

# Speech Drives Templates: Co-Speech Gesture Synthesis with Learned Templates

Shenhan Qian<sup>1†</sup> Zhi Tu<sup>1\*</sup> Yihao Zhi<sup>1\*</sup> Wen Liu<sup>1</sup> Shenghua Gao<sup>1,2,3†</sup>

<sup>1</sup>ShanghaiTech University

<sup>2</sup>Shanghai Engineering Research Center of Intelligent Vision and Imaging

<sup>3</sup>Shanghai Engineering Research Center of Energy Efficient and Custom AI IC

## Abstract

Co-speech gesture generation is to synthesize a gesture sequence that not only looks real but also matches with the input speech audio. Our method generates the movements of a complete upper body, including arms, hands, and the head. Although recent data-driven methods achieve great success, challenges still exist, such as limited variety, poor quality, and lack of objective metrics. Motivated by the fact that the speech cannot fully determine the gesture, we design a method that learns a set of gesture template vectors to model the latent conditions, which relieve the ambiguity. For our method, the template vector determines the general appearance of a generated gesture sequence, while the speech audio drives subtle movements of the body, both indispensable for synthesizing a realistic gesture sequence. Due to the intractability of an objective metric for gesture-speech synchronization, we adopt the lip-sync error as a proxy metric to tune and evaluate the synchronization ability of our model. Extensive experiments show the superiority of our method in both objective and subjective evaluations on quality and synchronization<sup>1</sup>.

Figure 1: Our method generates realistic gesture sequences from a piece of speech audio. With various template vectors, our method produces two different gesture sequences from the same audio, but the movements are synchronized for the hands, heads, and lips.

such as emotion, attitude, and intention.

## 1. Introduction

We humans have always been enthusiastic about making replicas of ourselves. Many successes have been achieved in generation of explicit behaviours, such as lip syncing [30], face swapping [32], or pose re-targeting [8]. But synthesizing implicit behaviors of humans, which plays a key role in synthesizing realistic digital humans, is far less explored. Co-speech gesture is such a kind of implicit behavior, referring to the movement of body parts when someone is speaking, which conveys rich non-verbal information

Early attempts on co-speech gesture synthesis are mainly rule-based [7, 21, 34], which suffer from poor naturalness because the non-verbal information is too delicate to be described by rules. Later efforts [24, 15, 22, 14, 12, 36] go beyond by learning human behaviors from collected data. A non-negligible barrier for data-driven methods is the multi-modal essence of the mapping from speech audio to the possible gestures. This means that for the same input audio, there exist multiple feasible solutions so that directly regressing to the ground-truth gesture casts an inconsistently biased mapping, preventing the model from learning the divergence in the dataset. In recent methods, a common way to cope with this challenge is adversarial learning [14, 1, 36] with discriminators narrowing the gap between generated and real ones. However, this can only improve the real-

<sup>\*</sup>Equal contribution.

<sup>†</sup>Corresponding author.

<sup>1</sup><https://github.com/ShenhanQian/SpeechDrivesTemplates>

(a) Plain regression versus conditional regression. (b) Regression loss curves on the training set.

Figure 2: With template vectors serving as the condition, we transform a plain regression with ambiguity into a conditional regression, resulting in a lower regression loss on the training set.

ism of gestures and have nothing to do with or even harm gesture-speech syncing. Therefore, as long as we expect stable syncing quality, the regression loss should be the core supervision.

Given that the regression loss is the only supervision that we can count on to learn gesture-speech synchronization and the input audio does not provide enough information to determine a gesture sequence exclusively, we complement the input with a condition vector. This condition vector provides the missing information (e.g., habits, emotion, or previous states) to rule out the gestures other than the ground truth one, thus transforming the mapping from one-to-many into one-to-one (Figure 2a). Concretely, we assign a zero vector to each paired audio-gesture sequence as the initial condition and update the vector along with the network's parameters to minimize the regression loss when training. The intuition here is that if the network can easily regress to the target gesture sequence merely with the audio, the condition vectors will stay the same; otherwise, the condition vector will update to reveal the discrepancy.

From all the learned condition vectors, we can select one and generate a gesture sequence from any audio clip. By switching the condition vector and the speech audio, we observe an interesting phenomenon: the condition vector plays the role of a gesture template. The condition vector determines the general appearance of gestures in a generated sequence, while the audio input adds subtle movements onto the gesture template to bring it to life and match it with the speech. Therefore, we call these condition vectors template vectors for our method. In Figure 1, we show two gesture sequences generated from the same speech audio with two different template vectors. The resulting gestures are clearly not the same but still match well in the movements of hands, heads, and lips, exhibiting our method's fidelity, variety, and synchronization ability.

Now that we can learn the template vectors with back-propagation, why don't we directly learn them by reconstruction? Therefore, we train a VAE (Variational Auto-Encoder [20]) to model the distribution of gesture sequences. With this VAE model, we can encode a ground-truth gesture sequence into a template vector and learn the one-to-one mapping from it and the speech audio to the ground-truth gesture sequence. Also, it is possible to decode a template vector to visualize its corresponding gesture sequence. With either back-propagation or VAE, we learn a set of template vectors that not only help lower the regression loss when training (Figure 2b) but also make generation with variety possible since we can sample one from the learned template vectors to manipulate the general appearance of a synthesized gesture sequence.

