audio-processing library³ used for feature extraction defaults to a different number of MFCCs depending on the sampling rate of the audio, which differs between the two datasets.

To prevent the style of the speech audio from interfering with the effect of style control in our evaluations (either by biasing the generated styles or raters’ perceptions of these styles), we held out two speech recordings in the *neutral* style (specifically 004_Neutral_3 and 005_Neutral_4), so as to have sufficient neutral speech material for our evaluation, and used the remaining data for training.

We trained and compared three conditions on this data: our proposed model (labelled LDA), the same model using classifier-free guidance of the style control during synthesis (LDA-G), and ZeroEGGS (ZE). The latter used the original model hyperparameters and code from the official codebase and data repository.⁴ For LDA-G, we used a guidance factor $\gamma = 1.5$, to study the impact of exaggerated stylistic expression obtained through classifier-free guidance.

Nine 10-second audio segments from the neutral-style test set of ZeroEGGS were used to generate animation in four different styles (*happy*, *angry*, *old*, and *public speaking*), yielding 36 segment-style combinations. Motion was visualised using the female avatar that was released together with the ZeroEGGS dataset.

Motion preference evaluation. We conducted the same type of preference test as in the first experiment, with the same question and response alternatives, but for the three systems trained on the ZeroEGGS data. Additional information about the user study is provided in Table 2, whilst Table 3 shows the results. The best performer was LDA, with ZE and LDA-G being statistically tied in terms of merit scores. In addition to SG earlier, the proposed model thus also outperforms ZeroEGGS in terms of preference ($p < 0.001$). That difference disappears when using guided diffusion to exaggerate style expression, but it is not surprising to find exaggerated motion less natural and less preferred.

³<https://github.com/CPJKU/madmom>

⁴<https://github.com/ubisoft/ubisoft-laforge-ZeroEGGS>



Fig. 4. Dance synthesised from our trained diffusion model in the *Locking* and *Krumping* styles. See Fig. 1 for the *Jazz* style. Avatar © Motorica AB.

Style-control evaluation. To measure the distinctiveness of stylistic expression, we conducted another experiment, where we displayed the same motion clips as in the previous experiment, but instead of asking for user preference we asked “*Based on the body movements alone (disregarding the face), which of the two clips looks most like STYLE?*”, where **STYLE** was one of the following: {“**the person is happy**”, “**the person is angry**”, “**an old person**”, “**a person giving a speech to the public**”}, using bold font to highlight key parts of the instructions as shown. The five response alternatives were “clearly the left one”, “probably the left one”, “I can not tell”, “probably the right one”, and “clearly the right one”. The instruction to disregard the facial expression was added since the ZeroEGGS avatar has a quite stern facial expression, which might contradict, e.g., the *happy* gesturing style.

In this experiment, the videos were silent in order to prevent speech content from affecting the judgement of gesturing style. (That one modality can affect the perception of the other has been confirmed in multiple studies, e.g., [Bosker and Peeters \[2021\]](#); [Jonell et al. \[2020\]](#); [Kucherenko et al. \[2021b\]](#).) Presentation was grouped by style, meaning that all nine *happy*-style comparisons were presented first, followed by the *angry*, *old*, and *public speaking* comparisons in that order. Before each new style, an interstitial screen was presented, informing the participant that the subsequent stimuli were going to be judged according to the style in question. The order of comparisons within a style was randomised for each participant.

An overview of the style-control user study is provided in Table 2, with the results shown in Table 3. LDA-G received the highest style-matching score, ahead of ZE ($p < 0.01$), which was ahead of LDA ($p < 0.001$). This confirms that we were able to successfully moderate style strength by using guided diffusion, to an extent that can surpass ZeroEGGS in distinctiveness.

4.4 Music-driven dance synthesis

As a second application of audio-driven motion generation, we also train and evaluate a music-driven dance model based on our approach. For this, we used a new dataset that combines new and existing high-quality motion-capture data. Specifically, we extracted a subset of the highest-quality recordings from the PSMD dataset from [Valle-Pérez et al. \[2021\]](#), using only material recorded using

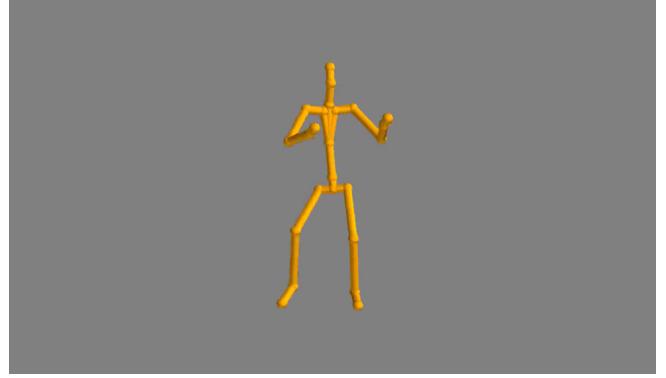


Fig. 5. 3D stick-figure skeleton visualisation excerpted from dance-evaluation video.

optical motion capture. The selected material contained the *Casual* style and three street dance styles (*Hip-Hop*, *Popping*, and *Krumping*). These were combined with an additional dataset of approximately 3.5 hours of high-quality recordings from three accomplished dancers in the genres *Jazz*, *Charleston*, *Tap dancing*, and *Locking*, yielding the 373 minutes of parallel music audio and dance motion-capture described in Table 1. We intend to release this dataset upon paper acceptance.

Compared to the most commonly used recent dance dataset, AIST++ from [Li et al. \[2021\]](#), our dataset is larger, captures entire songs, and adds a completely new set of styles. AIST++ was also not captured using marker-based mocap, leading to data artefacts such as floating and jittery motion, that may be reproduced by (or otherwise degrade) generative models trained on such data. This may explain why [Tseng et al. \[2023\]](#), a concurrent work on diffusion models for dance generation that was trained on AIST++, incorporated additional loss terms relating to, e.g., foot contacts, during training. Our models used only vanilla diffusion model loss terms and no foot stabilisation, smoothing, or other post-processing.

We trained both style-conditional and style-unconditional proposed models on this data (labelled LDA and LDA-U, respectively). These models were conditioned on a minimalist set of three audio features from music information retrieval, specifically spectral flux (1 feature), chroma [[Müller et al. 2005](#)] (1 feature), and the activation of the RNNDownBeat-processor [[Böck et al. 2016](#)] (1 feature), all obtained using the Madmom audio signal processing library, as before. This parsimonious feature set was chosen with the goal of reflecting the structure of the music whilst being sufficiently non-specific generalisable across music genres, so as to enable dancing in any style to any music. It also likely reduces the risk of overfitting, and we found that versions of our model that used much larger music-feature sets gave worse results in an informal comparison.

We also trained a *Bailando* [[Siyao et al. 2022](#)] model on the same dataset, as a representative of the state of the art in the field. [Siyao et al. \[2022\]](#) report strong results in subjective evaluations, being rated as better than other recent baseline systems at least 80% of the time, and even beating the ground truth in 40% of comparisons.

Bailando is an autoregressive probabilistic model with Transformers that operates on a discretised version of the pose sequence

using ideas from language modelling. Compared to the other models in this paper, it has a quite involved training procedure with four distinct steps that have to be performed in order. We used the official codebase⁵ and the original hyperparameters for training. The implementation uses 438-dimensional music features, but does not include any explicit style input, so the dance style is instead tightly coupled to what the music sounds like. In that sense, Bailando is more similar to our style-unconditional model (LDA-U) than our main proposed system (LDA).

We trained Bailando (BL) on 3D Cartesian joint positions following the training procedure of Siyao et al.. This restricts possible visualisations for the user studies, therefore we visualised the dance motion for these using videos with stick-figure animations of the skeleton motion, similar what the Bailando paper did [Siyao et al. 2022]. A screenshot of our 3D model is shown in Fig. 5. The absence of a ground plane and shadow in our visualisation is to level the playing field for Bailando, which often generates ground penetration or floating motion, since it parameterises the root motion in terms of vertical delta values, meaning that the height of the character in absolute coordinates easily may drift over time. Our proposed approach does not have this issue.

The two proposed model variants (LDA and LDA-U) were trained on joint rotations, as before, to be able to directly apply model output motion to skinned characters. However, for the user-study visualisation, the outputs of the proposed models were converted into 3D joint positions. An example of a skinned avatar driven by our style-conditional dance-generation model is provided in Fig. 4. Even in a still image the displayed styles are visually distinctive. Dance videos are provided on our project page. Our demonstrations include long dance sequences of over a thousand frames all generated in one single go. These show that our models, despite only being trained on sequences 150 frames in length, are able to generalise well to much longer sequence lengths. This is likely attributable to the use of translation-invariant self-attention in our architecture, cf. Press et al. [2022]; Wennberg and Henter [2021].

For our subjective evaluation, we compared the trained models (LDA, LDA-U, and BL) to each other and to the ground truth (GT) using held-out motion and songs. As in Sec. 4.3.2, we selected a subset of distinctive styles for the subjective comparison, namely *Jazz*, *Charleston*, *Hip-Hop*, *Locking*, *Krumping*, and *Casual*. We then generated dance motion for 36 10-second audio segments, 6 for each style of dance, using each of the models. Although each style used different musical accompaniment, there is no guarantee that style-unconditional models like LDA-U or BL will generate dance motion in the style of the music, especially for styles of dance that are performed to similar music. In contrast, our style-conditioned model can dance to a given piece of music in any style we request, as shown in our presentation video.

We ran a subjective preference test with the overall design and numbers reported in Table 2. For each comparison video in the study, participants were asked “*Which character’s dancing motion do you prefer, taking into account both how natural-looking the motion is and how well it matches the music?*”, with the same response alternatives as in previous preference tests.