Although previous work on co-speech gesture [14, 1, 36] limits the scope of gesture to hands and arms only, we advocate including head motion into co-speech gesture, not only for a more unified and harmonized synthesis of the upper body but also for the ease of evaluation. Due to the vagueness of gesture-syncing, existing work heavily rely on subjective evaluations. We propose to adopt the lip regression error as a proxy metric under the hypothesis that to learn gesture syncing well, a model should be able to learn good lip-syncing, as they both depend on the speech, and the latter one is much more deterministic. Furthermore, to assess the fidelity of generated gesture sequences, our trained VAE can be used to compute a Fr chet Template Distance (FTD) similar to the FGD proposed by Yoon et al. [36], measuring the distribution similarity between the generated ones and the real ones in the feature space.

Our contributions can be summarized as follows:

- We propose an audio-driven gesture synthesis method in a conditional learning manner. With the learning of template vectors, we relieve the ambiguity of co-speech gesture synthesis, enhancing the fidelity and variety without sacrificing synchronization quality.
- We objectify the evaluation of gesture-syncing by borrowing the lip-sync error as a proxy metric. Also, we propose the Fr chet Template Distance (FTD) to assess gesture fidelity.
- We show the superior synthesis quality of our method in both subjective and objective tests and provide intuitive visualizations of the learned template vectors.

## 2. Related Work

**Co-Speech Gesture Synthesis** Synthesizing co-speech gesture has been an active topic in robotics [23, 16, 37], graphics [2, 36], and vision [14, 1, 25]. A recent trend in this task is using in-the-wild videos [14, 1, 37] rather than those collected in lab scenarios with sensors, extending the

variety of the synthesized gestures. However, as stated by Yanget al. [39] model head movements explicitly in order to lift the naturalness of the talking head, but the synchronization quality is not further evaluated. which leads to under- tting of the data and lack of expressiveness of the results. Although adversarial learning can

be incorporated to enhance gesture delity as done by Ginosaret al. [14], the model still heavily relies on the regression loss to produce gestures synchronized with the audio, so the result is deterministic with no variety. Ahuja al. [1] disentangle the style and content of gestures by embedding every gesture into a common style space across subjects, achieving style transfer or preserving by switching the style embedding. However, the styles are defined in a per subject manner, featuring only one typical gesture for each subject. Alexandersoot al. [2] introduce the probabilistic model MoGlow based on normalizing flows [26] to model the mapping from gestures to Gaussian distributions conditioned on the input audio. This model samples latent vectors from Gaussian distributions when inferencing, thus is capable of modeling the one-to-many mapping elegantly. However, the normalizing flows [26] model only supports linear operations, limiting the expressiveness of the model. Our model relieves the ambiguity of one-to-many mapping with template vector learning and accomplishes diverse generation by sampling the template vector when inferencing.

Besides the method to generate, another huge challenge is evaluation. Due to the ambiguity of co-speech gestures, previous methods mostly rely on the human study to exhibit the effectiveness of their methods [14, 1, 2], which is reasonable but not objective. As to the objective metrics such as  $L_1=L_2$  distance, PCK(Percent of Correct Keypoints) reported in [14, 1, 2, 36], they are all based on the distance between the generated and the ground-truth, forming a contradiction between lower error and greater variety. An inspiring attempt on objective metrics is FGD (Finet Gesture Distance) proposed by Yoo et al. [36], which measures the distribution similarity in the feature space.

Talking Head and Lip-Syncing. Unlike previous methods on co-speech gesture synthesis, we treat the head as a part of the gesture, not only for the completeness of an upper-body agent but also for the indispensable non-verbal information conveyed by head movements. Representative face manipulation methods [32, 35, 38, 5, 13] are designed in a pose-transfer paradigm, which inherit face landmarks or model parameters [4] from a target video. Another stream of methods [19, 11, 10, 33, 27, 31] focus on manipulation of facial expressions or lips, given a piece of speech audio. Karraset al. [19] learned a latent code to model emotional states. Prajw et al. [27] train a discriminator in an offline manner to enhance lip syncing. These methods achieves plausible synchronization between the lip and the speech, but they cannot or can only manually control the head pose, producing unmatched head motion. Later, Chen al. [9]

### 3. Methods

Pipeline. Given a piece of speech audio as the input, we generate a sequence of gestures with natural poses and synchronized motions. An overview of our model is shown in Figure 3.

Formally, for an audio clip, we follow previous methods [14, 2] to transform the audio waveform into a mel-spectrogram, which is a 2D map with time and frequency on each axis. Then we send it into an audio encoder to get the audio feature  $A \in \mathbb{R}^{256 \times F}$ , where  $F$  is the number of frames. As another input, our network takes in a template vector  $t \in \mathbb{R}^C$  and stacks the replicas of it into a template feature  $\bar{T} \in \mathbb{R}^{C \times F}$  to align the timeline of the audio feature. Therefore, the complete input of our model is  $[A; \bar{T}] \in \mathbb{R}^{(256+C) \times F}$ , the concatenation of the audio feature  $A$  and the template feature  $\bar{T}$ .