⁵<https://github.com/lisiyao21/Bailando>

Table 4. Objective metrics. The Fréchet distances (FGD, FID_k , FID_g) are computed with respect to the full dataset. Low values are better. GT is a top-line condition based on the recorded motion capture in the test set. Higher beat-alignment scores (BAS) mean a closer match to the beats.

| Dataset Evaluation Measure | TSG | ZeroEGGS | Dance | | | | | |
|----------------------------|-------------|-------------|------------------------|--------------------------|-----------------------|----------------|--------|--|
| | Quality FGD | Quality FGD | Quality FID_k | Diversity FID_g | Rhythm Div_k | Div_g | BAS | |
| | 9.94 | 31.84 | 3.00 | 5.22 | 9.55 | 7.12 | 0.2662 | |
| GT | 9.94 | 31.84 | 3.00 | 5.22 | 9.55 | 7.12 | 0.2662 | |
| LDA | 25.77 | 59.07 | 6.62 | 7.41 | 9.78 | 5.77 | 0.2559 | |
| LDA-DW | 126.92 | - | - | - | - | - | - | |
| LDA-G | - | 47.68 | - | - | - | - | - | |
| LDA-U | - | - | 7.69 | 8.98 | 9.13 | 6.13 | 0.2600 | |
| SG | 118.61 | - | - | - | - | - | - | |
| ZE | - | 52.99 | - | - | - | - | - | |
| BL | - | - | 28.15 | 12.70 | 5.22 | 4.35 | 0.2311 | |

Table 3 summarises the results from dance preference evaluation. The ground-truth motion capture (GT) achieved the best scores, followed by LDA, LDA-U, and BL. Our statistical analysis found all differences to be significant ($p < 0.001$). We can conclude that our proposed diffusion model can generate dancing motion with a quality that surpasses the state of the art in the field, as represented by Bailando. Whilst not reaching the same level as human motion capture, LDA still exhibited almost 40% win rate against GT. The lower rating of LDA-U compared to LDA may be explained by the relatively small number of input music features, which might not be sufficient to provoke genre-appropriate dancing for LDA-U, whereas LDA has more information about what dancing would be appropriate owing to the style control we supplied.

It is our opinion that dances generated by our Bailando baseline BL actually have a better subjective motion quality than the dance examples presented with the original Bailando paper. We believe this difference is due to the consistently high quality of the motion capture in the new database we have assembled, suggesting that our data release will be of value to the community.

4.5 Objective metrics

Although our main evaluation directly quantified how human observers rate the different motion-generation approaches, we also computed a selection of objective metrics for the various conditions in our experiments. The majority of these metrics are based on the Fréchet Inception Distance (FID) [Heusel et al. 2017], which is the most accepted objective metric for evaluating generative models. The FID between a dataset \mathcal{D} and a set of synthetic samples \mathcal{S} is defined as the 2-Wasserstein distance between two multivariate Gaussian distributions, whose means and variances are estimated from features extracted from the individual samples in \mathcal{D} and \mathcal{S} using a domain-specific feature extractor. The FID thus quantifies how much the real and synthetic data distributions differ from each other, providing a proxy for perceived synthesis quality or convincingness. It cannot, however, capture whether or not synthesised examples accurately reflect the associated control input – for example whether motion accurately reflects a desired style, or how appropriate the motion is for the rhythm and content of the audio.

For the gesture-synthesis models, we used the pre-trained autoencoder network provided by Yoon et al. [2020] as the feature extractor.⁶ The resulting metric is known as the Fréchet Gesture Distance (FGD), and has been found to have moderate but nonzero correlation with gesture human-likeness ratings [Kucherenko et al. 2023]. For each gesture dataset in our experiments, we divided the test set into evenly spaced, non-overlapping 10-second sequences, leaving gaps for past- or future input context windows that the baseline models required. (For example, SG requires access to future speech audio during generation, and also needs an initial past context due to its use of autoregression.) After that we randomly generated three 10-second motion clips with each model for all of these test sequences, and used these to compute the FGD with respect to the full dataset.

For the dance-synthesis models, we also divided the test dataset into non-overlapping 10-second windows, generated motion clips with each model for each window, and computed the same metrics as Siyao et al. [2022]: an FID score using kinematic features [Onuma et al. 2008], denoted FID_k ; an FID score using geometric features [Müller et al. 2005], denoted FID_g ; the corresponding diversity scores, Div_k and Div_g , computed as the average Euclidean distance between the features of each possible pair of motion clips; and a beat-alignment score (“BAS”) based on the inverse of the average time between each music beat and its closest dance beat.

Table 4 summarises the objective results. We see that the best FGD and FID scores come from comparing the test-set motion capture to the natural motion capture in the database (row “GT”), which can be considered a kind of top line. Although the objective scores mostly align with human perception in our main experiments, there are a few outliers, e.g., LDA-DW has an FGD on par with the SG baseline, even though it significantly outperformed that baseline in the user study (Table 3). Similar outlying scores were observed in experiments to validate the FGD metric on large amounts of human judgements, as reported in Kucherenko et al. [2023]. This can possibly be related to the fact that motion-capture datasets are relatively small, with the low amount of test-set data available limiting the statistical accuracy of objective metrics, compared to what we are used to in large-data tasks such as image generation.

From the table, we can further see that our method produced more diverse dancing than the BL baseline, with the kinematic diversity on par with the natural dance. Our method also exhibited greater beat alignment than the baseline, coming close to that of the recorded professional dance motion, but we caution that good dancing is not a beat-matching task [Valle-Pérez et al. 2021] and natural dance and multimodal communication often contain a wide diversity of nested rhythms [Miller et al. 2013; Pouw et al. 2021].

4.6 Path-driven locomotion synthesis

To highlight the generality of our modelling approach, we also trained our diffusion model to perform path-driven locomotion generation. In this scenario, the root-node motion was constrained to follow along a path defined on the ground plane, which was parameterised similar to Habibie et al. [2017]; Holden et al. [2016], i.e., root-node rotation and forwards and sideways translation, a total

⁶<https://github.com/ai4r/Gesture-Generation-from-Trimodal-Context>



Fig. 6. Locomotion generated by our model, conditioned on a circular path and a style that always holds the left arm out. Avatar © Motorica AB.

of three numbers per frame. We trained these models on the recent 100STYLE dataset [Mason et al. 2022], which contains high-quality 3D motion capture in 100 diverse styles of locomotion. In addition to style information, the three numbers per frame that describe the root-node path were provided as conditioning information to the model.

The motion in Fig. 6 was generated from a circular path (constant forward and rotational velocity) in the style *RaisedLeftArm*. The motion is clearly consistent with both the style and the path control. Video examples are on the project page. The videos show that the model is able to generate motion without noticeable foot-skating (no foot stabilisation was applied to any motion in our paper), and that the model also is able to generate transitions between different root-node speeds, even whilst turning.

Path-driven locomotion was previously generated using diffusion models by Findlay et al. [2022], but only for stick figures. It is our personal opinion that our motion is noticeable steadier and better quality than what they demonstrated.

4.7 Summary

To conclude, our subjective evaluations find that our proposed audio-driven motion-generation models are significantly preferred over a number of strong baseline methods, on three different datasets covering both gesture generation and dance. We have also shown that classifier-free guidance can successfully moderate the stylistic expression strength of our models.

5 PRODUCTS OF EXPERT DIFFUSION MODELS

In this section, we extend the ideas behind classifier-free guidance in Sec. 3.3 to describe general product-of-expert ensembles from combining the predictions of several diffusion models. We first describe the theory, then compare the ideas to prior work, and finally present an experimental investigation.

5.1 Theory

Mathematically, classifier-free guidance in Eq. (6) comprises a barycentric combination of two diffusion-model predictions guiding the process expression to be more or less similar to – i.e., towards or away from – one of the models, namely the predictions of an unconditional model. This suggests a generalisation instead using a

barycentric combination of two conditional models

$$\begin{aligned}\widehat{\epsilon}_{(1-\gamma)s_1+\gamma s_2}(\mathbf{x}_{1:T}, \mathbf{a}_{1:T}, n) \\ = (1 - \gamma)\widehat{\epsilon}(\mathbf{x}_{1:T}, [\mathbf{a}_{1:T}^\top, \mathbf{s}_{1:1:T}^\top]^\top, n) \\ + \gamma\widehat{\epsilon}(\mathbf{x}_{1:T}, [\mathbf{a}_{1:T}^\top, \mathbf{s}_{2:1:T}^\top]^\top, n),\end{aligned}\quad (7)$$

to blend (i.e., interpolate) between two different styles s_1 and s_2 during the diffusion steps. We call this setup *guided interpolation*. We can furthermore extrapolate by choosing $\gamma \notin [0, 1]$, leading to style expressions that exaggerate one style in a manner that makes it even more distinctive from the other style.

We emphasise that guided interpolation is not the same as inpainting. Inpainting is a common use case of diffusion models, with Tevet et al. [2023] and Zhang et al. [2022a] both demonstrating the use of diffusion models for inpainting in the motion domain (i.e., *motion editing* or *inbetweening*), by filling in missing poses or joint data at different time frames. Guided interpolation, in contrast, interpolates between different probability distributions described by diffusion models, such as different motion styles.

The idea behind guided interpolation readily generalises to more than two models. Consider M diffusion models $\widehat{\epsilon}_m$ with different conditioning information $\mathbf{c}_{m, 1:T}$. These can be combined as

$$\widehat{\epsilon}_\gamma(\mathbf{x}_{1:T}, \{\mathbf{c}_{m, 1:T}\}_m, n) = \sum_{m=1}^M \gamma_m \widehat{\epsilon}_m(\mathbf{x}_{1:T}, \mathbf{c}_{m, 1:T}, n), \quad (8)$$

where $\sum_{m=1}^M \gamma_m = 1$, as required for a barycentric combination. (We do not require $\gamma_m \in [0, 1]$, to permit extrapolation and not only interpolation.) Note that $\widehat{\epsilon}_m$ can be different models, or instances of the same model with different conditioning input $\mathbf{c}_{m, 1:T}$ (e.g., different style input, as in Eq. (7)). It is not required that $\widehat{\epsilon}_m$ is always the same model nor that they were trained on the same data. They do not even have to accept the same conditioning information, and instead the dimensionality and content of $\mathbf{c}_{m, 1:T}$ can depend on m . All that is needed is that the output spaces match. This construction is highly general and allows combining an arbitrary number of potentially heterogeneous diffusion models into an ensemble, interpolating between their predictions at will during denoising.