Our gesture generation network is a UNet-alike 1D convolutional neural network that slides along the timeline with a 7-layer encoder, a 6-layer decoder, and skip-connections.

The output is a gesture sequence  $G \in \mathbb{R}^{2K \times F}$ , where  $2K$  corresponds to the 2D coordinates of upper-body keypoints in a frame, including the face, hands, and arms.

As a main supervision, we apply regression loss on a regressed gesture sequence

$$L_{\text{reg}} = \frac{1}{F} \sum_{i=1}^F \|G^{(i)} - \hat{G}^{(i)}\|_2;$$

where  $G^{(i)}$  and  $\hat{G}^{(i)}$  are the predicted and ground-truth gesture vectors in the  $i^{\text{th}}$  frame of  $G$ .

Image Synthesis. To ease visual evaluation of our generated gesture sequences, we train an image warping and translation module, inspired by Balakrishna et al. [3]. For each frame, we first warp pixels of each body part in the source image to the target location with local affine transformations to obtain a coarse result, then feed the concatenation of the coarse result and heatmaps of keypoints into an image translation network as a refinement. During the training session, source and target pairs are randomly combined.

#### 3.1. Complement Audio with Learned Conditions

We mainly rely on the regression loss to train our model because it is the only reliable source of supervision towards gesture sequences synchronized with the audio. However, since the mapping from the speech audio to a gesture sequence is not exclusive, i.e., there exist many other feasible gestures, simply regressing to the ground-truth gesture sequence causes ambiguity and leads to overly smooth results.

Figure 3: Our network takes an audio feature  $A$  and a template feature  $T$  as the input to generate a co-speech gesture sequence  $G$ . The template vectors are updated with back-propagation or encoded by a VAE.  $N$  is the number of frames,  $C$  is the dimension of the template vector, and  $k$  is the number of keypoints. With the generated gesture sequence as an intermediate representation, we can synthesize a realistic video with an image warping and translation module.

To remove the ambiguity, we should provide more information to our model. Concretely, we additionally feed in a condition vector, as shown in Figure 2a. Here, we expect the condition vector to narrow the range of potential gestures instead of pointing to a specific static gesture; otherwise, the role of the input audio will be weakened, which harms gesture-speech syncing. To this end, we assign one condition vector to each short gesture sequence (about 4 seconds long) instead of each frame and regress from the audio and the condition vector to the ground-truth gesture sequence. This relieves the ambiguity between speech and gestures, laying the foundation of our method.

We call this condition vector a template vector for our method because this vector determines the general appearance of the generated gesture sequence, while the input audio adds subtle movements to match the speech and the gesture sequence, just like the relationship between the template and the content.

**Learning Templates by Back-Propagation.** We initialize the template vector of each speech-gesture pair to a zero vector, supposing them to be subject to the same condition. When training, we back-propagate the regression loss and update template vectors along with parameters of the UNet. This means that the model is trained without extra information since all the template vectors are set to zero; when ambiguity occurs, the template vector will be updated to relieve the ambiguity. By storing the trained template vectors, we extract the latent condition for each sample from the dataset.

To regularize the template vector space, we apply a KL-

divergence loss

$$L_{KL} = D_{KL} \left( N \sum_t \mu_t^2; \sum_t \sigma_t^2 \right) \mathcal{N}(0; 1)$$

where  $\mu_t \in \mathbb{R}^C$  and  $\sigma_t^2 \in \mathbb{R}^C$  are the mean and variance vectors of template vectors in a mini-batch. Then the total loss function is defined as follows:

$$L = \lambda_{reg} L_{reg} + \lambda_{KL} L_{KL};$$

where  $\lambda_{reg}$  and  $\lambda_{KL}$  are weights applied to the loss terms. We set  $\lambda_{KL} = 1$  and  $\lambda_{reg} = 1$  in our experiments.

Updating template vectors by back-propagation brings several benefits. First, the regression loss converges faster than a plain regression from the audio, indicating a better fitting of the training set (see Figure 2b). Second, our model can generate diverse gestures by sampling arbitrary template vectors from the trained ones while maintaining highly synchronized gestures and lips. Third, interpolation of template vectors results in smooth changes of gestures, such as switching hands and changing the head orientation, demonstrating a compact condition space.

Despite the above benefits and inspirations, this method still has some limitations. First, since the template vector is assigned in a sample-wise way, each template will only be used and updated once an epoch, which requires careful tuning of hyper-parameters (e.g., learning rate, number of epochs) to let the template vectors converge. Second, although we can observe gesture variations caused by template switching, we still lack interpretation of the templates. Third, we can only conduct the mapping from a template vector to a gesture sequence but cannot go in the opposite



**Learning Templates by Reconstruction.** To resolve the above limitations, we consider learning template vectors by reconstruction with VAE [20]. This VAE first encodes a ground-truth gesture sequence  $G$  into a mean vector  $\mu \in \mathbb{R}^C$  and a variance vector  $\sigma^2 \in \mathbb{R}^C$ , then decode them into a reconstructed gesture sequence  $\hat{G}$ . Similarly, it is built up with fully 1D convolutions sliding along the timeline and is also trained with  $L_1$  loss and a KL-divergence loss.

Once the VAE is trained, it is frozen to be used as a template vector extractor for computation of FTD described in Section 3.2.

### 3.2. Evaluation of Coï½Speech Gesture Generation

Common evaluation metrics used by prior methods for co-speech gesture like  $L_1=L_2$  distance, accuracy, or PCK (percent of correct keypoints) are not ideal because what they measure is the distance between a generated sample and the ground truth, ignoring the diversity of feasible gestures for a given audio clip. Therefore, targeting these metrics will result in boring and inexpressive synthesis.

Intuitively, a good gesture synthesis should meet at least two requirements: naturalness and synchronization; but none of them can be easily measured with distance-based metrics. Next, we propose two metrics for gesture assessment in terms of synchronization and naturalness, respectively.

**Lip-Sync as A Proxy Metric.** Different from body gestures that are diverse, the lip shapes are almost consistent because pronouncing a syllable usually requires a particular mouth shape. Also, we observe better convergence of lip keypoints' regression losses than others on the validation set, which confirms the consistency of the mapping from speech audio to the lip.

Therefore, we adopt the distance between generated lip keypoints and the ground-truth as a proxy metric for synchronization measurement of the entire gesture. This proxy metric works for two reasons: 1) Both lip keypoints and other keypoints share the same network and features, and our method has no special design for lip syncing; 2) Although good lip syncing quality cannot guarantee good gesture quality, but lip syncing degradation is a good warning signal of bad gesture-syncing.

Formally, the proxy metric we use is the normalized lip-sync error

$$E_{ip} = \frac{\frac{1}{P} \sum_{i=1}^P \text{kd}^{(i)}_1 \cdot \text{kd}^{(i)}_2}{\max_{1 \leq n \leq F} \text{kd}^{(n)}} \quad (1)$$

where  $\text{kd}^{(i)}$  is the distance between the center keypoints of upper and lower lip in the  $i^{\text{th}}$  frame of the generated gesture sequence  $\hat{G}$ , and  $\text{kd}^{(i)}$  is the corresponding distance for ground-truth gesture sequence  $G$ .

**Fréchet Template Distance.** As aforementioned, directly measuring the distance between a generated gesture

sequence and the ground truth discourages variety. Here, we introduce FTD (Fréchet Template Distance) as a variation of FID (Fréchet Inception Distance) [17]. FTD measures the distribution distance between the synthesized and the real gesture sequences among a group of samples rather than a single sample. Therefore, in order to achieve a better FTD score, the generated results should be not only natural but also diverse.

In our experiments, FTD is computed on the entire test set as follows:

$$\text{FTD} = \frac{1}{N} \sum_{j=1}^N \|\mu_j - \mu\|^2 + \text{tr} \left( \frac{1}{N} \sum_{j=1}^N \Sigma_j + \Sigma - 2 \left( \frac{1}{N} \sum_{j=1}^N \Sigma_j \right)^{1/2} \right);$$

where  $\mu_j$  and  $\Sigma_j$  are the mean vector and covariance matrix of the template vectors  $\{\mu_1; \mu_2; \dots; \mu_N\}$ , encoded from synthesized gesture sequences  $\{G_1; G_2; \dots; G_N\}$  across the test set with the VAE described in Section 3.1, while  $N$  denotes the number of samples in the test set and  $\mu$  and  $\Sigma$  are the counterparts for the ground truth.

## 4. Experiments

**Datasets.** We test our method on the Speech2Gesture [14] dataset since it is the only one providing complete annotations for the upper body, especially for face keypoints. However, we only report results of two speakers, Oliver and Kubinec, of this dataset due to the unusable quality of the face and hand keypoints of other speakers (pseudo labels acquired with OpenPose [6]). For results on other speakers, please refer to the supplementary material. Furthermore, we collect data of two Mandarin speakers, Xing and Luo, to test the versatility of our method. The video clips of the four speakers have a length of about 25.13 hours in total after manual filtering of incorrect annotations. We train our model on each of the speakers separately because we focus on speaker-specific gesture learning.

**Evaluation.** We report three objective metrics for fair comparison: 1) the  $L_2$  distance that directly measures the distance between the prediction and the ground truth; 2) the normalized lip-sync error ( $E_{ip}$ ) as a proxy metric for gesture synchronization; 3) the Fréchet Template Distance (FTD) as a measurement of diversity.

We conduct an extensive human study to perceptually compare our method with baselines and verify the feasibility of our proposed objective metrics. We create videos with gesture sequences generated by different methods from the same pieces of speech audio, then publish them as an online questionnaire for human evaluation. For each of the four speakers, we randomly sample 8 pieces of speech audio for video generation. For each questionnaire, we randomly choose at least 2 of the 8 videos for each speaker to form a questionnaire with 10 video clips. During a test, a participant is exposed to the 10 videos one by one. Each video shows the results of competing methods synchronously with

audio. The results are anonymized by letters and visualized with both skeleton maps and synthesized images. After watching each video, a participant is asked to make three choices: 1) the one with the best lip-sync quality; 2) the one with the best gesture-sync quality; 3) the one with the most natural gestures. The final result is computed by the averaged percentage of each method selected as the best in each question. After the test, we collect 65 effective questionnaires in total.