The score-matching objective used for training diffusion models means that the diffusion models at every step approximate $\nabla_{\mathbf{x}_{n-1}} \ln p(\mathbf{x}_{n-1} | \mathbf{x}_n, \mathbf{c})$ [Dieleman 2022; Song and Ermon 2019]. By working backwards through the steps in Dieleman [2022], reverting the gradient operation and taking the exponent⁷, we can see that the proposed ensemble corresponds to performing denoising steps based on a product of multiple different denoising distributions,

$$\begin{aligned}p_\gamma(\mathbf{x}_{1:T, n-1} | \mathbf{x}_{1:T, n}, \{\mathbf{c}_{m, 1:T}\}_m) \\ \propto \prod_{m=1}^M p_m(\mathbf{x}_{1:T, n-1} | \mathbf{x}_{1:T, n}, \mathbf{c}_{m, 1:T})^{\gamma_m}.\end{aligned}\quad (9)$$

This is a product of several probability density functions, i.e., a *product of experts* [Hinton 2002]. The fact that the exponents sum

⁷This derivation is not completely rigorous, e.g., one needs to assume that the network predictions $\widehat{\epsilon}(\mathbf{x}_{n-1} | \mathbf{x}_n, \mathbf{c}, n)$ form a divergence-free vector field on \mathbf{x}_{n-1} , which happens if score matching is optimal, but need not be exactly true in practice, but the result is nonetheless elucidating.

to one avoids the probability-concentration issues seen with naïve product-of-experts models discussed in Shannon et al. [2011].

We note that guided interpolation through products of experts is different from conventional mechanisms for creating intermediate conditioning information in deep-learning models, such as averaging two inputs (which may lead to previously unseen input and undefined behaviour, especially if style labels are discrete) or averaging two latent-space embeddings (whose average similarly may fall into regions of latent space with poor coverage during training; cf. Tomczak and Welling [2018]). Instead of interpolating between two conditional inputs, our proposal effectively interpolates between the *behaviour* of several conditional diffusion processes, each of which is well defined. This is less likely to produce unnatural output, since both diffusion processes in isolation are good at driving noisy \mathbf{x}_n -values towards regions of outcome space perceived as natural.

Products of experts are a compelling paradigm for ensembling synthesis models. The combination of multiple experts restricts output away from regions that any single expert considers to be unnatural or otherwise inappropriate, i.e., that have low probability. (This happens because the experts in Eq. (8) steer the denoising process towards values that have high probability according to each the expert. Specifically, since the largest updates in the combination come from experts that find $\mathbf{x}_{1:T}$ to be improbable, the process will converge toward a point where all experts make small updates, and thus all agree that the probability of $\mathbf{x}_{1:T}$ is high.) An inductive bias that favours output that no component model considers unnatural is appealing for synthesis applications [Henter and Kleijn 2016; Theis et al. 2016], since it is easier for human observers to notice the presence of something undesirable than to notice the absence of something desirable (e.g., reduced output diversity). (This same principle also explains why GANs can yield high-quality samples even in the presence of high degrees of mode collapse.) This inductive bias contrasts against conventional additive mixtures like Gaussian mixture models (GMMs) and mixture density networks (MDNs) more generally [Bishop 1994], where each expert adds rather than takes away behaviours/outcomes, which can be problematic if the individual experts do not all maintain high output quality.

Despite their advantages, products of experts have hitherto seen little use for synthesis, as they have been considered difficult to sample from [MacKay 2003], especially in high dimensions. Diffusion models can sample from unnormalised models and give good results with few steps [Dhariwal and Nichol 2021; Nichol and Dhariwal 2021], removing this stumbling block and making highly general probabilistic product-of-experts models feasible for synthesis applications.

5.2 Related work on mixtures of experts

Mixtures of experts in general have been used before in motion generation using deep learning. Aside from conventional additive mixtures like the GMM mixture density networks in Fragkiadaki et al. [2015], mixtures of experts have have notably been used in mode-adaptive neural networks and their extensions, e.g., Ling et al. [2020]; Starke et al. [2022, 2020]; Xie et al. [2022]; Zhang et al. [2018]. Those experts correspond to different weight matrices, allowing the



Fig. 7. Snapshot of *old* (left) to *angry* (right) interpolation for $\gamma = -0.25$ to $\gamma = 1.25$. Poses on the far left and right constitute extrapolation. All examples were generated using the same random seed. Avatar © Ubisoft.

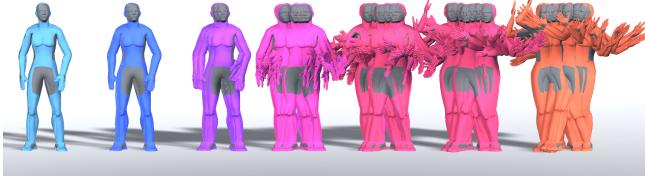


Fig. 8. 10 s overlay of *still* (left) to *public speaking* (right) interpolation for $\gamma = -0.25$ to $\gamma = 1.25$. Extrapolation is seen on the far left and right. All examples were generated using the same random seed. Avatar © Ubisoft.

network weights to change, e.g., during a walking cycle. However, these ideas are not a product of experts and have not yet been demonstrated for diffusion models.

An ensemble of diffusion model experts was presented in [Balaji et al. \[2022\]](#), but the experts have disjunct domains (they correspond to different steps n in the denoising process), so unlike a product of experts only one expert is used at any given point (denoising step). The most relevant prior works we have found [[Liu et al. 2022a](#); [Zhao et al. 2022](#)] are based on treating diffusion models as energy-based models. Of these, [Zhao et al. \[2022\]](#) combine a single diffusion model with several non-diffusion energy-based models obtained by removing the last layer of two classifiers. [Liu et al. \[2022a\]](#), in contrast, combine multiple diffusion-model predictions at synthesis time, leading to a similar formalism as presented here, although not stated in terms of a product of experts. All of these works consider image generation rather than motion synthesis.