**Implementation Details.** When preparing data, we segment videos into short clips of 64 frames in 15 FPS (about 4 seconds). To eliminate the scale difference across speakers and video resolutions, we re-scale the skeletons of each speaker according to their averaged shoulder widths. We set the dimension of template vector space = 32 in all the experiments. Although our method is not sensitive to too large a dimension leads to degradation of gesture-syncing and too low a dimension limits the expressiveness of the template space. We use a batch size of 32 for both training and test. We train our model with an Adam optimizer for 100 epochs. We use learning rate 0.0001, and downscale it for 10 times at the 90 and 98<sup>th</sup> epoch. When testing, we randomly sample a template vector from the trained ones corresponding to clips in the training set, making our results diverse and non-deterministic.

#### 4.1. Regression with Learned Templates

As the core of our method, template vector learning makes it possible to learn the one-to-many mapping from a piece of speech audio to feasible gesture sequences merely with a regression loss. In Table 1, we show quantitative comparison between different configurations of templates. The model without templates gets the worst FTD, indicating poor expressiveness of learned gestures. On the contrary, the model with frame-wise template vectors gets the worst lip-sync error ( $E_{lip}$ ), indicating degradation in gesture-syncing. This results from the excessive expressiveness of per-frame template vectors since the model can simply store per-frame gestures in the per-frame template vectors without extracting information from the audio signal. Meanwhile, our models with clip-wise template vector (learned

Figure 4: Visualization of ground-truth gestures versus generated gestures in the template space. By feeding in a gesture sequence to the encoder of our trained VAE, we obtain the template vector of it. For visualization, we project the template vectors onto a 2D plane with PCA.

either by back-propagation or VAE) achieve the best balance between synchronization and expressiveness with relatively low lip-sync error and FTD. In other words, our models with clip-wise templates produce more diverse gestures with almost no harm to synchronization.

To confirm the variety of our results, we use the encoder of our trained VAE to obtain the corresponding template vectors of both the ground-truth and the generated gesture sequences and visualize them by projection onto a 2D plane via PCA. As shown in Figure 4, for the model without templates, the encoded vectors gather around the origin. In contrast, the encoded vectors of our results from clip-wise templates span a larger space, showing a larger variety, which is consistent with the lower FTD values in Table 1.

#### 4.2. Comparison with Baselines

**Baselines.** Speech2Gesture [44] is a fully convolutional model that directly regresses from a mel-spectrogram to gesture sequences. To add keypoints of the face, we enlarge the number of channels for the last convolution layer. For the best balance between the regression loss and the adversarial loss, we set the weight for the latter one to 0.1. Audio to Body Dynamics [29] is a sequential model with separate LSTM [18] models for regression of body and hand keypoints. We add one more LSTM model for face keypoints. Following the original configuration, we feed in a 28-channel MFCC. We adjust the hidden layer dimension of LSTM models from 200 in the original implementation to 800 for the best performance. MoGlow [2] is a probabilistic gesture generator based on normalising flows [26]. We modify its output channels to adapt to our task. For better performance, we feed in mel-spectrogram instead of MFCC, and set the hidden layer dimension = 800 and the number of normalizing steps = 12.

**Objective Comparison.** We compare our models with the above baselines across four speakers. As shown in Table 2, our models produce the smallest normalized lip-sync error and the smallest FTD on all speakers, indicating superior gesture-syncing and expressiveness. Meanwhile, our

Table 1: Effects of template learning in different settings. Red digits refer to the worst among listed models. Our models with clip-wise templates achieve the best balance between synchronization and expressiveness.

	template type	$E_{lip}$ #	FTD #
w/o template	-	0.17	1.66
w/ template-BP	frame-wise	0.21	0.78
w/ template-BP	clip-wise	0.17	1.26
w/ template-VAE	clip-wise	0.17	0.92

Table 2: Comparison with baselines for gesture generation on two English speakers from the Speech2Gesture [14] dataset (Oliver and Kubinec) and two Mandarin speakers that we collect (Xing and Luo). Our models produce results with superior synchronization and expressiveness. Note that lower distance does not indicate better performance for our task.

	Oliver			Kubinec			Xing			Luo		
	L <sub>2</sub> dist.	E <sub>lip</sub> #	FTD #	L <sub>2</sub> dist.	E <sub>lip</sub> #	FTD #	L <sub>2</sub> dist.	E <sub>lip</sub> #	FTD #	L <sub>2</sub> dist.	E <sub>lip</sub> #	FTD #
Audio to Body [29]	49.7	0.19	3.48	70.9	0.17	4.51	50.9	0.18	4.75	48.4	0.16	2.70
Speech2Gesture [14]	53.5	0.23	8.30	64.9	0.20	4.53	48.0	0.19	4.49	63.7	0.20	3.10
MoGlow [2]	50.6	0.20	2.28	78.1	0.16	2.49	48.4	0.18	4.94	54.8	0.18	1.47
Ours (w/ template-BP)	50.6	0.17	1.26	83.7	0.15	1.98	50.0	0.17	2.72	51.5	0.16	1.21
Ours (w/ template-VAE)	62.4	0.17	0.92	100.7	0.15	1.07	57.8	0.18	1.72	80.8	0.17	0.69

models produce relatively high  $L_2$  distances. This is expected since our results are generated with randomly sampled template vectors, which should not always conform to the ground truth gesture.