Concurrent work by [Ma et al. \[2022\]](#) also considers using multiple diffusion models to create intermediate behaviours, but by randomly choosing the prediction of only a single model at any given denoising step n . They dub this approach *alternating control*. By making the probability of choosing one of their two different models depend on n , the resulting synthesis process can be made to favour one type of motion for the coarse outline of the motion, but with details more closely based on another motion type.

5.3 Experiments

Interpolating between gesture styles. To demonstrate the effects of product-of-expert diffusion models for motion, we performed experiments with guided interpolation between different gesturing styles, by mixing predictions from the style-conditional model in Sec. 4.3.2 under two different style inputs. We note that stylistic interpolation should both affect shape aspects, such as the overall posture of the character, and temporal aspects, such as the gesture frequency and

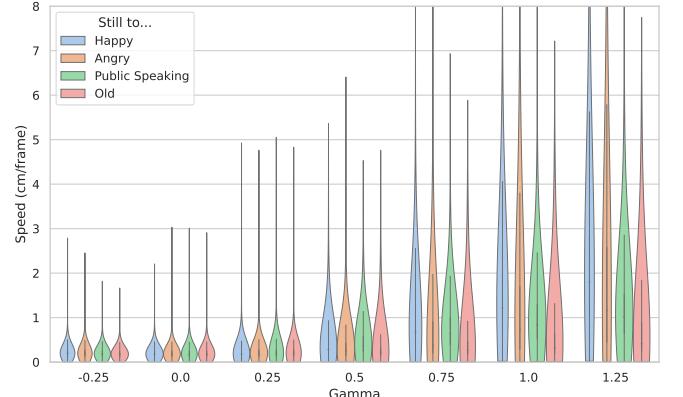


Fig. 9. Violin plot of wrist-speed distributions during guided interpolation between the *still* style and four other speaking styles (*happy*, *angry*, *old*, and *public speaking/oration*).

speed. To investigate the shape aspects, we interpolated between the *old* (hunched over) and *angry* (upright) styles using the same speech and random seed. Results are visualised in Fig. 7. We see a definite progression in overall character posture as we interpolate from the hunched-over style to the upright one.

To demonstrate how guided interpolation affects temporal aspects of gesticulation, we interpolated between the *still* and *public speaking* styles, where the latter is very animated whereas the former has almost no motion. The results of 10 s of animation are shown overlaid in Fig. 8, and display a clear and steady increase in the range of body movement throughout the interpolation. To see interpolations in motion, please refer to the project page.

To lend additional substance to the above observations, we performed an objective evaluation of the behaviour of guided interpolation between gesturing styles, specifically when interpolating from the *still* style to the four styles used in our user study. We considered both endpoints, three intermediate steps, and one step of extrapolation on either side ($\gamma = \{-0.25, 0, \dots, 1.25\}$). To generate data for the evaluation we randomly sampled 5 motions for each 10-second audio clip covering the test data, resulting in 125 clips for each γ -value and style. We then computed the instantaneous speed (magnitude of the displacement vector from the previous frame) in 3D space of the two wrists averaged together for each frame. Hand and arm motion is central to co-speech gestures [[Nyatsanga et al. 2023](#)], and this wrist-speed distribution has been used as the basis of objective gesture evaluation before [[Kucherenko et al. 2021a](#)].

The speed distributions of the wrists are graphed in Fig. 9. As expected, we see that model behaviour (motion statistics) change monotonically from one distribution to the other along the spectrum of γ -values in the guided interpolation. The transition is not linear, however, since we are not interpolating in Euclidean space, but instead trading off between relatively high-probability regions of the two model distributions, to find and sample from the set of motions where the combined (weighted) probability is the greatest.

Interpolating between locomotion styles. Aside from gestures, we also performed guided interpolation with other models from Sec. 4. Video examples are presented on the project page. Of note is the

demonstration of interpolation between the *Aeroplane* and *HighKnees* locomotion styles, where the exaggerated *HighKnees* style also holds the arms even closer to the body than before, in clear contrast against the outstretched arms of the *Aeroplane* style that has negative weight in the exaggerated barycentric combination.

Dynamically transitioning between styles. In addition to static style interpolation, we also demonstrate that guided interpolation can be used to dynamically transition between styles in longer motion sequences. This is done by letting the weights γ_m in Eq. (8) depend on t , so that the motion distribution gradually transitions between different models for different points in time. This is an important control mechanism for many graphics applications, where state transitions between different motion types are frequent. Videos of dynamic style transitions can be found on the project page.

Combining highly different models. As a final demonstration, we present results from ensembling two models trained on two very different datasets and with different conditional inputs. Specifically, we combine our style-conditional dance model from Sec. 4.4 with a model trained to perform mixed martial arts (MMA) motion. The latter model was trained on a motion-capture dataset we recorded of a championship-level MMA athlete moving around in a fighting stance whilst punching, kicking, elbowing, and kneeing a focus mitt held by a sparring partner. We trained models on this data using a similar recipe as for the dance and locomotion data, but in this case the only conditioning information was eight binary values. These were always zero except whilst executing one of the four aforementioned combat moves using the extremities on either the left or the right side (a total of eight possible moves). This yielded a model that could throw punches, kick, etc., on command, using the arm or leg of one’s choice. To combine this with the dancing model, we created a small choreography with a sequence of kicks and punches, whose timings were determined by the beat of a piece of music (by using the beat onset feature), enabling us to generate fighting moves in time with the music.

The results of a 50-50 dance-fighting combination of the two models highlight the nature of the product of experts to seek the intersection of two distributions: the character moves naturally and in time with the beat, but few clear dance moves or fighting moves are present, since these have low probability under at least one of the models, making them improbable also under the combined distribution. We can see that the character generally holds their arms and hands at a level appropriate for MMA, which is a subset of the hand heights exhibited during dancing, again consistent with expectations. To see interpolation videos for this model combination, please consult the project page.

6 LIMITATIONS

The most obvious and talked-about limitation of diffusion models is their slow generation speed, a consequence to the many denoising steps required to sample from the learnt models. The architectures in our paper take around a second to generate each motion example. Since our goal has been to advance the quality of audio-driven motion generation using diffusion, with a focus on offline generation, we have not spent any effort on optimising for synthesis speed. We

expect that synthesis time can be sped up considerably using recent innovations for diffusion models [Dhariwal and Nichol 2021; Lam et al. 2022; Meng et al. 2022; Nichol and Dhariwal 2021; Salimans and Ho 2022], and that additional approaches for accomplishing this goal also will be published in the near future. As it stands, however, synthesis speed is clearly an area that can be improved. Our use of a parallel architecture, whilst appealing for GPU-based generation, is also not suitable for real-time interaction or integration into game engines. There, autoregressive models like Alexanderson et al. [2020a]; Ghorbani et al. [2023]; Siyao et al. [2022] might be a better fit.

Another important limitation of the models trained in this paper is that, whilst being visually strong, they do not learn to capture all aspects that go into purposeful gesturing and dancing, such as semantics for speech or the global structure of music for a dance choreography. There are many reasons for this, but both of these limitations can be related to the set of input features used. Whilst speech audio in principle contains everything a human needs to make sense of a spoken message, and thus to put meaning into associated co-speech gestures, it is not possible for models to learn to make sense of language (let alone its grounding in the real world) from our acoustic features and the small amount of material seen during training. As a consequence, one cannot expect the presented systems to generate gestures that serve a communicative function. A starting point for improving this situation would be to follow Ahuja et al. [2020a]; Ao et al. [2022]; Kucherenko et al. [2020]; Yoon et al. [2020] and provide information derived from text transcriptions, such as semantic word embeddings trained on large written corpora, e.g., BERT [Devlin et al. 2019].

For dancing, it is similarly true that the information currently provided to the proposed models does not allow higher-level structure in the input to become apparent, as the feature set we used in our demonstrations is both low-dimensional and limited to musical characteristics that change rapidly over time. These features do not have any explicit indicator of measures, verse or refrain, or the start and end of a performance, to name a few examples. In addition, the model also only sees a few seconds of dance at a time during training, complicating the task of learning to recreate longer correlations that represent overall choreography. A path towards enabling our models to generate more cohesive dance performance would be to consider a hierarchical modelling approach with explicit structure information, like in Aristidou et al. [2022].

For the proposed products of experts, their strong ability to focus on the intersection of a set of probability distributions can be both a strength and a weakness. Although perfectly consistent with what the mathematics tell us, it can nonetheless sometimes be counterintuitive to see interpolation give rise to less distinctive motion, or less motion overall, than the models on either side of an interpolation spectrum. Whilst focussing on the intersection is sometimes desirable (for instance when using a strong prior model trained on a lot of motion data to stabilise the output of a model trained on a small amount of material), that is not always the case. An example of the latter is our mix of dancing and fighting, which most of the time engages in neither activity and appears less exciting as a result. If one explicitly wants to generate output that alternates between different motion types in an interpolation, a conventional additive

mixture model might be a better choice, for example by using a hidden Markov state to switch between different autoregressive motion models. The individual models in such a construction may still be strong generative models such as normalising flows [Ghosh et al. 2020, 2021b] or diffusion models. A more continuously adjustable version of the same effect may be achieved by changing the mixing coefficients γ_m between the different experts in the guided interpolation framework for different points in time.

7 CONCLUSIONS AND FUTURE WORK

We have introduced diffusion models for audio-driven probabilistic modelling problems in 3D motion generation. As part of this, we describe a new diffusion-model architecture with Conformers. Our experiments consider several applications of audio-driven motion generation, and also path-driven locomotion, and present an extensive gold-standard evaluation of the advantages of the method against leading deep generative model baselines on several datasets. The experimental results validate that the model outperforms previous state-of-the-art models in terms of motion quality and also enable controlling the strength of stylistic expression. We additionally describe how to create product-of-expert ensembles with diffusion models, and show how they, for example, enable a novel type of interpolation and combining diverse diffusion models with different control parameters.