**Subjective Comparison.** For a perceptual comparison between methods, we invite volunteers to watch anonymized results and choose the best in three aspects. Examples of synthesized images used in the human study are shown in Figure 7. According to the bar chart in Figure 5, our models show significant advantages over baseline models. It is to be mentioned that this human study verifies the strong correlation between the performance of lip syncing and body syncing, which endorses our proposal of adopting the normalized lip-sync error  $E_{lp}$  as a proxy metric to measure the extent of how a gesture is synchronous with the speech audio.

Figure 6: Visualization of the template vector space. Each scatter plot is a projection of the template vector space of a subject, which is close to a Gaussian distribution. The green point in a scatter plot is the endpoint of a sampled template vector, while the orange one refers to its opposite vector. Each line of skeleton sequences corresponds to a template vector by color. For each subject, the gesture sequences of opposite template vectors exhibit clear semantic symmetry.

Figure 5: Human study on participants' preference in lip and body synchronization and naturalness among methods (in percentage).

plate vectors, we adopt a closed-form factorization algorithm proposed by Shen and Zhou [28] for latent semantics discovery. Taking the weight matrix of the first layer of the VAE's decoder, we conduct eigenvalue decomposition and keep the eigenvector with the largest eigenvalue. From the results for Oliver and Xing in Figure 6, we observe high semantic symmetry such as the position and orientation of heads and hands.

### 4.3. Visualization of Template Space

For a better interpretation of the template vectors, we explore the property of the vector space. We visualize the corresponding gestures of a particular template vector and its opposite by feeding the vectors into our trained VAE's decoder, respectively. Instead of manually selecting tem-

### 4.4. Long-Term Generation with Templates

Now that we can generate gesture sequences with diverse appearances by switching template vectors, how about generating a longer sequence? Given that the building blocks of our network are convolutions, our method is born with the ability to generalize to longer input audio. However, with a fixed template vector, our method will still look repeti-

Figure 7: Examples of image frames synthesized from generated gesture sequences with our image synthesis module. In the 1<sup>st</sup> and the 2<sup>d</sup> lines are Oliver and Kubinec from the Speech2Gesture [14] dataset.

tious in a longer term. Therefore, the next problem before us is how to model the transition of template vectors across frames. Towards this goal, we provide a simple solution.

The key idea here is to generate a long and varying template vector sequence from random signals. Our template sequence generator takes a sequence  $z^R \in \mathbb{R}^{C \times F}$  of driving signal sampled from Gaussian distribution as the input and outputs a long template sequence  $z^C \in \mathbb{R}^{C \times F}$ . To assure that the template vector  $z^C$  at each frame of  $T$  resembles the trained clip-wise template vectors, we feed it to a discriminator. Additionally, we apply an adjacency loss ( $L_{adj}$ ) to enforce local continuity of the template sequence  $T$  and a KL divergence ( $L_{KL}$ ) loss to encourage diffusion of template vectors on an entire template sequence. The total loss function for long-term template sequence generation is defined as follows:

$$L_T = L_{GAN} + \lambda_{KL} L_{KL} + \lambda_{adj} L_{adj};$$

where  $\lambda_{KL} = 1$ ;  $\lambda_{adj} = 1$  in our experiments. The results of long-term generation can be found in supplementary video.

#### 4.5. Ablation Studies

**Transposed Instance Normalization.** In our experiments, we observe significant improvements in  $E_{lip}$  and FTD by substituting BN (Batch Normalization) with IN (Instance Normalization) as shown in the 1<sup>st</sup> and the 2<sup>nd</sup> row in Table 3. However, models with IN produce results with high-frequent vibrations. Therefore, we propose the transposed instance normalization (TIN) which conducts normalization on the dimension of keypoints ( $2K; F$ ) rather than frames ( $2K; F$ ). This operation produces stable gesture sequences with comparable performance (the row in Table 3).

**Hierarchical Gesture Representation.** Considering the kinematics of the human body, we try to decouple body parts by a hierarchical body representation with separate root nodes for keypoints of the face, arms, and hands. Com-

Table 3: Ablation study on the normalization operation and body representation. Experiments are conducted on our model without template vectors on Oliver. IN denotes our proposed transposed instance normalization. Hierarchical denotes that gesture keypoints are split into four parts, and each part has its local root node.

	Hierarchical	$E_{lip}$ #	FTD #
BN		0.20	7.01
IN		0.19	1.54
IN		0.19	1.53
IN	X	0.17	1.66

paring the 3<sup>rd</sup> row and the 4<sup>th</sup> row of Table 3, we can see an obvious improvement on lip syncing ( $E_{lip}$ ).

## 5. Conclusion

This paper aims to synthesize a gesture sequence of the complete upper body given speech audio as input. Based on the fact that speech cannot fully determine gestures, we propose to learn a set of gesture templates, which relieve the ambiguity and increase the variety and delicacy of synthesized gestures. Furthermore, we propose to use the normalized lip-sync error as a proxy metric for gesture synchronization and FTD as a measurement of delicacy. Quantitative and qualitative results on four speakers across two languages show the superiority of our method.

## Acknowledgments

The work was supported by National Key R&D Program of China (2018AAA0100704), NSFC #61932020, Science and Technology Commission of Shanghai Municipality (Grant No. 20ZR1436000), and “Shuguang Program” supported by Shanghai Education Development Foundation and Shanghai Municipal Education Commission. We thank UniDT (Shanghai) Co., Ltd for the assistance in collecting Com-data of Mandarin speakers.



## References

- [1] Chaitanya Ahuja, Dong Won Lee, Yukiko I Nakano, and Louis-Philippe Morency. Style transfer for co-speech gesture animation: A multi-speaker conditional-mixture approach. In *European Conference on Computer Vision* 2020. 1, 2, 3
- [2] Simon Alexanderson, Gustav Eje Henter, Taras Kucherenko, and Jonas Beskow. Style-controllable speech-driven gesture synthesis using normalising flows. *Computer Graphics Forum*, volume 39, pages 487–496. Wiley Online Library, 2020. 2, 3, 6, 7
- [3] Guha Balakrishnan, Amy Zhao, Adrian V Dalca, Fredo Durand, and John Guttag. Synthesizing images of humans in unseen poses. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* pages 8340–8348, 2018. 3
- [4] Volker Blanz and Thomas Vetter. A morphable model for the synthesis of 3d faces. *Proceedings of the 26th annual conference on Computer graphics and interactive techniques* pages 187–194, 1999. 3
- [5] Egor Burkov, Igor Pasechnik, Artur Grigorev, and Victor Lempitsky. Neural head reenactment with latent pose descriptors. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* pages 13786–13795, 2020. 3
- [6] Zhe Cao, Gines Hidalgo, Tomas Simon, Shih-En Wei, and Yaser Sheikh. Openpose: realtime multi-person 2d pose estimation using part affinity fields. *IEEE transactions on pattern analysis and machine intelligence*, 43(1):172–186, 2019. 5
- [7] Justine Cassell, Catherine Pelachaud, Norman Badler, Mark Steedman, Brett Achorn, Tripp Becket, Brett Douville, Scott Prevost, and Matthew Stone. Animated conversation: rule-based generation of facial expression, gesture & spoken intonation for multiple conversational agents. *Proceedings of the 21st annual conference on Computer graphics and interactive techniques* pages 413–420, 1994. 1
- [8] Caroline Chan, Shiry Ginosar, Tinghui Zhou, and Alexei A Efros. Everybody dance now. *Proceedings of the IEEE/CVF International Conference on Computer Vision* pages 5933–5942, 2019. 1
- [9] Lele Chen, Guofeng Cui, Celong Liu, Zhong Li, Ziyi Kou, Yi Xu, and Chenliang Xu. Talking-head generation with rhythmic head motion. In *European Conference on Computer Vision*, pages 35–51. Springer, 2020. 3
- [10] Lele Chen, Zhiheng Li, Ross K Maddox, Zhiyao Duan, and Chenliang Xu. Lip movements generation at a glance. In *Proceedings of the European Conference on Computer Vision (ECCV)* pages 520–535, 2018. 3
- [11] Joon Son Chung, Amir Jamaludin, and Andrew Zisserman. You said that? *arXiv preprint arXiv:1705.02966* 2017. 3
- [12] Ylva Ferstl, Michael Neff, and Rachel McDonnell. Multi-objective adversarial gesture generation. *Motion, Interaction and Games* pages 1–10. 2019. 1
- [13] Guy Gafni, Justus Thies, Michael Zollhofer, and Matthias Nießner. Dynamic neural radiance fields for monocular 4d facial avatar reconstruction. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* pages 8649–8658, 2021. 3
- [14] Shiry Ginosar, Amir Bar, Gefen Kohavi, Caroline Chan, Andrew Owens, and Jitendra Malik. Learning individual styles of conversational gesture. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* pages 3497–3506, 2019. 1, 2, 3, 5, 6, 7, 8
- [15] Dai Hasegawa, Naoshi Kaneko, Shinichi Shirakawa, Hiroshi Sakuta, and Kazuhiko Sumi. Evaluation of speech-to-gesture generation using bi-directional lstm network. *Proceedings of the 18th International Conference on Intelligent Virtual Agents* pages 79–86, 2018. 1
- [16] Dai Hasegawa, Naoshi Kaneko, Shinichi Shirakawa, Hiroshi Sakuta, and Kazuhiko Sumi. Evaluation of speech-to-gesture generation using bi-directional lstm network. *Proceedings of the 18th International Conference on Intelligent Virtual Agents IVA '18*, page 79–86, New York, NY, USA, 2018. Association for Computing Machinery. 2
- [17] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. *Advances in neural information processing systems* 30, 2017. 5
- [18] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Comput.* 9(8):1735–1780, Nov. 1997. 6
- [19] Tero Karras, Timo Aila, Samuli Laine, Antti Herva, and Jaakko Lehtinen. Audio-driven facial animation by joint end-to-end learning of pose and emotion. *ACM Transactions on Graphics (TOG)* 36(4):1–12, 2017. 3
- [20] Diederik P. Kingma and Max Welling. Auto-Encoding Variational Bayes. In *2nd International Conference on Learning Representations, ICLR 2014, Banff, AB, Canada, April 14-16, 2014, Conference Track Proceedings* 2014. 2, 5
- [21] Stefan Kopp, Brigitte Krenn, Stacy Marsella, Andrew N Marshall, Catherine Pelachaud, Hannes Pirker, Kristinn R Thórisson, and Hannes Vilhjálmsson. Towards a common framework for multimodal generation: The behavior markup language. In *International workshop on intelligent virtual agents* pages 205–217. Springer, 2006. 1
- [22] Taras Kucherenko, Dai Hasegawa, Gustav Eje Henter, Naoshi Kaneko, and Hedvig Kjellström. Analyzing input and output representations for speech-driven gesture generation. In *Proceedings of the 19th ACM International Conference on Intelligent Virtual Agents* pages 97–104, 2019. 1
- [23] Taras Kucherenko, Dai Hasegawa, Gustav Eje Henter, Naoshi Kaneko, and Hedvig Kjellström. Analyzing input and output representations for speech-driven gesture generation. In *Proceedings of the 19th ACM International Conference on Intelligent Virtual Agents* page 97–104. Association for Computing Machinery, 2019. 2
- [24] Sergey Levine, Philipp Krhenkhl, Sebastian Thrun, and Vladlen Koltun. Gesture controllers. *ACM SIGGRAPH 2010 papers* pages 1–11. 2010. 1
- [25] Miao Liao, Sibozhang, Peng Wang, Hao Zhu, Xinxin Zuo, and Ruigang Yang. Speech2video synthesis with 3d skeleton regularization and expressive body poses. *Proceedings of the Asian Conference on Computer Vision* 2020. 2