Future work includes accelerated output generation [Dhariwal and Nichol 2021; Lam et al. 2022; Meng et al. 2022; Nichol and Dhariwal 2021; Salimans and Ho 2022]; conditioning motion on both audio and text, for example to enable generating semantic and communicative gestures that synchronise with speech (cf. Ahuja et al. [2020a]; Ao et al. [2022]; Kucherenko et al. [2020]; Yoon et al. [2020]); and even synthesising multiple modalities such as speech and gesture together [Alexanderson et al. 2020b; Wang et al. 2021]. Separately, the community should leverage these powerful models to make a difference in applications of audio-driven motion generation, both in research, e.g., in human-agent interaction, and outside academia.

The ideas of guided interpolation and their mathematical formulation, meanwhile, open the door to a vast array of product-of-diffusion models, in ensembling, interpolation, and beyond. For example, it also seems compelling to use pre-trained diffusion models as strong prior distributions in both supervised tasks and reinforcement learning, as a possible alternative to using ideas like MotionBERT [Zhu et al. 2022] or fine-tuning a strong, pre-trained “foundation model” [Bommasani et al. 2021]; cf. Holmquist and Wandt [2022]. Unlike conventional fine-tuning, there is no need to train or modify a potentially large existing model. Because the prior model is used without modification, prior information is furthermore never lost, removing the risk of catastrophic forgetting that may occur if conventional fine-tuning is run for too long.

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A EXPERIMENTAL DETAILS

A.1 Data processing and model training

Each and every input and output feature was standardised to mean zero and standard deviation one, save for binary features on $\{0, 1\}$. For the gesture datasets we used the original skeletons in the corresponding database, while the other datasets were retargeted to all use a shared skeleton. The data was augmented by lateral mirroring, and by time stretching the sequences by a random factor chosen uniformly on $[0.9, 1.1]$ for 20% of the training updates on the dancing and MMA data, and 10% of the updates on other datasets. Lateral mirroring was not applied to the data from the specific locomotion styles that distinguish between left and right.

Finger data, if present, were not included in the modelling, since finger motion capture is difficult and often suffers from quality issues. We instead used a fixed hand pose in all experiments. This is quite standard even for gestures, with all submissions to the 2020 GENE gesture-generation challenge [Kucherenko et al. 2021b] and a majority of submissions to the 2022 GENE challenge [Yoon et al. 2022] (including the best-performing deep generative model [Ghorbani et al. 2022]) using a fixed hand pose in their generated gestures.

During hyperparameter tuning, we also noticed a subtle trade-off between the number of residual blocks and the number of Conformers stacked within each block, when keeping the total number of parameters approximately fixed. When using $L = 10$ blocks with 4 Conformer layers in each, motion was more deliberate. When instead using $L = 20$ blocks with 2 Conformer layers each, the overall amount of motion increased. Subjectively, we found more deliberate motion to be appropriate in most scenarios (where we thus used the former hyperparameter setting), whereas dance instead benefited from an increased amount of motion overall (where we thus used the latter hyperparameter setting). However, the actual difference is quite subtle, and both settings give similar-looking results and similar motion quality on both data types.

Our final models after hyperparameter tuning used a β_n range of 0.0074 to 0.78 with linear noise schedule across $N = 100$ diffusion steps on the gesture datasets and a range of 0.01 to 0.7 and $N = 150$ steps on the other datasets. Except for on the MMA data, our proposed models used 8 heads, 256 attention channels, 512-dimensional embeddings, and 1024 channels in the feedforward and Conformer

networks, and a dilation cycle of length $\bar{l} = 3$. (The one model we trained using the original DiffWave architecture, and thus without Conformers, used a dilation cycle of length 10 instead.) The model trained on the MMA data used 512 channels in the feedforward and Conformer networks and a reduced embedding dimension, as an adaptation to the smaller dataset size. Training used the Adam optimiser [Kingma and Ba 2015] with $\text{lr}_{\max} = 6e-4$, 3k warm-up steps and a learning rate decay factor of $0.5e-5$ per 10 iterations, meaning that the learning rate was multiplied by $(1 - 0.5 \cdot 10^{-5})$ every ten model updates.

Unlike the proposed systems, the ZE baseline in the evaluation on the ZeroEGGS data does not use one-hot encoding for style input, but instead requires a motion clip as its style-conditioning input. This clip is then translated into a latent vector by the encoder. To best match the ZE training procedure, we derived these style inputs from randomly sampled sequences of lengths 256–512 taken from a training video of the given style.

A.2 User studies

User study participants were recruited from the US, Canada, UK, Ireland, Australia, and New Zealand using Prolific. Participants were required to be fluent in English. They were asked to use headphones unless the videos in the experiment were silent. All experiments ran in a web browser and presented 36 20-second comparison videos to each participant, unless stated otherwise. The user studies were run in a web browser via the jsPsych package⁸.

Except where stated otherwise, each participant was exposed to motion from each audio clip once, with the order of these clips and of the two videos in each pair being randomised for each participant. The median completion time for the experiments was 15 minutes. The median hourly compensation was approximately 12 GBP.

Attention checks occurred at two random points in each experiment, consisting of the spoken message “Attention: please select the rightmost option”, but for experiments where audio was omitted from the stimuli the same message was instead displayed as text in the lower part of the video during the second half of the clip. Subjects that failed both attention checks were disqualified and their data not used. (Prolific’s policies do not permit disqualifying subjects based on a single failed attention check in these tests.) Responses given to attention-check stimuli were not included in the analyses.

⁸<https://jspsych.org>