- [26] George Papamakarios, Eric Nalisnick, Danilo Jimenez Rezende, Shakir Mohamed, and Balaji Lakshminarayanan. Normalizing flows for probabilistic modeling and inference. arXiv preprint arXiv:1912.02762, 2019. 3, 6
- [27] KR Prajwal, Rudrabha Mukhopadhyay, Vinay P Namboodiri, and CV Jawahar. A lip sync expert is all you need for speech to lip generation in the wild. *Proceedings of the 28th ACM International Conference on Multimedia*, pages 484–492, 2020. 3
- [28] Yujun Shen and Bolei Zhou. Closed-form factorization of latent semantics in gans. 2021. 7
- [29] Eli Shlizerman, Lucio M. Dery, Hayden Schoen, and Ira Kemelmacher-Shlizerman. Audio to body dynamics. In *2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18–22, 2018*, pages 7574–7583. IEEE Computer Society, 2018. 6, 7
- [30] Supasorn Suwajanakorn, Steven M Seitz, and Ira Kemelmacher-Shlizerman. Synthesizing obama: learning lip sync from audio. *ACM Transactions on Graphics (ToG)*, 36(4):1–13, 2017. 1
- [31] Justus Thies, Mohamed Elgharib, Ayush Tewari, Christian Theobalt, and Matthias Nießner. Neural voice puppetry: Audio-driven facial reenactment. *European Conference on Computer Vision*, pages 716–731. Springer, 2020. 3
- [32] Justus Thies, Michael Zollhofer, Marc Stamminger, Christian Theobalt, and Matthias Nießner. Face2face: Real-time face capture and reenactment of rgb videos. *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2387–2395, 2016. 1, 3
- [33] Konstantinos Vougioukas, Stavros Petridis, and Maja Pantic. Realistic speech-driven facial animation with gan. *International Journal of Computer Vision*, pages 1–16, 2019. 3
- [34] Petra Wagner, Zsófia Malisz, and Stefan Kopp. Gesture and speech in interaction: An overview. *Speech Communication*, 57:209–232, 2014. 1
- [35] Ting-Chun Wang, Ming-Yu Liu, Jun-Yan Zhu, Guilin Liu, Andrew Tao, Jan Kautz, and Bryan Catanzaro. Video-to-video synthesis. In *Conference on Neural Information Processing Systems (NeurIPS)*, 2018. 3
- [36] Youngwoo Yoon, Bok Cha, Joo-Haeng Lee, Minsu Jang, Jaeyeon Lee, Jaehong Kim, and Geehyuk Lee. Speech gesture generation from the trimodal context of text, audio, and speaker identity. *ACM Transactions on Graphics (TOG)*, 39(6):1–16, 2020. 1, 2, 3
- [37] Youngwoo Yoon, Woo-Ri Ko, Minsu Jang, Jaeyeon Lee, Jaehong Kim, and Geehyuk Lee. Robots learn social skills: End-to-end learning of co-speech gesture generation for humanoid robots. In *2019 International Conference on Robotics and Automation (ICRA)*, pages 4303–4309. IEEE, 2019. 2
- [38] Egor Zakharov, Aliaksandra Shysheya, Egor Burkov, and Victor Lempitsky. Few-shot adversarial learning of realistic neural talking head models. *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 9459–9468, 2019. 3
- [39] Yang Zhou, Xintong Han, Eli Shechtman, Jose Echevarria, Evangelos Kalogerakis, and Dingzeyu Li. Makeittalk: Speaker-aware talking-head animation. *ACM Transactions on Graphics*, 39(6), 2020. 3